

Article

Internet of Plants (IoP): An IoT-Based Platform for Environmental Monitoring and Phenological Analysis

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Abstract

The Internet of Plants (IoP) represents the convergence of Artificial Intelligence (AI), Big Data analytics, and the Internet of Things (IoT) within protected agricultural systems. This study presents an IoP platform designed to collect, process, and analyze real-time environmental data using specialized IoT sensors capable of monitoring critical variables, including carbon dioxide concentration (CO₂), pH, air temperature, and relative humidity in hydroponic production systems. The proposed framework integrates advanced machine-learning algorithms, including Random Forest Regressor and Long Short-Term Memory (LSTM) neural networks, to process large volumes of environmental data and support crop management. In addition, the platform incorporates Vapor Pressure Deficit (VPD) and Growing Degree Days (GDD) analyses to provide crop-specific recommendations and support informed decision-making. This platform establishes a benchmark for smart agriculture in Mexico's Laja-Bajío region, facilitating informed decision-making and maximizing the sustainability of food systems. Experimental validation was conducted under both controlled and semi-controlled environments using Swiss chard (*Beta vulgaris* subsp. *cicla* L.) and lettuce (*Lactuca sativa* L.) cultivated in hydroponic systems. These environments represented contrasting climatic conditions, allowing evaluation of platform stability and forecasting performance under varying thermal regimes. The Random Forest Regressor model, trained using growth chamber data consisting of 19,836 valid observations, reproduced the deterministic VPD relationship with a coefficient of determination (R²) of 0.90 and a root mean square error (RMSE) of 0.08 kPa, confirming internal consistency and identifying temperature as the dominant contributing variable rather than predicting an independent outcome. The dynamic alarm system, integrated with crop phenological stages, demonstrated greater effectiveness than conventional static-threshold approaches by generating alerts according to crop developmental requirements. Furthermore, the web-based visualization platform enabled users to interpret environmental conditions through intuitive graphical representations, facilitating decision-making without requiring specialized technical expertise. The results demonstrate the feasibility of the IoP platform as a comprehensive environmental management tool for protected agricultural systems. The proposed framework provides a scalable solution for precision agriculture applications in the Laja-Bajío region of Mexico and in other regions with similar production systems.



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1. Introduction

Modern agriculture is undergoing a transformation driven by the need to feed a global population projected to reach 9.7 billion by 2050. According to the Food and Agriculture Organization of the United Nations (FAO), changes to traditional production methods will be required—in line with the 2022–2031 Strategic Framework—which explores current trends to identify alternative futures for agri-food, socio-economic, and environmental systems. The FAO notes that immense volumes of digital data and unprecedented analytical capabilities could drive the transformation of agri-food systems; however, this process is not without potential risks. While digitalization is expected to improve the operational efficiency of agri-food systems, Big Data platforms have recently entered this sector and may already have attained dominant positions [1]. In this context, the integration of artificial intelligence (AI), Big Data analytics, and the Internet of Things (IoT) creates opportunities to optimize the management of protected crops and respond effectively to the evolving challenges of the global agricultural landscape. The Internet of Plants (IoP) emerges as a natural extension of the IoT applied to agricultural environments, focusing on creating smart networks of connected objects that can be remotely identified, monitored, and controlled. This technology could drive an evolutionary change in agriculture and the food supply chain, enhancing both productivity and sustainability of production systems.

IoP-enabled technologies combine real-time sensor networks, advanced data analytics, and machine-learning algorithms to optimize the management of protected crops. The primary objective is to create a technological ecosystem that enables growers to anticipate crop needs and proactively adjust management practices, thereby maximizing productivity while minimizing resource waste.

Protected cultivation systems offer precise control over environmental conditions but face growing challenges regarding resource-use efficiency [2]. The IoP offers an opportunity to modernize agricultural practices by integrating specialized sensors that collect real-time data on critical parameters—such as CO₂, pH, air temperature, and relative humidity—thereby creating a framework in which all elements are interconnected through metadata and semantic criteria that feed into computational models [3]. This connectivity enables the creation of autonomous systems that can respond rapidly to events without centralized replanning.

The current state of research in smart agriculture shows rapid growth in IoT-based technologies for agricultural production [4]. Nevertheless, a significant gap remains between the theoretical potential of these technologies and their practical implementation in commercial agricultural systems, particularly in developing regions such as Mexico. Addressing this gap requires developing integrated, scalable, and user-friendly platforms that deliver useful information directly to producers.

To evaluate the platform, two crops representative of the Laja–Bajío region in Mexico were selected: lettuce (*Lactuca sativa* L.) and Swiss chard (*Beta vulgaris* subsp. *cicla* L.). These species were chosen for their regional economic importance, their compatibility with soilless production systems, and—bottom line for validation—their contrasting physiological profiles: lettuce has a narrow thermal optimum and a short production cycle, whereas Swiss chard tolerates a much wider temperature range over a longer growing period. This contrast enables evaluation of the platform's stability and predictive performance under

markedly different thermal regimes, using species whose environmental sensitivity is well documented in the literature.

Despite the increasing amount of research on IoT-based environmental monitoring for protected agriculture (see Section 2, Related Work), existing systems typically address isolated components of the problem: some calculate VPD as a diagnostic variable without linking it to the phenological stage; others apply machine-learning models for yield prediction without connecting them to real-time alert generation; and others detect anomalous sensor readings without translating that detection into actionable, crop-stage-aware alerts. This work addresses the absence of a unified platform in which real-time GDD accumulation automatically determines the crop's phenological stage, that stage dynamically adjusts alert thresholds, and those thresholds are anticipated—rather than merely diagnosed—using predictive models.

The primary contribution of this research lies not in any of these elements in isolation but in their systematic integration. Specifically, this paper introduces (i) a six-layer platform wherein IoT sensors feed data into a relational database that computes VPD and GDD in real-time; (ii) an automated phenological staging mechanism, whereby accumulated GDD determines the crop's current developmental stage without manual intervention; (iii) a dynamic alert system in which the phenological stage adjusts alert thresholds accordingly, thereby closing the loop between environmental data, derived variables, phenological status, and preventive action; (iv) a predictive layer combining a Random Forest Regressor (for real-time VPD diagnosis) with an LSTM network (for short-term forecasting), thus anticipating conditions rather than merely reacting to them; and (v) experimental validation of the entire system across two contrasting microclimatic environments—a climate-controlled growth chamber and a passive greenhouse—using two physiologically distinct crops (lettuce and chard) over a continuous 45-day period.

This closed loop—comprising environmental data, derived variables, phenological stages, adaptive thresholds, predictions, and preventive alerts—serves as the platform's distinctive contribution in contrast to existing systems that function with static thresholds disconnected from the crop's physiological condition.

The remainder of this article is organized as follows: Section 2 reviews related work and places this study's contribution within the context of current research; Section 3 describes the architecture of the IoP platform and the materials and methods used, including the reference physiological parameters for the validation crops; Section 4 presents the experimental results; Section 5 discusses these findings in relation to existing approaches; and Section 6 presents the conclusions and directions for future work.

2. Related Work

Although many studies focus on individual aspects, few combine them into a single operational platform, which is exactly the gap IoP fills. The system reported in [5] implemented a four-layer IoT architecture (device, fog, cloud, and application) for an aeroponic greenhouse; the platform used ThingSpeak for cloud-based analytics and historical visualization, calculating Vapor Pressure Deficit (VPD) from leaf temperature and relative humidity to detect water stress from the transplant stage onward. This study established the technical feasibility of VPD-based stress monitoring under aeroponic conditions in the Laja-Bajío region but did not incorporate Growing Degree Day (GDD) accumulation, phenology-aware thresholding, or forecasting models, treating VPD as a diagnostic rather than a predictive variable. The review in [6] synthesized 55 studies on in-season crop yield prediction and found that no single modeling approach consistently outperformed others across crops, regions, and prediction horizons. Random Forest emerged as the most widely used algorithm for its robustness, low sensitivity to noise, and stable performance with

heterogeneous environmental, meteorological, soil, and satellite inputs, whereas LSTM networks were identified as ideal for time-series data and seasonal dynamics. The review also distinguished between data-driven machine-learning models and deterministic process-based models, such as APSIM and WOFOST. This distinction directly informs IoP's design, which couples a Random Forest Regressor for diagnosing current VPD status with an LSTM network for short-term forecasting, while reserving deterministic GDD accumulation for phenological projection. Finally, the automated identification of anomalous behaviors reported in [7]—based on attention mechanisms—flags readings as outliers but does not translate them into alerts that account for the phenological stage. IoP incorporates this detection capability into its alert module but links it to phenology-based thresholds, thereby closing the loop between the detected anomaly and timely corrective action (Table 1).

Table 1. Comparative summary of representative IoT-based platforms for VPD, GDD, and decision support.

Reference System	IoT Architecture	VPD/GDD	Dynamic Phenology	Predictive Model	Adaptive Alerts	Experimental Validation	Ref.
Aeroponic Greenhouse (Laja-Bajío)	4 layers (device, Fog, ThingSpeak application)	VPD yes (diagnosis), GDD no	No	No	No (VPD as a non-anticipatory diagnostic variable)	Yes, real-world conditions.	[5]
Optimality Degrees of Microclimate Parameters	Sensor fusion (T, RH, VPD)	VPD yes (normalized index), GDD no	Partial (evaluated by stage)	No	No, a static index does not generate an alert.	Yes, a commercial greenhouse.	[8]
Review of 55 performance prediction studies	NA	NA	No	Comprehensive comparison of RF and LSTM	No	NA	[6]
Anomaly detection	Not specified	No	No	Yes, through an attention mechanism,	Partial indicates anomalies not linked to phenology.	NA	[7]
Decision support system (greenhouse)	Sensor network and web platform	Microclimate parameters, without explicit VPD/GDD	No	No	No, it depends on the user's interpretation.	Yes, field tests.	[9]
Lettuce Hydroponics using LSTM	IoT and LSTM sensor	No, LSTM for nutrients	No	Yes (LSTM)	Partial (static thresholds vs. prediction)	Yes, a 60-day lettuce crop.	[10]
IoP (this work)	6 layers (sensors, communication, cloud, AI, application and integration)	Yes, both are calculated in real time, and GDD is estimated via models.	Si	Yes, RF for diagnosis and LSTM for prognosis	Yes, thresholds dynamically adjusted by phenological stages.	Yes, 45 days in the growth chamber and greenhouse.	

The primary contribution of this work lies not in any of these elements in isolation, but in their systemic integration: a platform where IoT sensors feed a relational database that calculates VPD and GDD in real time; predictive models estimate progression through upcoming stages; accumulated GDD automatically determines the crop's phenological stage; and that stage dynamically adjusts alert thresholds, which are then anticipated by Random Forest and LSTM predictive models. This closed-loop chain—comprising environmental data, derived variables, phenological status, adaptive thresholds, predictions, and proactive alerts—constitutes the IoP platform's distinguishing contribution compared to existing systems that operate using static thresholds disconnected from the crop's physiological stage. The system was experimentally validated using two species with contrasting

profiles—lettuce and Swiss chard—across two environments with different microclimatic conditions—a growth chamber and a greenhouse.

3. Materials and Methods

3.1. Study Variables in IoP

Lettuce (*Lactuca sativa* L.) is a long-day species that exhibits strong sensitivity to environmental conditions [11], making it particularly well-suited for evaluating the predictive capabilities of the IoP platform. Air temperature is the primary environmental factor regulating lettuce metabolism and development. Optimal daytime temperatures range between 18 and 22 °C, whereas temperatures exceeding 26 °C can induce premature bolting and reduce commercial quality [12,13]. The optimal thermal range justifies the need for continuous, high-frequency monitoring, in which readings taken every 5 min allow detection of deviations before physiological damage becomes irreversible. Relative humidity levels between 60% and 80% are generally considered optimal for lettuce production. Under these conditions, the target VPD ranges from 0.4 to 0.8 kPa, promoting adequate transpiration and nutrient transport while minimizing water stress and stomatal closure [14]. The cumulative thermal requirement for completion of the lettuce production cycle—from germination through vegetative growth and harvest—is approximately 600–700 GDD [4,15].

Swiss chard (*Beta vulgaris* subsp. *cicla* L.) was selected as a complementary species because its physiological characteristics differ significantly from those of lettuce. Whereas lettuce has a relatively narrow thermal optimum and a short production cycle, Swiss chard has a broader temperature tolerance and a longer growth period, typically 45 to 90 days, thereby enabling the study of the IoP system's dynamics under conditions of prolonged monitoring and greater seasonal climatic variability [16]. In physiological terms, Swiss chard tolerates a much wider temperature range than lettuce. Optimal daytime temperatures for Swiss chard fall between 16 and 24 °C. Mature plants tolerate light frost (up to about −5 °C) and can withstand temperatures approaching 30 °C without substantial reductions in leaf quality [17]. Swiss chard typically performs best within a VPD range of 0.5–1.0 kPa. Thermal accumulation requirements range from 600 to 800 GDD, depending on cultivar and environmental conditions [4]. Because Swiss chard can be harvested multiple times during a production cycle, it also provides valuable opportunities to evaluate long-term monitoring performance and correlations between environmental conditions and cumulative yield [18].

Table 2 summarizes the ranges for VPD, optimal temperature, and GDD, organized by growth stage; these represent concepts that are particularly important given the controlled nature of the environment. These parameters serve as reference values for the platform's alert thresholds and enable the incorporation of new species into the system's catalog.

Accurate monitoring and control of temperature and Vapor Pressure Deficit have been documented in the literature as strategies to optimize plant growth, diminish disease incidence, and avert water stress. Numerous studies have demonstrated that optimal environmental thresholds vary with crop species and developmental stage, underscoring the importance of dynamic environmental management in protected production systems. Significant differences exist among crop groups regarding thermal accumulation requirements. Leafy vegetables such as lettuce and spinach typically complete their production cycles after accumulating approximately 600–800 degree-days. In contrast, solanaceous crops, including tomato and pepper, generally require between 1800 and 2500 growing degree days to complete development. Because specific thermal requirements for Swiss chard are less extensively documented in the literature, values incorporated into the IoP database were estimated using available studies on closely related *Beta vulgaris* species.

Table 2. Physiological and thermal parameters for protected crops monitored by the IoP platform.

Crop	Stage	Environmental Parameter		T _{base}	Met.	Germ.	Growing Degree Days (GDD)			Cycle	Ref.
		VPD (kPa)	Temp. (°C)				Flower.	Maturity.			
Tomato	Vegetative	0.8–1.0	22–25	10	2	85–100	500–600	1200–1400	1800–2000		[19–21]
	Fruiting	1.0–1.5	23–27								
Cucumber	Vegetative	0.6–0.8	22–24	10–12	1	80–100	350–400	700–800	1100–1300		[20,22]
	Fruiting	0.8–1.0	23–25								
Lettuce	Complete Cycle	0.4–0.8	15–20	4–5	1	45–50	—	600–700	600–700		[4,13,23]
Bell pepper	Vegetative	0.8–1.2	20–25	10	2	120–130	500–600	1400–1800	2000–2500		[24,25]
	Fruiting	1.0–1.4	22–27								
Chili pepper	Vegetative	0.8–1.3	21–26	10	2	120–140	500–600	1200–1600	1800–2300		[25,26]
	Fruiting	1.0–1.4	22–29								
Spinach	Complete Cycle	0.3–0.8	18–20	4–5	1	40–50	—	400–500	400–600		[23,27,28]
Swiss Chard	Complete Cycle	0.5–1.0	16–24	4–5	1	40–50	—	600–800	600–800		[23,28,29]
Strawberry	Vegetative	0.5–0.9	18–22	5–6	1	—	400–500	800–1000	1500–2500		[30,31]
	Fruiting	0.7–1.1	20–24								
Blackberry	Vegetative	0.6–1.0	20–24	6	1	—	600–800	1500–1800	2500–3000		[32,33]
	Fruiting	0.8–1.2	22–26								

Unlike open-field production systems, where environmental conditions are largely determined by natural climatic fluctuations, protected agriculture systems—including greenhouses, growth chambers, and hydroponic facilities—allow precise regulation of environmental conditions. Under these circumstances, Growing Degree Days (GDD) become not only a predictive tool but also a management instrument that can support scheduling, crop planning, and environmental optimization in the context of IoP. The GDD concept is based on the principle that plant development is strongly associated with the accumulation of thermal energy above a species-specific base temperature. In controlled environments, this relationship can be exploited with precision unattainable in conventional field production systems. Temperature—one of the most controllable environmental parameters in these systems—emerges as a strategic factor in scheduling and optimizing entire production cycles. Nevertheless, McMaster et al. [4] identified two principal methods for calculating GDD, each of which can result in substantial estimates of thermal accumulation and affect the precision of phenological predictions related to the development of crops such as Swiss chard, wheat, and maize. Table 2 presents the Growing Degree Days (GDD) required for the main phenological stages of several species of interest in the region’s protected agriculture sector, including the two species used to validate the IoP platform (lettuce and Swiss chard) and those slated for future inclusion in the catalog. The base temperature values and the recommended calculation method (Method 1: no adjustment for minimum temperature; Method 2: adjustment applied when T_{min} < T_{base}, in accordance with McMaster et al. [4]) vary by species; this underscores the necessity for the platform to store these parameters distinctly within the database for each specific crop [34].

Monitoring environmental variables across the five layers is central to the IoP platform, with each parameter playing a specific role in optimizing plant growth. The selection of variables was based on their direct impact on the critical physiological processes of the crops under study, as well as their capacity to be monitored in protected environments.

The monitored variables include air temperature, relative humidity, vapor pressure deficit (calculated using the Tetens equation), and growing degree days (estimated using two methods, according to McMaster et al., 1997 [4]). Additionally, pH and CO₂ concentration are continuously monitored to optimize the system.

Air temperature is the primary variable that directly influences the rates of photosynthesis, cellular respiration, and overall plant metabolism. In hydroponic systems, the established optimal range—typically between 18 °C and 26 °C—varies by species; it tends to be narrower for leafy crops (e.g., 15–24 °C for lettuce and Swiss chard) and broader for solanaceous crops (e.g., 21–29 °C for serrano peppers). This variable is strongly correlated with relative humidity and directly affects the calculation of the vapor pressure deficit.

Vapor Pressure Deficit (VPD) is a derived yet fundamental variable that combines temperature and relative humidity to determine the transpiration potential of plants. Calculated using Tetens' equation, VPD provides a more precise metric than relative humidity alone for assessing water stress and growth conditions.

Growing Degree Days (GDD) are an agroclimatic tool that quantifies the thermal accumulation required for phenological development. Using two calculation methods—according to McMaster et al. (1997) [4]—GDD enable the prediction of transitions between phenological stages and facilitate harvest planning.

Additionally, the solution pH, temperature, and atmospheric CO₂ concentration were continuously monitored as supporting variables to comprehensively optimize the growth environment.

3.1.1. Vapor Pressure Deficit (VPD) Algorithm

VPD was calculated from temperature and relative humidity measurements using Equation (1):

$$VPD = e_s - e_a \quad (1)$$

where e_s corresponds to the saturated vapor pressure (kPa), calculated as $0.611 * \exp((17.27 * T) / (T + 237.3))$; e_a represents the current vapor pressure (kPa), estimated as $e_s * (HR/100)$; T is the air temperature (°C); and HR is the relative humidity (%).

VPD was calculated for each 5 min interval, and hourly, diurnal, nocturnal, and daily average values were derived for each monitoring point.

3.1.2. Growing Degree Days (GDD) Algorithm

GDDs were calculated using the simple average method with temperature thresholds, as shown in Equation [19]:

$$GDD = \Sigma [(T_{max} + T_{min}) / 2 - T_{base}] \quad (2)$$

where T_{max} denotes the daily maximum temperature (°C)—capped at T_{upper} if it exceeds this threshold—and T_{min} denotes the daily minimum temperature (°C)—replaced by T_{base} if it falls below this value; T_{base} represents the base temperature for Swiss chard (4 °C), and T_{upper} defines the upper limit for effective development (30 °C).

GDD values were accumulated throughout the crop cycle, and correlations were established with the observed phenological stages.

3.2. IoP Platform Design

The Internet of Plants (IoP) platform, shown in Figure 1, was designed as a comprehensive technological framework following a component-based architecture that integrates IoT sensors [35], cloud computing processing, and artificial intelligence algorithms. The platform is structured into six layers: (1) an IoT sensor layer for data collection; (2) a communication layer for data transmission; (3) a cloud storage and data management layer; (4) a processing layer featuring artificial intelligence algorithms; (5) an application layer for visualization and control; and (6) a layer for inter-layer integration and communication. This design addresses the demands of modern agricultural and computational systems,

in which integrating multiple heterogeneous data sources requires well-defined abstractions to ensure scalability, modularity, and fault tolerance [36]. This layered separation enables incremental updates to specific components without causing abrupt system interruptions, which is particularly relevant in agricultural production environments, where the platform's continuous monitoring and operational reliability are critical [37].

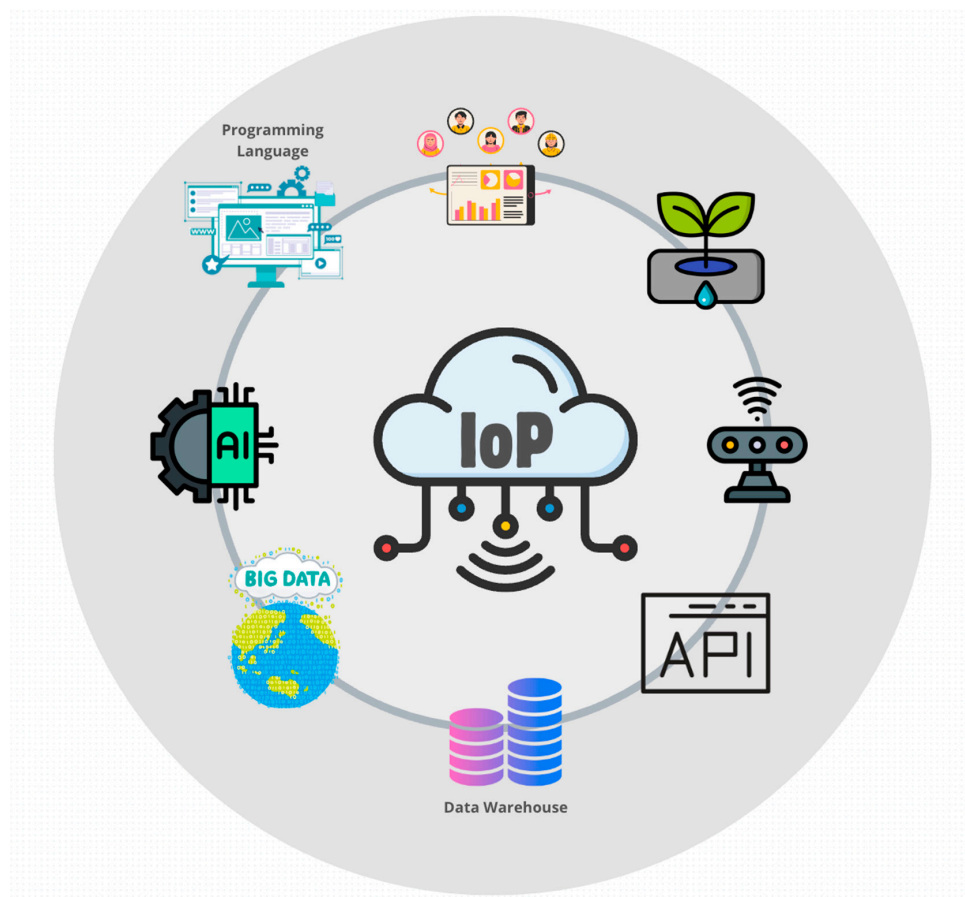


Figure 1. Internet of Plants IoP.

3.2.1. IoT Sensor and Data Acquisition Layer

This layer consists of a distributed network of specialized IoT sensors positioned throughout greenhouses and controlled-environment production systems. This layer corresponds to the perception level in the multi-layer IoT architecture and serves as the entry point for all data that feeds the upper layers for processing and predictive analysis. In precision agriculture, wireless sensor networks have improved crop management by enabling continuous, automated monitoring of critical environmental parameters such as temperature, relative humidity, CO₂ concentration, and photoluminous flux [38].

In IoP, specialized sensors for high-humidity environments were selected (Table 3), consistent with the work of Herrera et al. [39]. The JXBS-3001-TH-RS sensor was chosen for simultaneous measurement of air temperature (−40 °C to 80 °C) and relative humidity (0–100% RH), with ±0.2 °C and ±2% RH accuracy, respectively—characteristics that ensure reliable data in environments where relative humidity often exceeds 85%. The RS-GH-N01-AL sensor was integrated to measure photoluminescent flux (0–2500 μmol m^{−2}s^{−1}), a complementary variable that enables correlation of photosynthetically active radiation with crop physiological responses. Both sensors were integrated using ESP32 microcontrollers, selected for their built-in WiFi and Bluetooth connectivity, low power consumption, and sufficient processing capacity to implement data validation logic directly at the node.

Table 3. Specifications of IoT sensor nodes and microcontrollers deployed by the IoP platform in greenhouses and growth chambers (2024–2026).

Identification				Technical Specifications				IoP Display			
Sensor Model	Variable Measured	Measurement Range	Accuracy	Resol.	Communication Protocol	Source	Energy Consumption	Freq.	Location	IoP Function	Ref.
JXBS-3001-TH-RS	Air Temperature	−40 °C to 80 °C	±0.2 °C	0.1 °C	RS-485 Modbus RTU	12–24 V DC	≤0.4 W	5 min	Greenhouse and Chamber (1 height)	VPD Calculation (Tetens), GDD (McMaster), dynamic alerts, input RF/LSTM	[39]
	Relative Humidity	0–100% HR	±2% HR	0.1% HR							
RS-GH-N01-AL	Photoluminescent Flux (PAR)	0–2500 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$	±5%	1 μmol	RS-485 Modbus RTU	12–24 V DC	≤0.5 W	5 min	Crop canopy	PAR–Photosynthesis Correlation, a complement to predictive models	[39]
JXBS-3001-CO2-RS	CO ₂	0–5000 ppm	±(50 ppm + 3% reading)	1 ppm	RS-485 Modbus RTU	12–24 V DC	≤1 W	5 min	Canopy height	Concentration monitoring for carbon enrichment and ventilation	[39]

Each ESP32 node performs preprocessing before transmission: (i) physical range validation, discarding readings outside plausible limits ($T < -10\text{ }^{\circ}\text{C}$ or $>60\text{ }^{\circ}\text{C}$, RH outside 0–100%); (ii) temporal averaging of consecutive raw samples to attenuate high-frequency sensor noise; and (iii) packaging fields field1–field6 into JSON for transmission via HTTP/POST. Effective transmission intervals vary across nodes based on network conditions and node configuration; the resulting series are therefore resampled to a uniform 5 min resolution during downstream processing. This on-node preprocessing reduces transmission and storage load and constitutes the first of two quality-control levels, complemented downstream in the ETL. This edge computing reduces data transmission volume and boosts energy efficiency, vital for long-term operation. The distributed architecture provides spatial redundancy for capturing environmental data, enabling detection of temperature and humidity variations within the cultivation area and early identification of microclimates that could affect crops such as lettuce and Swiss chard [40,41]. In agriculture, edge computing is especially valuable for quick processing and localized decisions, such as automatic greenhouse regulation. The nodes were set to record data every 5 min, an interval optimal for tracking rapid changes in greenhouse conditions. Longer intervals risk missing events such as ventilation or irrigation, while shorter ones generate more data without significant benefit to phenological monitoring [42]. Table 4 outlines the complete data flow of the IoP platform, from sensor data collection to dashboard display. Each pipeline stage operates at designated frequencies and uses specific components and data formats.

Table 4. Data pipeline of the IoP platform: stages, components, inputs, outputs, and sampling frequency.

Stages	Components	Inputs	Outputs	Frequency
Acquisition	JXBS-3001-TH-RS to ESP32	RS-485 analog signal	JSON (T, HR, CO ₂ , PAR)	5 min
Transmission	ESP32 to ThingSpeak	HTTP/POST JSON	field1–field6 (VARCHAR)	5 min
ETL	Python /psycpg2	ThingSpeak REST API	PostgreSQL (NUMERIC)	5 min
Derived calculation	SQL Functions	T, HR	VPD (kPa), GDD (°C·day)	Per record
RF Prediction	Random Forest (sklearn)	T, HR, hour, GDD, stage	Predicted VPD + importance	Per record
LSTM Prediction	TensorFlow/Keras	36 records (3 h)	T, HR (6 intervals, 30 min)	5 min

3.2.2. Communication and Data Transmission Layer

The second layer implements a communication protocol that uses Wi-Fi for primary data transmission. Messages are structured in JSON format and include a timestamp,

sensor identifier, measured values, and device status codes. Transmission frequency is dynamically adjusted based on environmental variability—during stable conditions, transmissions occur at 5 min intervals. Communication security is ensured through TLS 1.3 encryption and digital certificate-based authentication, which safeguard data integrity and prevent unauthorized access to the system—a critical factor for the overall reliability of the platform. Using the HTTP/REST protocol to communicate with ThingSpeak facilitates interoperability with multiple systems and reduces integration complexity, as ThingSpeak functions as an IoT analytics platform that aggregates, visualizes, and analyzes real-time data streams from connected devices, as illustrated in Figure 2 [43].

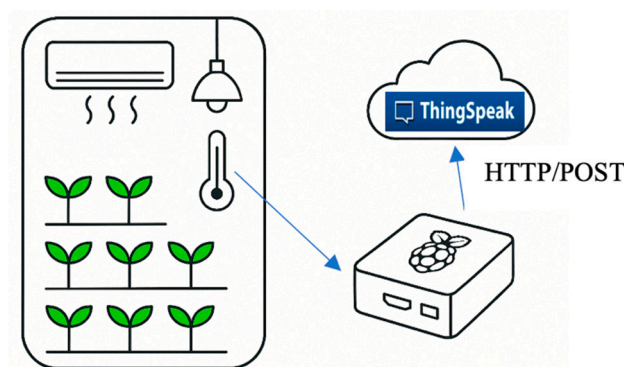


Figure 2. Communication protocol for data transmission from sensors to ThingSpeak.

3.2.3. Cloud Storage and Data Management Layer

The third architectural layer consists of a storage infrastructure within a data warehouse scheme, built on cloud computing services that ensure data availability, durability, and worldwide access. It features a relational database engine, metadata, and configuration optimized for high-frequency time-series data. Additionally, the system offers advanced automated backup features, including replication, to safeguard historical data vital for developing long-term predictive models. Backups are incremental: daily for critical data and weekly for historical data, with customizable retention policies to suit specific needs. PostgreSQL serves as the relational engine, chosen for its proven robustness in IoT contexts and its ability to handle time-series data, device metadata, and relationships among agricultural entities within a single database, thereby reducing the complexity of multi-database systems [44]. The integration of ThingSpeak (for real-time data capture) and PostgreSQL (for persistent historical storage) follows a two-stage architecture common in smart agriculture systems: an ephemeral cloud layer manages network latency, and a normalized relational IoP data layer guarantees long-term data integrity, permanence, and durability (Figure 3).

3.2.4. Processing Layer with Artificial Intelligence Algorithms

The fourth layer serves as the analytical core of the system depicted in Figure 4, where machine-learning algorithms and advanced analytics transform raw data into actionable information. The protected systems generate continuous streams of multivariate time series characterized by specific features, seasonal variations, and cross-correlations among variables—factors that demand machine-learning approaches capable of capturing complex dependencies and nonlinear relationships between environmental parameters [45]. Artificial intelligence—specifically machine learning—has enabled the optimization of microclimate analysis and modeling in greenhouses, thereby overcoming the limitations of traditional models. These traditional models require the collection and analysis of numerous physical parameters in the greenhouse task, a task rendered complex by the dynamic nature of the variables involved [46].

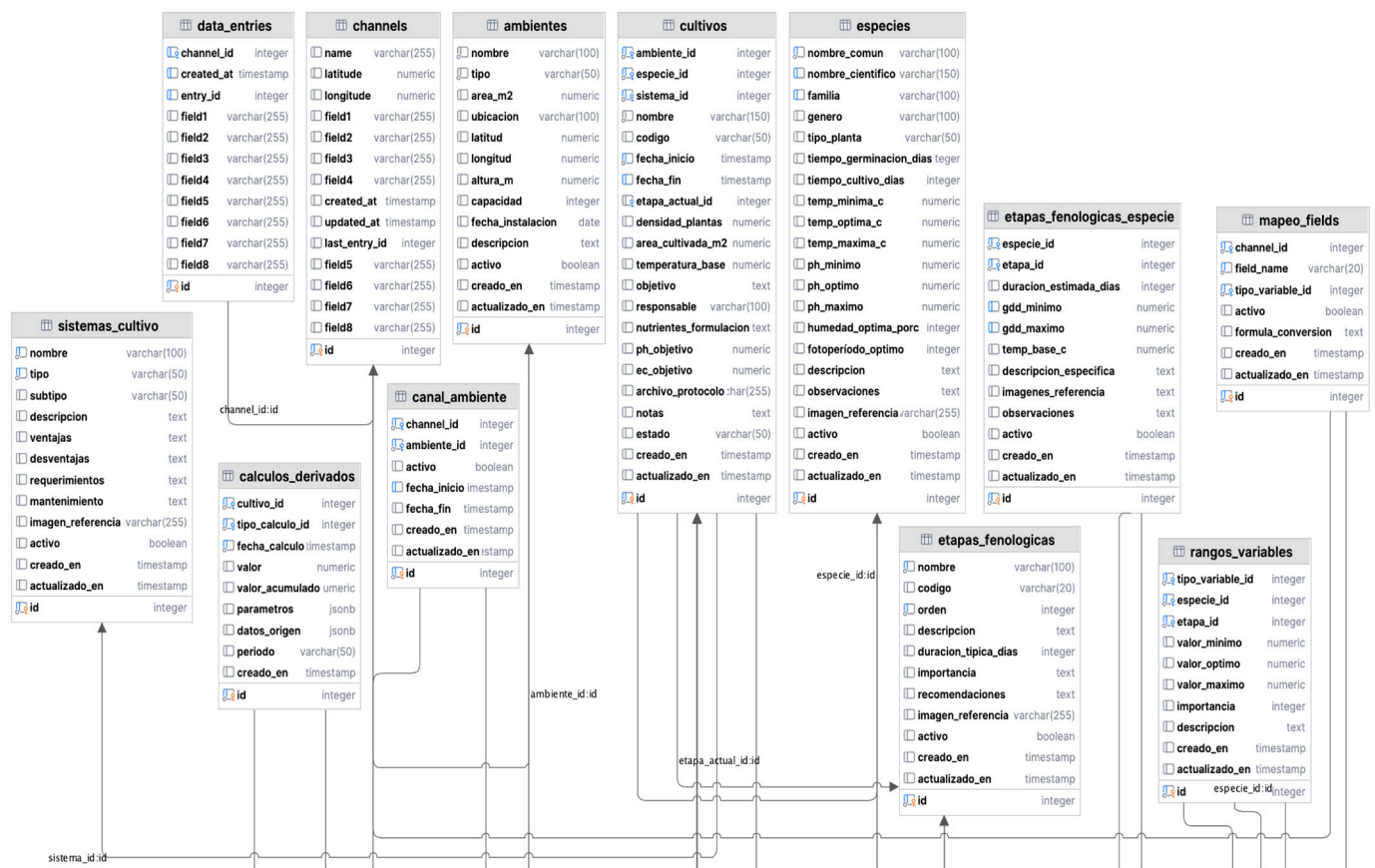


Figure 3. PostgreSQL database management system (relational model).

This layer uses a microservices architecture that enables horizontal scalability and independent updates of analytical components. It supports real-time analysis for immediate alerts, hourly batch analysis for short-term optimizations, and periodic analysis to refine predictive models. Real-time algorithms continuously monitor environmental conditions and trigger alerts when parameters exceed predefined thresholds. The processing structure allows each level to operate at its own frequency and with its own latency tolerance, optimizing computational resource use based on the urgency of the generated information [47,48].

This layered design addresses the need for systems capable of making rapid, localized decisions in response to unpredictable agricultural events, such as abrupt temperature changes, pest outbreaks, or sudden variations in relative humidity, where relying exclusively on cloud processing can introduce unacceptable latencies, leading to delayed responses and losses in crop yield or quality [48,49].

The Random Forest Regressor algorithm was implemented to characterize the relationship between environmental variables [50]. This approach has proven particularly suitable for agricultural systems due to its robustness to outliers and its ability to model complex nonlinear relationships among variables such as temperature, relative humidity, and radiation. The model configuration was optimized through cross-validation, selecting 100 estimators and a maximum depth of 10 levels as a compromise between predictive accuracy and computational efficiency, a critical consideration in IoT environments. Recent studies on microclimate prediction in greenhouses report that ensemble techniques, such as Random Forest, perform well at estimating environmental variables under controlled conditions, achieving coefficients of determination greater than 0.90 across various experimental scenarios. Additionally, the ability of Random Forest to estimate variable importance allows the identification of environmental factors that exert the greatest influence on VPD

across different phenological stages of crops such as lettuce and chard, facilitating more precise and timely agronomic decisions [51,52].

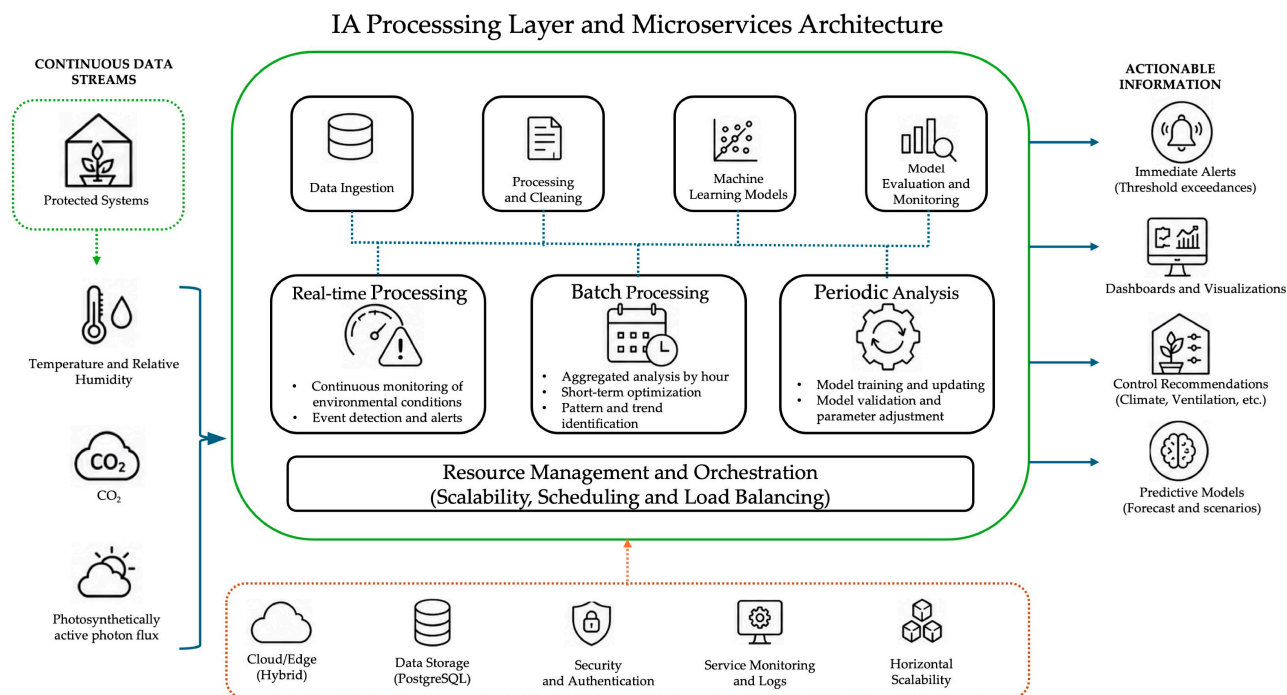


Figure 4. Processing layer with artificial intelligence algorithms (machine learning) and microservices architecture.

LSTM neural networks were integrated at the refinement analysis level to forecast temperature and relative humidity over horizons of 5 to 30 min. LSTM captures temporal dependencies that classical methods like ARIMA cannot adequately model in nonlinear systems such as greenhouse microclimates, yielding R^2 values greater than 0.90 for temperature and greater than 0.80 for relative humidity, consistent with results reported in hydroponic greenhouse climate prediction [53]. On the IoP platform, the LSTM implementation was carried out in Python 3.10.12 using the TensorFlow/Keras library on the back end of a server running PostgreSQL. The model receives sequences of normalized readings from the "data_entries" table, which stores the raw high-frequency sensor stream. Since transmission intervals vary across nodes owing to network conditions, the raw series is resampled to a uniform 5 min resolution by temporal averaging prior to model input; this averaging also attenuates high-frequency sensor noise. The input vector comprises temperature, relative humidity, calculated VPD, and time of day, with a configurable time window of 36 records (equivalent to 3 h at 5 min resolution). The model outputs temperature and relative humidity predictions for the next six 5 min intervals, spanning a 30 min forecast horizon, which directly feed into the predictive alarm system described at the end of Section 3.2.6. VPD is not predicted by the network: it is derived deterministically from the forecast temperature and relative humidity through Tetens' equation, consistent with the direct calculation applied to current measurements. When the LSTM prediction anticipates that the derived VPD will exceed the thresholds for the current phenological stage, the system generates a preemptive alert before the adverse condition materializes [54]. Given the temporal autocorrelation inherent in 5 min sampling series, the data-splitting strategy for the LSTM models was strictly chronological rather than random: the earliest 80% of observations were assigned to training and the most recent 20% to testing, with no shuffling at any stage. Sequence windows of 36 records were constructed independently within each partition, so that no input window spans the training–test boundary. A random 80/20 split

was deliberately avoided, as temporally adjacent records—separated by only 5 min and therefore highly correlated—would appear simultaneously in both partitions, inflating the reported forecast accuracy and the preventive-alert performance derived from it.

The platform's strategy thus combines four methodologically distinct components: the direct, deterministic calculation of current VPD from measured temperature and relative humidity using Tetens' equation; the deterministic accumulation of GDD, which drives phenological staging and the dynamic thresholds that underpin agronomic decision support; LSTM networks for short-term forecasting of unobserved values; and the Random Forest Regressor for identifying the relative influence of environmental variables and assessing model transferability across environments. This separation leverages the complementary strengths of physically based models and machine learning within a hybrid approach, with each component addressing a problem the others cannot.

The model serves two purposes: quantifying the relative importance of environmental variables on atmospheric water condition and assessing the transferability of a model fitted in the growth chamber to the greenhouse. R^2 and RMSE are reported to verify internal consistency with respect to the known physical function, not as evidence of predictive capability on an independent outcome. The algorithm queries the "data_entries" and "species" tables in PostgreSQL, filtering for records from the active cultivation cycle and discarding invalid data. It then constructs a feature vector comprising temperature, relative humidity, time of day, day of the year, accumulated GDD, and an encoded phenological stage, with the calculated VPD as the reference variable. The model is configured with 100 estimators, a maximum depth of 10 levels, a minimum of five samples per node, and full parallelization [55]. To prevent data leakage caused by the temporal autocorrelation inherent in 5 min sampling series, the dataset split was performed chronologically rather than randomly: the first 36 days (80%) were assigned to training and the last 9 days (20%) to testing, without randomization. Cross-validation was also applied. The model is evaluated on the test set using the R^2 coefficient, and the relative importance of each predictor variable is extracted and ranked.

3.2.5. Application Layer for Visualization and Control

The fifth layer offers web interfaces catering to producers and system administrators, crafted with an awareness of the diverse levels of technological proficiency among users within the agricultural sector [47]. Conventional tabular displays are often challenging for producers to interpret and may hinder engagement with IoT monitoring systems [56,57]. Developed using PHP 8.4 and integrated with PostgreSQL, the interface comprises separate dashboards for the greenhouse and the growth chamber. These dashboards include time-series trend graphs, color-coded "traffic-light" indicators based on thresholds for the current phenological stage (green = optimal, yellow = tolerable, red = critical), and an active alerts panel that shows severity levels and cumulative exposure durations. Additionally, the interface features temperature-humidity scatter plots with overlaid VPD estimates (see Figure 5)—aligned with Shamshiri's guidelines [19]—and provides data export options in CSV, JSON, and Excel formats to accommodate various user profiles [58].

3.2.6. Integration and Communication Between Layers

The integration among the layers shown in Figure 6 of the IoP platform is achieved through standardized RESTful APIs that serve as communication middleware, connecting embedded IoT devices, cloud services, and end-user applications. The RESTful architecture—based on the HTTP request-response mechanism—constitutes an established standard for interoperability within heterogeneous IoT ecosystems, offering an interface that is easily understood by both developers and machine-to-machine (M2M) systems [59].

These RESTful APIs manage the end-to-end data flow across the entire IoT chain: from the ESP32 sensor nodes (edge devices) to the ThingSpeak platform (cloud gateway) via HTTP/POST; from ThingSpeak to the Python/psycopg2 backend—which feeds the PostgreSQL database (relational data lake)—via HTTP/GET requests to the REST API; from the database to the machine-learning models (IoT analytics layer); and finally, from the backend to the PHP web interface that serves IoT dashboards to the end user (application layer). This REST-based communication chain ensures decoupling between layers—a fundamental principle in IoT architectures that allows each component to be updated, replaced, or scaled independently without disrupting the overall system’s operation.

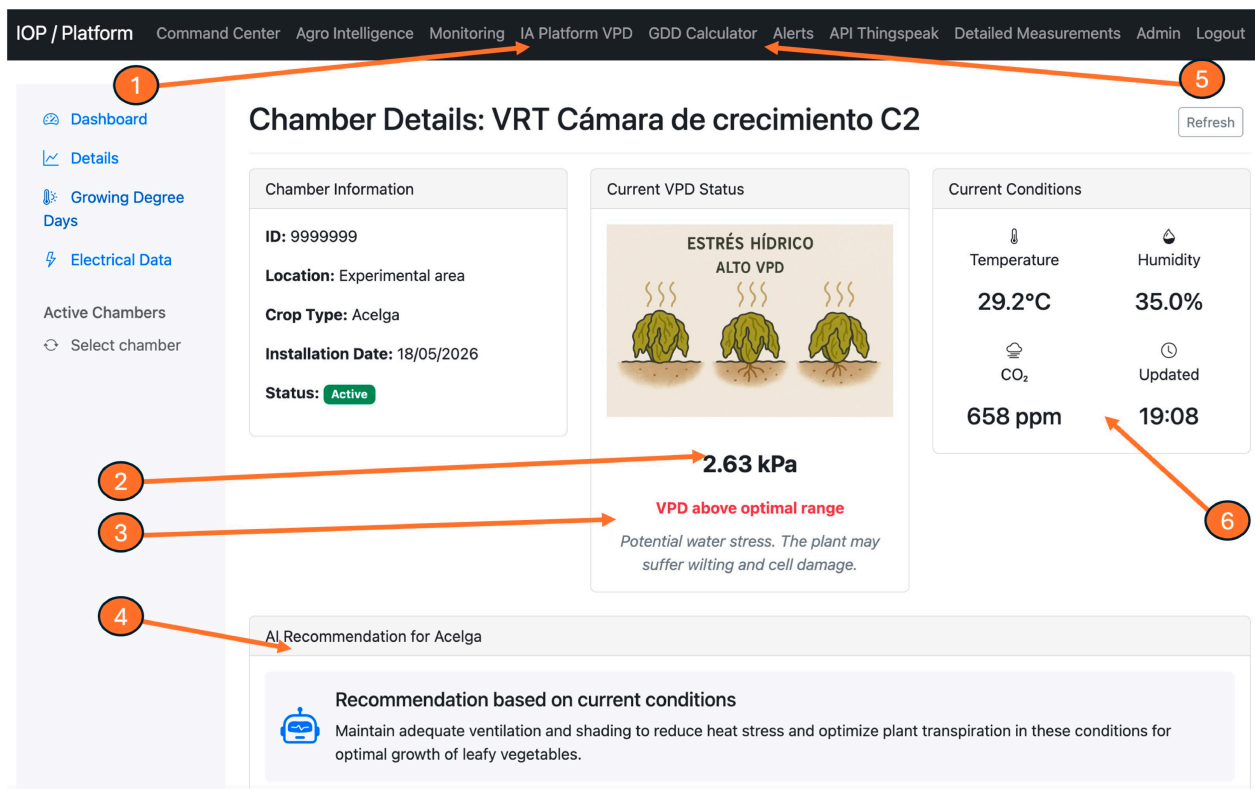


Figure 5. In the (VRT) growth chamber, Swiss chard at 29.2 °C and 35.0% relative humidity has a current VPD of 2.63 kPa, which is well above the optimal range. This condition may lead to severe water stress, resulting in plant wilting and cell damage. (1) Main menu on the platform, (2) Current VPD status, (3) LSTM-based analysis identifies a VPD value above the optimal range, (4) AI recommendation, the current environmental conditions suggest elevated VPD and possible temperature stress, (5) GDD calculator and phenological development estimator, (6) current conditions.

Operating on a microservices architecture enables horizontal scalability and the independent updating of various analytical components. Processing is structured into three tiers: real-time analysis for immediate alerts, hourly batch analysis for short-term optimizations, and periodic analysis for refining predictive models. Real-time algorithms continuously monitor environmental conditions to generate alerts whenever parameters exceed predefined thresholds, as illustrated in Figure 7. This hierarchical processing structure allows each tier to operate at its own frequency and latency tolerance, thereby optimizing computational resource utilization based on the urgency of the generated information. This tiered design addresses a need documented in the literature for systems capable of making rapid, localized decisions regarding unpredictable agricultural events—such as abrupt temperature shifts, pest outbreaks, or sudden fluctuations in relative humidity—where relying

exclusively on cloud-based processing can introduce unacceptable latencies, resulting in delayed responses and losses in crop yield or quality [58].

Integration and Communication Between Layers

Secure and efficient data flow enables interoperability, real-time responses, and intelligent decision-making across the IoP platform.

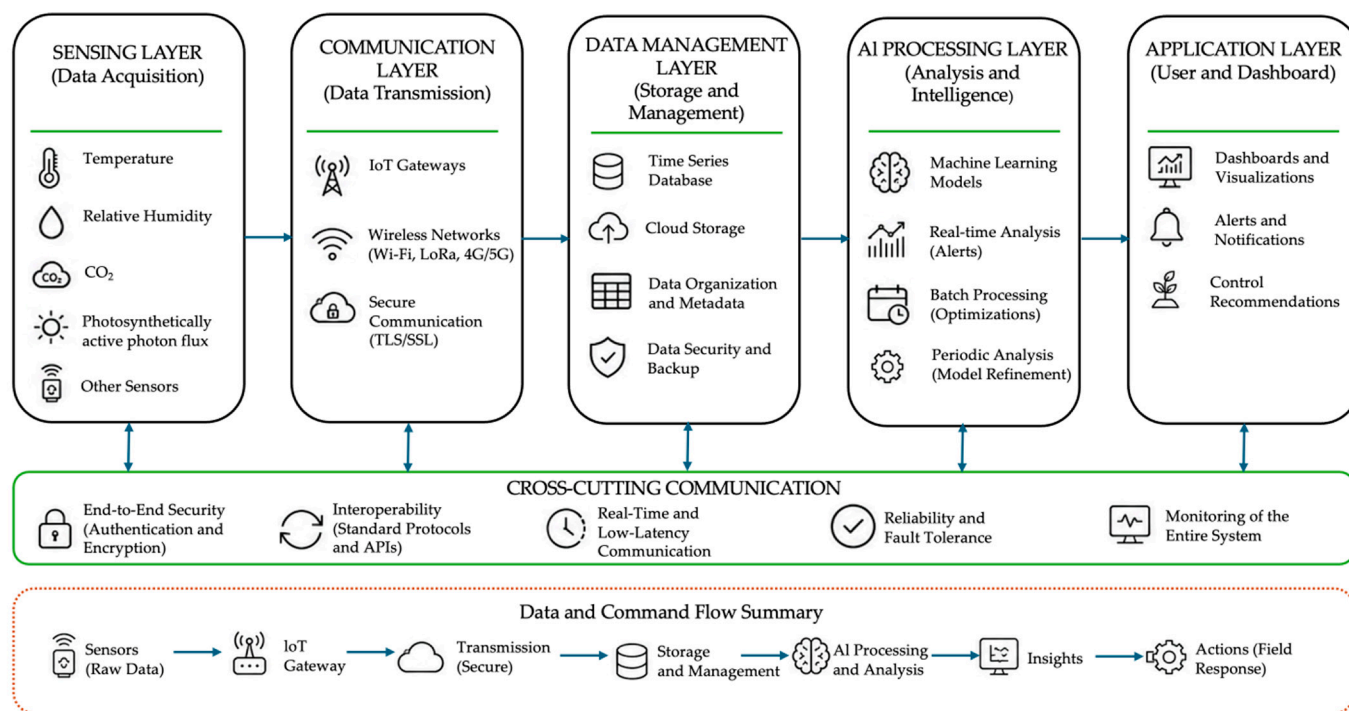


Figure 6. Integration and communication between layers.

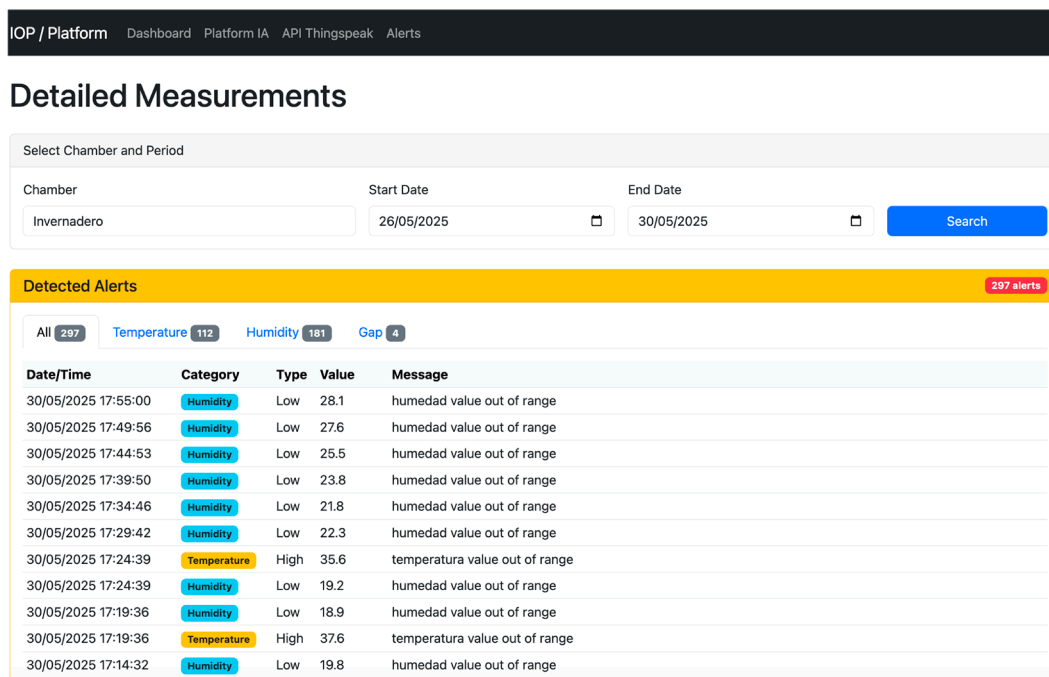


Figure 7. Detailed threshold measurements from the greenhouse alarm module.

4. Results

4.1. Operational Performance of the IoP Platform

IoP operated almost continuously during a 45-day evaluation period spanning April and May 2025, which corresponded to the dry season in the Laja–Bajío region, in two environments at (20°32.4804' N, 100°48.7774' W, 1750 m above sea level): a climate-controlled growth chamber with regulation of temperature, humidity, and photoperiod (12:12 h of light and darkness), and a passive greenhouse without an active cooling system.

The growth chamber processed a total of 25,223 temperature and relative humidity measurements—based on active nodes—achieving 97.1% availability (1051.2 effective hours out of 1080 possible hours). Interruptions totaled 19.4 h due to WiFi signal loss (1.8%) and 11.9 h due to power failures (1.1%), resulting in a data loss of 2.9% of the total expected measurements. The greenhouse—exposed to more adverse weather conditions that impacted both environmental variables and the stability of the electronic equipment—recorded an availability of 94.5% (1020 effective hours), with a total of 23,817 measurements processed. In this environment, WiFi interruptions were higher (34.6 h, 3.2%), as were power interruptions (24.8 h, 2.3%), resulting in 5.5% data loss. These availability figures demonstrate the robustness of the two-stage ThingSpeak–PostgreSQL architecture implemented in the platform, particularly considering that the ESP32 nodes operated continuously in environments where relative humidity frequently exceeded 85% within the growth chamber.

The data flow from the JXBS-3001-TH-RS and RS-GH-N01-AL sensors to ThingSpeak via HTTP/POST—and subsequently to PostgreSQL via the Python/psycpg2 ETL process—executed without critical integrity errors throughout the entire period. The UNIQUE constraint on '(channel_id, entry_id)' in the 'data_entries' table successfully prevented record duplication across the 49,040 combined records from both environments. The normalization process—which transforms the VARCHAR fields from ThingSpeak (field1 through field6) into native numeric types within the 'environmental_readings' table—identified and flagged as invalid 1.3% of outlier readings in the growth chamber and 3.8% in the greenhouse; these outliers were primarily associated with transient spikes occurring during the startup of the air conditioning system and the opening of ventilation vents, respectively.

4.2. Comparative Environmental Characterization: Growth Chamber vs. Greenhouse

The two experimental environments exhibited markedly distinct climatic profiles, confirming the appropriateness of their selection as contrasting scenarios for validating the IoP platform. Table 5 summarizes the descriptive statistics of the monitored variables and the percentage of time each variable remained within the optimal range defined for Swiss chard crops.

Table 5. Comparative environmental characterization between growth chamber and greenhouse for Swiss chard cultivation.

Variable	Growth Chamber	Greenhouse	Growth Chamber Optimal Range %	Greenhouse Optimal Range %
Temperature (°C)	16.3–18.9	10.1–40.4	98.4%	58.3%
Relative humidity (%)	58.3–84.7	21.9–96.2	89.7%	-
VPD (kPa)	0.41–1.03	0.2–5.7 *	94.1%	-
Thermal amplitude (°C)	2.6	30.3	-	-

* Includes values in the fungal risk zone (<0.2 kPa) and severe water stress zone (>1.5 kPa), values based on the observed environmental range and alarm behavior.

The growth chamber maintained the temperature within a narrow range (16.3–18.9 °C, a span of just 2.6 °C), reflecting the effectiveness of the climate control system—comprising LED lighting and air conditioning—operating under controlled 12:12 h light-dark photoperiods. For 98.4% of the time, the temperature remained within the optimal range for Swiss chard (16–24 °C), creating ideal conditions for sustained foliar growth. Relative humidity fluctuated between 58.3% and 84.7%, remaining within range 89.7% of the time; meanwhile, the VPD—calculated using Tetens' equation—varied between 0.41 and 1.03 kPa, staying within the optimal range (0.5–1.0 kPa) for 94.1% of the period. These results indicate that the growth chamber provided a stable environment in which environmental stress was virtually negligible.

In contrast, the greenhouse exhibited a thermal amplitude of 30.3 °C (ranging from 10.1 °C to 40.4 °C), with temperatures within the optimal range for only 58.3% of the time. Minimum temperatures (10.1 °C) occurred in the early morning hours of April, while peaks of 40.4 °C coincided with periods of maximum solar radiation in May, significantly exceeding the critical zone (>28 °C) defined in the thresholding algorithm. Relative humidity within the greenhouse ranged from 21.9% to 96.2%, reflecting the transition from very dry conditions at midday to nocturnal condensation. Greenhouse VPD reached up to 5.7 kPa—nearly five times the threshold for severe water stress (>1.5 kPa)—during peak-temperature hours and periods of lowest relative humidity; such conditions could induce partial or severe stomatal closure and significantly limit photosynthetic activity in Swiss chard if sustained. Vertical profiles from the three nodes revealed temperature gradients of up to 3.2 °C between the lower and upper levels during periods of maximum solar radiation in the greenhouse, confirming the importance of a multi-level sensor distribution for capturing the thermal stratification that induces differential VPD conditions between the leaf canopy and the root zone.

4.3. VPD-GDD Correlation and Automated Phenological Monitoring

Phenological analysis revealed a significant correlation ($R^2 = 0.89$) between combined VPD-GDD values and leaf development in Swiss chard crops. GDD accumulated at an average rate of 14.2 ± 2.1 °C per day in the growth chamber and 16.8 ± 3.5 °C per day in the greenhouse, indicating that phenological transitions occurred more rapidly in the greenhouse due to higher thermal accumulation from elevated daytime temperatures. Table 6 presents the phenological transitions detected by the automated system—based on accumulated GDD—and their concordance with manual observations conducted every three days.

Table 6. Phenological transitions based on accumulated GDD and agreement with manual observations.

Phenological Stage	GDD Range	Automatic Detection Day	Manual Observation Day	Concordance (%)
Establishment	40–60	5	6	90
Vegetative	120–250	18	20	92
Foliar expansion	300–450	28	30	88
Harvest	600–700	38	45	85

Automatic stage detection based on accumulated GDD coincided (Figure 8) with manual observations in 92% of cases in the growth chamber and in 85% in the greenhouse. The lower concordance in the greenhouse was attributed to greater daily thermal variability, which generates irregular GDD accumulations, with days of extreme temperature peaks (>30 °C—limited to T_{upper} in the algorithm) alternating with cool days, resulting in a less predictable phenological progression than in the controlled chamber. The transition

from vegetative growth to progressive harvest occurred 7 days earlier in the greenhouse compared to the growth chamber (day 38 vs. day 45), confirming that accelerated thermal accumulation in less-regulated environments shifts the phenological timeline and requires the alert system to dynamically adjust its thresholds.

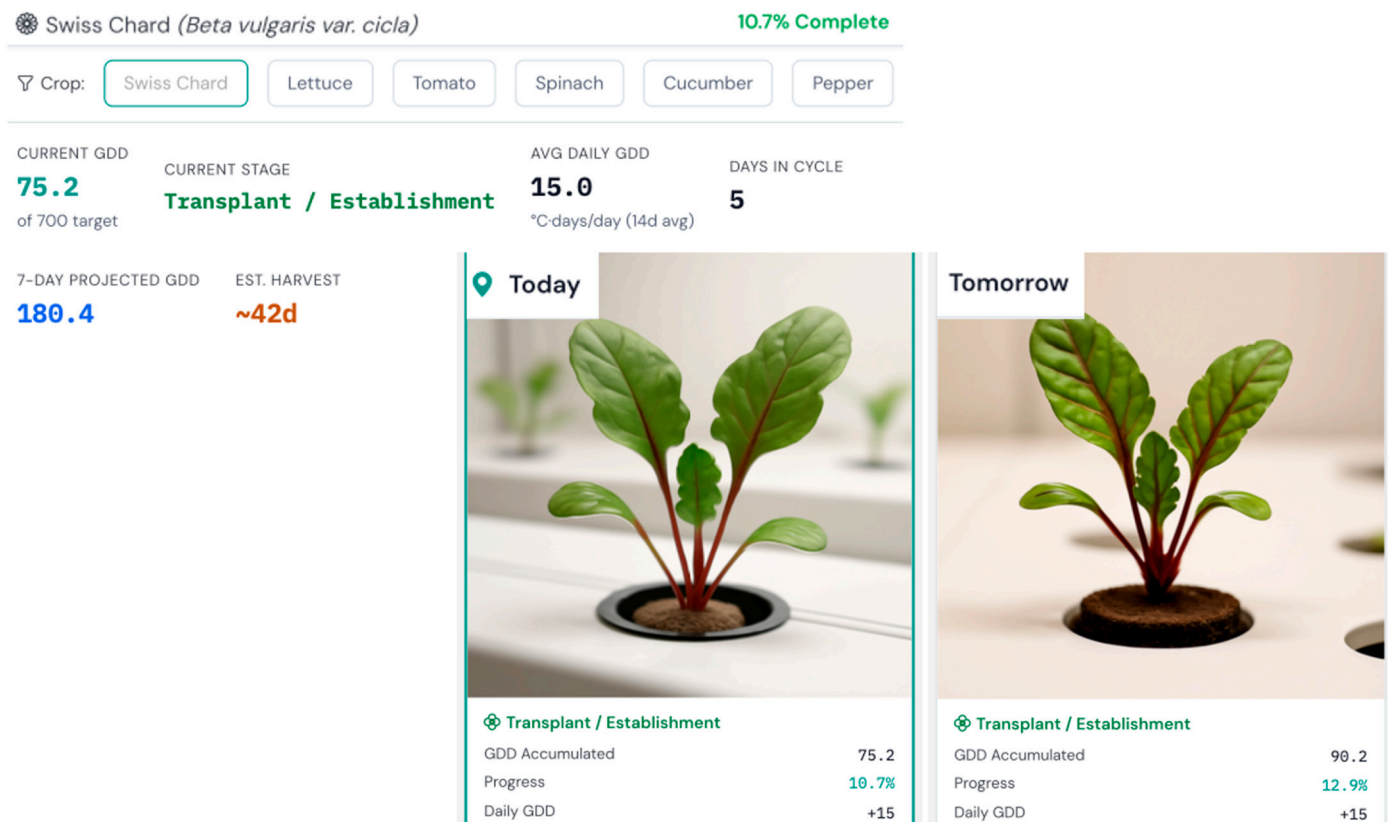


Figure 8. Forecast of crop growth, stage identification, and estimated harvest date.

4.4. Performance of Predictive Models

The Random Forest Regressor, trained on growth chamber data (19,836 valid records after quality filtering), achieved an R^2 of 0.90 and an RMSE of 0.08 kPa for VPD. A relative variable importance analysis showed that air temperature was the dominant contributing variable (importance = 0.52), followed by relative humidity (0.31), time of day (0.09), accumulated GDD (0.05), and encoded phenological stage (0.03). When the chamber-trained model was applied to greenhouse data, the R^2 dropped to 0.81 and the RMSE increased to 0.19 kPa, reflecting greater variability and extreme conditions not represented in the training dataset. Retraining the model with combined data from both environments (80% training, 20% testing, stratified by environment) improved generalization, yielding an R^2 of 0.91 and an RMSE of 0.12 kPa on the mixed test set. This suggests that a unified model can operate in both scenarios with acceptable accuracy, but that environment-specific models offer superior performance when sufficient training data are available.

Networks trained on sequences of 36 records (a 3 h window) to predict the subsequent 6 intervals (a 30 min horizon) achieved an R^2 of 0.97 for temperature and 0.83 for relative humidity within the growth chamber. In the greenhouse, performance yielded an R^2 of 0.91 for temperature and 0.72 for relative humidity, with more pronounced degradation during the transition hours between daytime and nighttime, when changes are most abrupt. Combining the LSTM forecast with the calculation of future VPD—derived using Tetens' formula—enabled the generation of preventive alerts with an average lead time of 15 min, thereby providing the operator with a response window that was previously

unavailable under the reactive alert system, which relied solely on thresholds applied to current measurements. In total, the LSTM forecasting system issued 28 preventive alerts during the experimental period. Of these, 23 were confirmed—defined as instances in which the forecasted adverse condition materialized within the 30 min forecast horizon—yielding an 82% confirmation rate (23/28), while the remaining 5 were false positives (18%). Missed events (adverse conditions that occurred without a preceding alert) were not systematically quantified, as continuous agronomic ground-truth observation was not conducted for every event; this is acknowledged as a limitation.

The growth chamber generated 23 notifications over 45 days, of which 12 were temperature alerts (primarily due to air-conditioning issues caused by power failures) and 8 were VPD alerts (associated with momentary drops in relative humidity when the chamber door was opened), and the remainder corresponded to other monitored variables. The greenhouse, in contrast, accumulated 186 notifications; of these, 108 were temperature alerts concentrated between 11:00 a.m. and 4:00 p.m., when direct solar radiation raised the internal temperature above 24 °C, and 67 were VPD alerts, predominantly falling into the “water stress” (VPD 1.3–1.5 kPa) and “severe water stress” (VPD > 1.5 kPa) categories, with the remainder corresponding to other monitored variables. The average response time of the alarm system was 5–6 min—consistent with the IoT sensors’ sampling interval—representing an improvement over manual monitoring, where detection and correction times can extend for hours.

This contextualization proved particularly valuable in the greenhouse, where an identical VPD reading of 1.4 kPa triggers alerts of varying severity depending on whether it occurs during the seedling stage (high sensitivity, “critical” severity) or during the progressive harvest stage (greater tolerance, “warning” severity). The progressive temporal severity system demonstrated its utility by distinguishing between transient excursions—which resolved within less than 15 min without intervention—and sustained conditions requiring corrective action. In the greenhouse, 121 of the 186 recorded excursions (approximately 65%) were transient, whereas only 65 (approximately 35%) were sustained conditions warranting intervention; a static-threshold system that does not account for exposure duration would have reported all 186 as alarms. The temporal severity criterion therefore reduced non-actionable (false) alarms by an estimated 65% relative to the static-threshold count, while retaining the 35% of events that represented genuinely sustained conditions (Table 7).

Table 7. Transient and sustained temperature excursions in the growth chamber and greenhouse.

System	Total Notifications	Temperature Alerts	VPD	Other *	Transient Conditions	Sustained Conditions	% Transient Conditions	% Sustained Conditions
Growth chamber	23	12	8	3	20	3	86.95%	13.04%
Greenhouse	186	108	67	11	121	65	65.05%	34.94%

* CO₂ and PAR sensors.

False alarms (transient/non-actionable alarms) were operationally defined as alerts in which the monitored variable returned to the optimal range within less than 15 min without operator intervention. Both counting schemes were applied retrospectively to the same set of recorded events and the same threshold values, differing only in whether exposure duration was considered: under the static-threshold criteria, every excursion crossing a threshold is counted as an alert, whereas under the progressive temporal severity criteria only sustained excursions are counted. This figure therefore constitutes an estimate derived from processing the recorded events under the counting criteria, rather than the outcome of operating two independent alert systems in parallel. It should also be noted that

continuous agronomic observations of foliar stress were not conducted for each individual alert, a limitation acknowledged by the study.

4.5. Integration of the IoP Database and Data Pipeline

The PostgreSQL relational schema was organized around five principal entities: “data_entries” (raw ThingSpeak records), “calculos_derivados” (normalized readings using native numeric types, including calculated VPD and GDD), “etapas_fenologicas” (definitions of phenological stages with GDD ranges per species), “etapas_fenologicas_especie” (identification of transitions with accumulated GDD and detection methods), and “especies” (crop-specific, configurable physiological parameters).

The PostgreSQL database scheme proved functional for historical storage and analytical querying throughout the experimental period. The pipeline processed 49,040 sensor readings into normalized derived values during the experimental period using native numeric types, each including the VPD and GDD contributions automatically calculated by the SQL functions “calculate_vpd()” and “calculate_gdd()”. Drawing from the “mapeo_fields,” “calculos_derivados,” and “etapas_fenologicas” tables, 90 daily summaries were generated (45 days $\times$ 2 environments); each summary contained statistics on temperature (min, max, avg), relative humidity, daytime and nighttime VPD, daily GDD, accumulated GDD, and the current phenological stage, thereby constituting the direct training dataset for the machine-learning models. The “etapas_fenologicas” and “etapas_fenologicas_especie” tables recorded 6 automatic phenological transitions (3 per environment), each documented with the exact accumulated GDD at the moment of transition and the detection method (automatic). The materialized view—which combines the daily summaries with temporal features (day of the year, week, and 3-, 7-, and 14-day moving averages)—was refreshed every 24 h without impacting the performance of real-time queries from the PHP dashboard, thereby demonstrating the viability of PostgreSQL as a unified engine for time-series IoT data and relational agronomic metadata within a single instance.

Indexing was designed around the platform’s predominant query patterns. For the ‘calculos_derivados’ table, a composite index—‘idx_calculos_cultivo_tipo (cultivo_id, tipo_calculo_id)’—was created to support retrieval by crop cycle and calculation type (e.g., VPD, GDD), alongside ‘idx_calculos_fecha (fecha_calculo)’ for time-range filtering. For the ‘cultivos’ table, foreign key indexes—‘(ambiente_id, especie_id, sistema_id)’—and ‘idx_cultivos_fechas (fecha_inicio, fecha_fin)’ were implemented to facilitate historical queries based on cycle windows. Additionally, partial indexes were employed for the most frequently accessed entities—‘idx_cultivos_activos ON cultivos(id) WHERE fecha_fin IS NULL’ and ‘idx_canal_ambiente_activo ON canal_ambiente(channel_id) WHERE activo = TRUE’. These restrict the index structure to the current cycle and active channel mapping, thereby reducing index size and real-time query costs without compromising continuous write operations.

Data integrity during continuous combination—ensured by the “UNIQUE (channel_id, entry_id)” constraint on the “data_entries” table—confers idempotency on the ETL process: insertion retries after network failures do not create duplicates because each reading is uniquely identified by its source channel and its ThingSpeak entry ID. This same constraint provides the unique index the query planner uses to access data by channel and time range. Referential integrity is maintained through explicit foreign keys linking derived entities to their corresponding crop cycle, species, and environment, ensuring that no derived record can exist without its associated agronomic context.

Inactivity was measured under operational conditions: the representative dashboard query was resolved in 25.4 ms using indexed access. Database growth is linear with respect

to the number of active channels and their transmission frequency, and the resulting volume is managed without partitioning.

Reproducibility depends on three design decisions. First, raw records are preserved intact in “data_entries” without being overwritten, allowing any derived value to be recomputed from the original source. Second, VPD and GDD are implemented as deterministic SQL functions (`calculate_vpd()`, `calculate_gdd()`) within the database engine rather than in application code, ensuring that the same raw record always yields the same derived value, regardless of the client invoking them. Third, phenological thresholds and optimal ranges by species and stage are stored as configurable records in “etapas_fenologicas,” “etapas_fenologicas_especie,” and “rangos_variables”—rather than as constants embedded in the code—so the exact conditions under which each alert was issued remain auditable.

4.6. Results from the Visualization and User Experience Platform

The web interface—developed in PHP 8.4 with a direct connection to PostgreSQL—ran continuously throughout the 45-day experimental period, serving IoT dashboards to the two defined user profiles: producers and system administrators. The main dashboard updates at the same rate as the IoT sensors, set to 5 min intervals. Both the general view of the crop cycle—based on daily summaries—and the detailed view—featuring 5 min resolution and direct queries to the “data_entries” table—reflect environmental conditions with a maximum latency of this interval. This performance remained stable even as the database volume exceeded 49,000 normalized records, demonstrating the system’s capacity to handle data querying and visualization in near real time without perceptible performance degradation. Queries parameterized by date range, crop identifier, and variable type executed without perceptible performance degradation, thanks to the indices implemented in PostgreSQL.

The traffic-light indicator system—green for the optimal range, yellow for the tolerance zone, and red for the critical zone—was the component most valued by users during the usage sessions. The indicators updated in real time with each new sensor reading (every 5 min) and reflected the dynamic thresholds of the current phenological stage: for instance, during the seedling stage, the temperature indicator turned yellow at 22 °C, whereas during the progressive harvest stage, that same threshold was relaxed to 26 °C, reflecting the greater tolerance of the mature plant. This automatic adaptation of visual thresholds based on the phenological stage—as detected by accumulated GDD—is a feature that distinguishes the IoP interface from conventional ThingSpeak dashboards, where thresholds are static and do not account for the crop’s physiological state.

The temperature-humidity scatter plots with superimposed VPD isolines (Figure 4) enabled users to visually interpret the position of current greenhouse and growth chamber conditions within the psychrometric space without manual calculations. This visualization revealed patterns not evident in conventional time-series trend charts: in the growth chamber, readings consistently clustered within the optimal VPD zone (0.5–1.0 kPa), forming a compact cluster; whereas in the greenhouse, readings were widely dispersed along the temperature axis, crossing multiple VPD isolines—ranging from the fungal risk zone (<0.2 kPa) during humid early mornings to the severe water stress zone (>1.5 kPa) during dry afternoons. The active alerts panel, displaying severity and accumulated exposure time (Figure 5), provided the operator with an immediate visual hierarchy for prioritizing responses, placing critical alerts with the longest exposure times at the top and recent warnings at the bottom.

The export capabilities were actively utilized during the experimental period: 12 exports in CSV format were generated for statistical analysis of VPD-GDD correlations in Python; 3 exports in JSON format were created for integration with training scripts

for the Random Forest and LSTM models; and 28 exports in Excel format were produced for the technical team's weekly operational reviews. The temporal zoom functionality—which allows users to navigate from a full-cycle overview to individual 5 min readings, with customizable start and end dates set directly within the platform—was used specifically for the retrospective analysis of alarm events. This enabled identification of the conditions preceding each alert and facilitated assessment of whether the operator's response was timely.

The visualization platform thus served as the primary point of contact between the IoT ecosystem and human decision-making, closing the data loop that begins with the ESP32 sensors and culminates in a management action informed by the producer.

5. Discussion

The results demonstrate the IoP platform's performance as an integrated system capable of monitoring, analyzing, and predicting environmental conditions in protected agriculture with high precision. The multilayer architecture demonstrated operational robustness during the experimental period, achieving availability rates of 97.1% in the growth chamber and 94.5% in the greenhouse—figures that exceed reported standards for comparable ESP32-based agricultural IoT systems, where availability rates of 90–95% are considered acceptable [13]. The 2.6-percentage-point difference between the two environments is attributed to the greater exposure of the electronic equipment to adverse conditions within the greenhouses, specifically temperatures reaching up to 40.4 °C and relative humidity up to 96.2%, which increased WiFi connectivity interruptions from 19.4 to 34.6 h. The integration of ThingSpeak as an ephemeral ingestion layer, paired with PostgreSQL for permanent storage, eliminated the historical data retention limitations inherent to the cloud platform, thereby enabling longitudinal analyses spanning multiple crop cycles. For future deployments in greenhouses with similar environmental conditions, these results suggest incorporating IP65-rated protection for sensor nodes and a communication backup mechanism (such as LoRaWAN or local SD card storage) to reduce data loss to below 3%.

The expansion of the IoP platform into additional production contexts depends on three key factors: the cultivated species, the type of facility, and regional climatic conditions. The system's modular design enables this extension, as the physiological parameters for each species—such as temperature ranges, VPD, GDD, and base temperature—are stored as configurable database records rather than being hard-coded within the algorithms. This approach allows for the integration of new species without necessitating modifications to the software architecture.

This research focuses on intelligent environmental regulation rather than physiological crop experimentation. Consequently, the correlation between VPD-GDD and crop development is established solely through visual observation of leaf morphology, without quantitative agronomic measurements (such as plant height, fresh weight, or disease incidence). Therefore, the findings must be interpreted within this scope and should not be extrapolated to claims of increased yield or reduced disease.

The correlation ($R^2 = 0.89$) between combined VPD and GDD and leaf development supports integrating both bioclimatic indicators as key variables in the predictive system. This result aligns with the underlying physiological rationale: VPD is associated with transpiration rates and nutrient flux toward the leaves, whereas accumulated GDD quantifies the thermal energy available for cell division and elongation. The difference in GDD accumulation rates between the growth chamber (14.2 °C·day) and the greenhouse (16.8 °C·day) underscores the importance of environment-specific predictive models, given that the more rapid phenological transitions observed in the greenhouse—specifically, a 7-day lead time in the transition to progressive harvesting—necessitate more frequent and

proactive management adjustments. The 92% concordance between automated GDD-based detection and manual observations in the growth chamber—compared with 85% in the greenhouse—suggests that in environments with high daily thermal variability, supplementing the GDD criterion with periodic manual observations or image analysis may enhance the accuracy of automated phenological monitoring.

Since VPD is calculated deterministically from temperature and relative humidity, the Random Forest Regressor ($R^2 = 0.90$, RMSE = 0.08 kPa) verifies internal consistency rather than predictive capability and supports its suitability for multivariate data with cross-correlations in IoT systems with limited computational resources [50,51,60]. The identification of temperature as the dominant contributing variable reinforces the rationale for the platform's high-frequency monitoring, since small thermal variations produce proportionally larger changes in the calculated VPD. The most significant deployment finding is the performance degradation when the model—originally trained on growth chamber data—was applied to the greenhouse (R^2 dropped from 0.90 to 0.81), followed by a partial recovery after retraining with combined data. This indicates that a unified model can operate in both scenarios with acceptable accuracy; however, installation-specific models—made possible by a database structure that stores historical data separately—offer superior performance when sufficient training data are available. LSTM networks effectively complemented the Random Forest model for short-term forecasting, achieving an R^2 of 0.97 for temperature prediction within the growth chamber. This capability enabled the generation of preventive alerts 15 min in advance with an 82% confirmation rate—a functionality previously unavailable with the reactive alert system, which relied solely on thresholds applied to current measurements.

The alarm system—based on dynamic thresholds with phenological integration—represented the IoP platform's distinguishing contribution compared with conventional monitoring systems that use static thresholds. The marked difference in the number of alerts between the greenhouse (186 notifications, 4.1 per day) and the growth chamber (23 notifications, 0.5 per day) faithfully reflects the environmental stability of each setting and objectively quantifies the gap between a controlled environment (VPD within the optimal range 94.1% of the time) and a semi-naturalized one (VPD within the optimal range 47.8%). The phenological contextualization of alerts facilitated response prioritization; for instance, a VPD reading of 1.4 kPa triggers a “critical” severity level during the seedling stage but only a “warning” during the progressive harvest stage. The progressive temporal scheme reduced non-actionable (false) alarms by an estimated 65% compared with a static-threshold system by distinguishing between transient excursions that resolved spontaneously within 15 min and sustained conditions requiring intervention, while retaining the 35% of events that represented genuinely sustained conditions. Nevertheless, the volume of 186 alerts in the greenhouse could lead to operator fatigue during prolonged deployments; future iterations should implement mechanisms for intelligent alert grouping and prioritization based on cumulative impact on GDD.

The web visualization platform confirmed that, for profiles of producers in the Laja-Bajío region—characterized by heterogeneous levels of digital literacy—intuitive visual representations, such as traffic-light indicators with adaptive thresholds, are more effective than tabular numerical reports [56,57,60]. Temperature-humidity scatter plots with superimposed VPD isolines revealed clustering patterns (a compact cluster in the growth chamber versus wide dispersion in the greenhouse) that were not evident in conventional time-series charts. This suggests that this psychrometric representation should be incorporated as a standard visualization feature in IoT platforms for protected agriculture. The selection of lettuce and Swiss chard as study species proved apt for validating the platform's flexibility, given that their contrasting physiological profiles—a narrow thermal

range of 15–20 °C for lettuce versus a broad range of 16–24 °C for Swiss chard, and target VPDs of 0.4–0.8 kPa versus 0.5–1.0 kPa—required the system to manage differentiated threshold ranges within the same IoT infrastructure.

The study's limitations include the 45-day experimental period coincided with the dry season (April–May), necessitating validation during the rainy season—when external humidity significantly alters the greenhouse's microclimatic profile; the algorithms were optimized for Swiss chard and lettuce, requiring calibration for other species; and reliance on Wi-Fi connectivity poses challenges for rural locations with limited infrastructure. Alarm activation patterns—particularly the 186 VPD notifications in the greenhouse—may vary significantly during the rainy season (June–September), when external relative humidity exceeds 80%.

Future iterations should incorporate PAR radiation sensors and inline electrical conductivity sensors, expand the species catalog to include high-commercial-value Solanaceae crops such as tomatoes and Serrano peppers, implement LoRaWAN protocols, and explore reinforcement learning models for automated actuator control in response to system predictions.

The contribution of the IoP platform lies not in the novelty of its individual technological components—whose maturity and reliability are well established—but in the integration architecture that binds them into a cohesive system for protected agriculture. In the literature reviewed, agricultural IoT systems remain largely confined to monitoring and visualization, without incorporating derived variables of physiological significance [4–6,35,39]; machine-learning models are seldom coupled to the crop's phenological context, and alarm systems rarely employ dynamic thresholds that adapt to the plant's developmental stage. The IoP platform addresses these gaps by linking the IoT perception layer to the automated calculation of VPD and GDD, to phenological staging based on thermal accumulation, and to the generation of alerts whose context and severity are contingent on the detected developmental stage. This combination has not been reported as an integrated system in the literature under review.

6. Conclusions

This research presented the Internet of Plants (IoP) platform—an integrated IoT-based system for environmental monitoring, predictive analysis, and control via dynamic alerts in protected agriculture—validated over a 45-day period in a greenhouse and a growth chamber in Mexico's Laja-Bajío region, using Swiss chard and lettuce grown in hydroponic systems. The multilayer architecture—comprising ESP32 sensor nodes equipped with JXBS-3001-TH-RS and RS-GH-N01-AL sensors; Wi-Fi/HTTP communication with ThingSpeak; permanent data storage in PostgreSQL; data processing via Random Forest Regressor and LSTM networks; a dynamic alarm system featuring phenological integration; and web-based visualization interfaces developed in PHP—proved robust, scalable, and operationally viable, demonstrating a combined availability exceeding 95% and successfully processing 49,040 measurements without critical integrity errors.

The main conclusions are as follows: (1) Integrating VPD and GDD as derived variables enables more precise characterization of crop physiological status than using individual environmental variables, yielding an R^2 of 0.89 between combined VPD-GDD and leaf development and a 92% concordance between automated detection of phenological transitions and manual observations. (2) The Random Forest Regressor reproduced the deterministic VPD relationship with an $R^2 > 0.90$ and an RMSE of 0.08 kPa, confirming internal consistency rather than predicting an independent outcome; the analysis identified temperature as the dominant contributing variable (importance = 0.52) and showed that site-specific models transfer more reliably than unified models across environments, sup-

porting its applicability as a lightweight variable-importance and transferability tool in IoT systems with limited computational resources. (3) LSTM networks achieved an R^2 of 0.97 for temperature prediction with a 30 min horizon, enabling preventive alerts with a 15 min lead time and an 82% confirmation rate—a functionality absent in conventional reactive alert systems. (4) The dynamic alarm system—featuring phenological integration and progressive temporal severity—reduced non-actionable (false) alarms by an estimated 65% in the greenhouse relative to a static-threshold count that does not account for exposure duration, while retaining the 35% of events that represented sustained conditions warranting intervention. (5) The contrast between the growth chamber (VPD within the optimal range: 94.1%; 23 alerts) and the greenhouse (47.8%; 186 alerts) objectively quantified the environmental gap between the two systems, providing data to guide investment in climate control infrastructure.

Future Work

The IoP platform proved to be a functional IoT implementation for protected agriculture in the Laja-Bajío region—or similar areas—that comprehensively and systematically integrates the five layers of the IoT ecosystem—from field sensors to predictive models and decision interfaces—into a single coherent system. This system provides growers with monitoring, prediction, and alerting tools to anticipate crop needs and adjust management practices in real time. Priorities for future work include in the short term, validation during the rainy season and the incorporation of PAR radiation and inline electrical conductivity sensors; in the medium term, expanding the species catalog to include high-commercial-value solanaceous crops and implementing LoRaWAN protocols in areas with limited connectivity; and in the long term, exploring reinforcement learning models for the automated control of actuators in response to system predictions.

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References

1. Food and Agriculture Organization of the United Nations. *The Future of Food and Agriculture: Drivers and Triggers for Transformation*; The Future of Food and Agriculture, No. 3; FAO: Rome, Italy, 2022. [CrossRef]
2. Regmi, A.; Rueda-Kunz, D.; Liu, H.; Trevino, J.; Kathi, S.; Simpson, C. Comparing resource use efficiencies in hydroponic and aeroponic production systems. *Technol. Hortic.* **2024**, *4*, e005. [CrossRef]
3. Rosen, R.; Von Wichert, G.; Lo, G.; Bettenhausen, K.D. About the importance of autonomy and digital twins for the future of manufacturing. *IFAC-PapersOnLine* **2015**, *48*, 567–572. [CrossRef]

4. McMaster, G.S.; Wilhelm, W.; Wilhelm, W.W. Growing degree-days: One equation, two interpretations. *Agric. For. Meteorol.* **1997**, *87*, 291–300. [\[CrossRef\]](#)
5. Méndez-Guzmán, H.A.; Padilla-Medina, J.A.; Martínez-Nolasco, C.; Martínez-Nolasco, J.J.; Barranco-Gutiérrez, A.I.; Contreras-Medina, L.M.; Leon-Rodriguez, M. IoT-based monitoring system applied to aeroponics greenhouse. *Sensors* **2022**, *22*, 5646. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Liu, Z.; Di, L.; Yang, R.; Guo, L.; Zhang, C.; Li, H.; Shao, B. In-season crop yield prediction: State of the art and future research direction. *Int. J. Appl. Earth Obs. Geoinf.* **2026**, *146*, 105129. [\[CrossRef\]](#)
7. Cheng, W.; Ma, T.; Wang, X.; Wang, G. Anomaly detection for Internet of Things time series data using generative adversarial networks with attention mechanism in smart agriculture. *Front. Plant Sci.* **2022**, *13*, 890563. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Rezvani, S.M.; Abyaneh, H.Z.; Shamshiri, R.R.; Balasundram, S.K.; Dworak, V.; Goodarzi, M.; Sultan, M.; Mahns, B. IoT-Based Sensor Data Fusion for Determining Optimality Degrees of Microclimate Parameters in Commercial Greenhouse Production of Tomato. *Sensors* **2020**, *20*, 6474. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Săcăleanu, D.-I.; Matache, M.-G.; Roșu, Ș.-G.; Florea, B.-C.; Manciu, I.-P.; Perișoară, L.-A. IoT-Enhanced Decision Support System for Real-Time Greenhouse Microclimate Monitoring and Control. *Technologies* **2024**, *12*, 230. [\[CrossRef\]](#)
10. Devaraju, S.; Muthusamy, D.; Chandrappa, S.K.; Jathar, C.; Banothu, S.; Atheeswaran, A. Smart hydroponic farming system using IoT-integrated deep learning for real-time nutrient monitoring and climate control. *Ecohydrol. Hydrobiol.* **2026**, *26*, 100754. [\[CrossRef\]](#)
11. Kim, M.J.; Moon, Y.; Tou, J.C.; Mou, B.; Waterland, N.L. Nutritional value, bioactive compounds and health benefits of lettuce (*Lactuca sativa* L.). *J. Food Compos. Anal.* **2016**, *49*, 19–34. [\[CrossRef\]](#)
12. INEGI. Resultados Definitivos del Censo Agropecuario 2022, Estado de Guanajuato. Comunicado de Prensa Núm. 679/23. Según el Censo 2022. 2023. Available online: https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2023/CA_Def/CA_Def2022_Gto.pdf (accessed on 4 April 2026).
13. Ahmed, H.A.; Tong, Y.-X.; Yang, Q.-C. Optimal control of environmental conditions affecting lettuce plant growth in a controlled environment with artificial lighting: A review. *S. Afr. J. Bot.* **2020**, *130*, 75–89. [\[CrossRef\]](#)
14. Amitrano, C.; Roupahel, Y.; De Pascale, S.; De Micco, V. Vapour Pressure Deficit (VPD) Drives the Balance of Hydraulic-Related Anatomical Traits in Lettuce Leaves. *Plants* **2022**, *11*, 2369. [\[CrossRef\]](#) [\[PubMed\]](#)
15. French, A.N.; Sanchez, C.A.; Hunsaker, D.J.; Anderson, R.G.; Saber, M.N.; Wisniewski, E.H. Lettuce evapotranspiration and crop coefficients using eddy covariance and remote sensing observations. *Irrig. Sci.* **2024**, *42*, 1245–1272. [\[CrossRef\]](#)
16. Moreno-Aguilera, C.Y.; Herrera-Arroyo, R.O.; Santoyo-Mora, M.; Martínez-Nolasco, C.; Sámano-Ortega, V.; Martínez Nolasco, J.J.; Petitti, A.; Romeo, L. Evaluation of LED Spectral Treatments on Morphological and Nutritional Parameters of Swiss Chard (*Beta vulgaris* var. cicla) in a Controlled Environment Agriculture System. *Agriculture* **2026**, *16*, 165. [\[CrossRef\]](#)
17. Reinsdorf, E.; Koch, H.; Märlander, B. Phenotype related differences in frost tolerance of winter sugar beet (*Beta vulgaris* L.). *Field Crops Res.* **2013**, *151*, 27–34. [\[CrossRef\]](#)
18. Rubatzky, V.E.; Yamaguchi, M.; World Vegetable Center. *World Vegetables: Principles, Production, and Nutritive Values*, 2nd ed.; Springer: New York, NY, USA, 2012. [\[CrossRef\]](#)
19. Shamshiri, R.R.; Jones, J.W.; Thorp, K.R.; Ahmad, D.; Man, H.C.; Taheri, S. Review of optimum temperature, humidity, and vapour pressure deficit for microclimate evaluation and control in greenhouse cultivation of tomato: A review. *Int. Agrophys.* **2018**, *32*, 287–302. [\[CrossRef\]](#)
20. Zhang, X.; He, D.; Niu, G.; Yan, Z.; Song, J. Effects of environment lighting on the growth, photosynthesis, and quality of hydroponic lettuce in a plant factory. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 33–40. Available online: <https://ijabe.org/index.php/ijabe/article/view/3420> (accessed on 2 February 2026). [\[CrossRef\]](#)
21. Scholberg, J.; McNeal, B.L.; Jones, J.W.; Boote, K.J.; Stanley, C.D.; Obreza, T.A. Growth and Canopy Characteristics of Field-Grown Tomato. *Agron. J.* **2000**, *92*, 152–159. [\[CrossRef\]](#)
22. Perry, K.B.; Wehner, T.C.; Johnson, G.L. Comparison of 14 Methods to Determine Heat Unit Requirements for Cucumber Harvest. *HortScience* **1986**, *21*, 419–423. [\[CrossRef\]](#)
23. Dufault, R.J.; Ward, B.; Hassell, R.L. Dynamic relationships between field temperatures and romaine lettuce yield and head quality. *Sci. Hortic.* **2009**, *120*, 452–459. [\[CrossRef\]](#)
24. Abdelkhalik, A.; Pascual, B.; Nájera, I.; Domene, M.A.; Baixauli, C.; Pascual-Seva, N. Effects of deficit irrigation on the yield and irrigation water use efficiency of drip-irrigated sweet pepper (*Capsicum annuum* L.) under Mediterranean conditions. *Irrig. Sci.* **2020**, *38*, 89–104. [\[CrossRef\]](#)
25. Wurr, D.C.E.; Fellows, J.R.; Phelps, K. Investigating trends in vegetable crop response to increasing temperature associated with climate change. *Sci. Hortic.* **1996**, *66*, 255–263. [\[CrossRef\]](#)
26. Garcia-Caparros, P.; Contreras, J.I.; Baeza, R.; Segura, M.L.; Lao, M.T. Integral management of irrigation water in intensive horticultural systems of Almería. *Sustainability* **2017**, *9*, 2271. [\[CrossRef\]](#)

27. Iwabuchi, K.; Saito, G.; Goto, E.; Takakura, T. Effect of vapor pressure deficit on spinach growth under hypobaric conditions. *Acta Hortic.* **1996**, *440*, 60–64. [CrossRef] [PubMed]
28. González, M.I.; del Pozo, A.; Cotroneo, D.; Perterra, R. Días a floración en espinaca (*Spinacia oleracea* L.) en diversas épocas de siembra: Respuesta a la temperatura y al fotoperíodo. *Agric. Téc.* **2004**, *64*, 331–337. [CrossRef]
29. Papadopoulos, A.P.; Pararajasingham, S.; Shipp, J.L.; Jarvis, W.R.; Jewett, T.J.; Clarke, N.D. Integrated Management of Greenhouse Vegetable Crops. In *Horticultural Reviews*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 1997; pp. 1–39. [CrossRef]
30. Lu, Y.; Gong, M.; Li, J.; Ma, J. Optimizing Controlled Environmental Agriculture for Strawberry Cultivation Using RL-Informer Model. *Agronomy* **2023**, *13*, 2057. [CrossRef]
31. Cruz, L.C.; Velasco, V.A.V.; Villa, M.S.; Luna, J.R.; del Valle, J.R.E. Strawberry crop (*Fragaria ananassa* Duch.) in hydroponic systems with substrate mixtures. *Acta Agron.* **2023**, *72*, 70–77. [CrossRef]
32. Milošević, T.; Milošević, N.; Glišić, I.; Mladenović, J. Fruit quality attributes of blackberry grown under limited environmental conditions. *Plant Soil Environ.* **2012**, *58*, 322–327. [CrossRef]
33. Grey, T.L.; Hurdle, N.L.; Rucker, K.; Basinger, N.T. Blueberry and blackberry are tolerant to repeated indaziflam applications. *Weed Technol.* **2021**, *35*, 560–564. [CrossRef]
34. Bonhomme, R. Bases and limits to using ‘degree.day’ units. *Eur. J. Agron.* **2000**, *13*, 1–10. [CrossRef]
35. Moreno-Aguilera, C.Y.; Botello-Álvarez, J.E.; Martínez-Nolasco, J.J.; Padilla-Medina, J.A.; Martínez-Nolasco, C.; Herrera-Arroyo, R.O. Hydroponic cultivation experiment monitored by an Internet of Things system. *Agrociencia* **2025**, *59*, 966–982. [CrossRef]
36. Atzori, L.; Iera, A.; Morabito, G. The Internet of Things: A survey. *Comput. Netw.* **2010**, *54*, 2787–2805. [CrossRef]
37. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big Data in Smart Farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
38. Soussi, A.; Zero, E.; Sacile, R.; Trincherio, D.; Fossa, M. Smart Sensors and Smart Data for Precision Agriculture: A Review. *Sensors* **2024**, *24*, 2647. [CrossRef] [PubMed]
39. Herrera-Arroyo, R.; Martínez-Nolasco, J.; Botello-Álvarez, E.; Sámano-Ortega, V.; Martínez-Nolasco, C.; Moreno-Aguilera, C. Smart Hydroponic Cultivation System for Lettuce (*Lactuca sativa* L.) Growth Under Different Nutrient Solution Concentrations in a Controlled Environment. *Appl. Syst. Innov.* **2025**, *8*, 110. [CrossRef]
40. Correa-Quiroz, J.J.; Toribio-Barrueto, M.A.; Castro-Vargas, C. IoT System with ESP32 for Smart Drip Irrigation and Climate Monitoring in Greenhouses. *Emerg. Sci. J.* **2025**, *9*, 1133–1157. [CrossRef]
41. Gong, L.; Yu, M.; Jiang, S.; Cutsuridis, V.; Pearson, S. Deep Learning Based Prediction on Greenhouse Crop Yield Combined TCN and RNN. *Sensors* **2021**, *21*, 4537. [CrossRef] [PubMed]
42. Shamshiri, R.; Kalantari, F.; Ting, K.C.; Thorp, K.R.; Hameed, I.A.; Weltzien, C.; Ahmad, D.; Shad, Z.M. Advances in greenhouse automation and controlled environment agriculture: A transition to plant factories and urban agriculture. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 1–22. [CrossRef]
43. Deshmukh, N.; Arora, S.; Pimprale, V. Design and Implementation of ThingSpeak IoT Platform for Environmental Parameter Monitoring. In *ICT: Applications and Social Interfaces*; Advances in Intelligent Systems and Computing; Springer: Singapore, 2024. [CrossRef]
44. Bosch Sensortec. *BME280 Datasheet: Combined Humidity and Pressure Sensor (Rev. 1.24)*; Bosch Sensortec GmbH: Reutlingen, Germany, 2024. Available online: <https://www.bosch-sensortec.com/media/boschsensortec/downloads/datasheets/bst-bme280-ds002.pdf> (accessed on 14 April 2026).
45. Sun, W.; Chang, F.-J. Empowering Greenhouse Cultivation: Dynamic Factors and Machine Learning Unite for Advanced Microclimate Prediction. *Water* **2023**, *15*, 3548. [CrossRef]
46. Xu, D.; Ren, L.; Zhang, X. Predicting Multidimensional Environmental Factor Trends in Greenhouse Microclimates Using a Hybrid Ensemble Approach. *J. Sens.* **2023**, *2023*, 6486940. [CrossRef]
47. Pahl, C. Containerization and the PaaS cloud. *IEEE Cloud Comput.* **2015**, *2*, 24–31. [CrossRef]
48. Yu, P.; Teng, F.; Zhu, W.; Shen, C.; Chen, Z.; Song, J. Cloud–edge–device collaborative computing in smart agriculture: Architectures, applications, and future perspectives. *Front. Plant Sci.* **2025**, *16*, 1668545. [CrossRef] [PubMed]
49. Shi, W.; Cao, J.; Zhang, Q.; Li, Y.; Xu, L. Edge computing: Vision and challenges. *IEEE Internet Things J.* **2016**, *3*, 637–646. [CrossRef]
50. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
51. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [CrossRef]
52. Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. *Comput. Electron. Agric.* **2018**, *145*, 311–318. [CrossRef]
53. Liu, Y.; Li, D.; Wan, S.; Wang, F.; Dou, W.; Xu, X.; Li, S.; Ma, R.; Qi, L. A long short-term memory-based model for greenhouse climate prediction. *Int. J. Intell. Syst.* **2022**, *37*, 135–151. [CrossRef]
54. Petrakis, T.; Kavga, A.; Thomopoulos, V.; Argiriou, A.A. Neural Network Model for Greenhouse Microclimate Predictions. *Agriculture* **2022**, *12*, 780. [CrossRef]

55. Cletus, F.; John, A.E. Comparative Analysis of Machine Learning Models For Greenhouse Microclimate Prediction. *Brill. Res. Artif. Intell.* **2024**, *4*, 162–175. [[CrossRef](#)]
56. Lamsal, R.R.; Karthikeyan, P.; Otero, P.; Ariza, A. Design and Implementation of Internet of Things (IoT) Platform Targeted for Smallholder Farmers: From Nepal Perspective. *Agriculture* **2023**, *13*, 1900. [[CrossRef](#)]
57. Dineva, K.; Atanasova, T. Cloud Data-Driven Intelligent Monitoring System for Interactive Smart Farming. *Sensors* **2022**, *22*, 6566. [[CrossRef](#)] [[PubMed](#)]
58. Siddiqui, H.; Khendek, F.; Toeroe, M. Microservices based architectures for IoT systems—State-of-the-art review. *Internet Things* **2023**, *23*, 100854. [[CrossRef](#)]
59. Penchalaiah, N.; Nelson Emmanuel, J.; Suraj Kamal, S.; Lakshmi Narayana, C.V. IoT Based Smart Farming Using Thingspeak and MATLAB. In *ICCCE 2020; Lecture Notes in Electrical Engineering*; Kumar, A., Mozar, S., Eds.; Springer: Singapore, 2021; Volume 698. [[CrossRef](#)]
60. Collado, E.; Valdés, E.; García, A.; Sáez, Y. Design and implementation of a low-cost IoT-based agroclimatic monitoring system for greenhouses. *AIMS Electron. Electr. Eng.* **2021**, *5*, 251–283. [[CrossRef](#)]

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