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Application of Precision Agriculture and IoT-Based Smart Irrigation in Greenhouse Vegetable Production

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Abstract

Precision agriculture (PA) and Internet of Things (IoT)-based smart irrigation represent transformative technologies for optimizing greenhouse vegetable production, addressing global challenges like population growth (projected 9.7 billion by 2050), water scarcity, and climate variability. This review synthesizes the integration of IoT sensors (soil moisture, EC, pH, microclimate monitors) with data analytics (AI/ML models) and automated actuators for real-time resource management in crops such as tomatoes, cucumbers, and peppers. Key components include wireless sensor networks (WSNs) using protocols like ZigBee/LoRa for data transmission, edge/fog computing for low-latency processing, and predictive algorithms (e.g., LSTM, SVM) that reduce water use by 20–50% while enhancing yield (10–30%) and nutrient efficiency. Case studies from China, Europe, and India demonstrate practical implementations, such as variable rate irrigation (VRI) and fertigation systems, achieving up to 40% energy savings and minimized leaching. Challenges encompass high initial costs, data security, and sensor accuracy in humid environments, with future directions emphasizing AI-driven digital twins, blockchain for traceability, and hybrid renewable energy integration for sustainable, resilient greenhouse systems.

Keywords: Precision Agriculture, Iot, Smart Irrigation, Greenhouse Vegetable Production, Wireless Sensor Networks, Data Analytics, AI/ML, Water Use Efficiency, Yield Optimization, Digital Twins, Fertigation, Climate Resilience

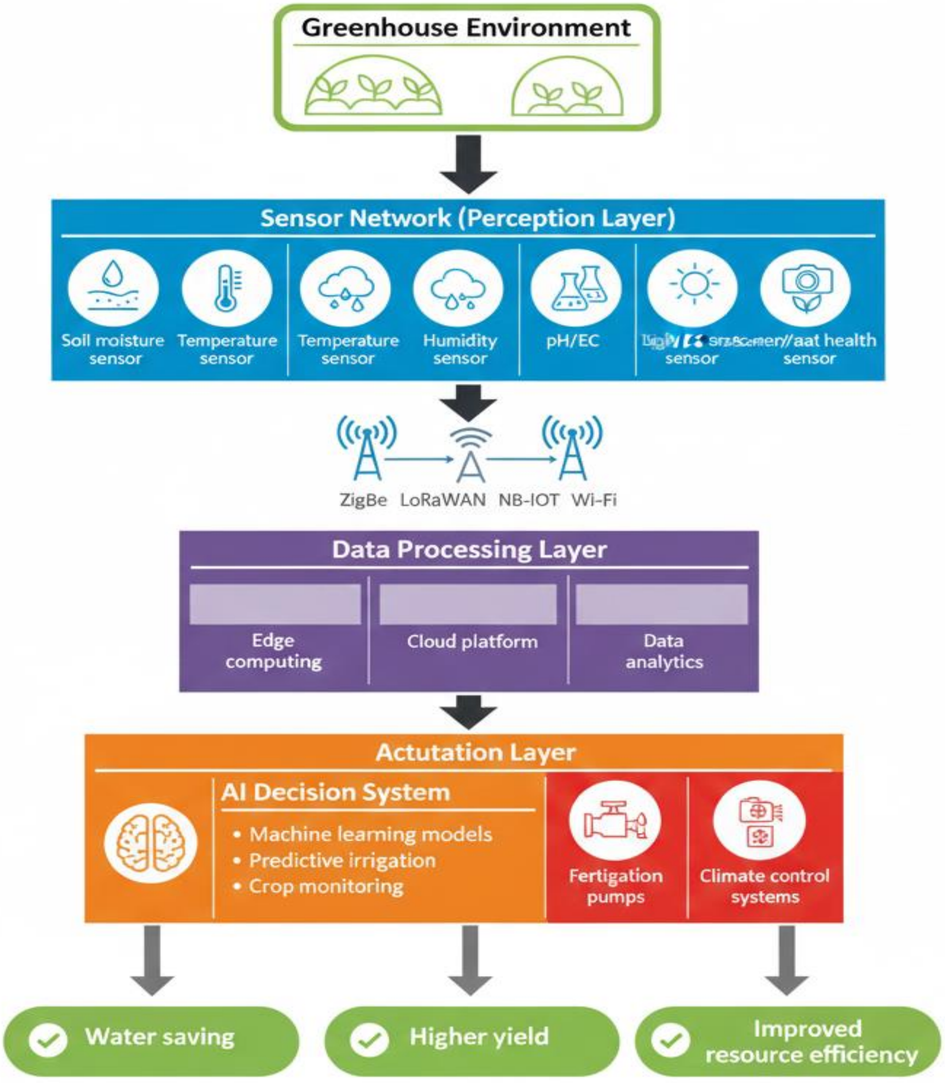
1. Introduction

The global agricultural sector is currently navigating an era of unprecedented systemic pressure, driven by the geometric growth of the human population and the concurrent degradation of natural resources. With the global population projected to reach 9.7 billion by the mid-21st century, the demand for high-quality, nutrient-dense food has never been more acute (Saha et al., 2025). Traditional open-field agriculture is increasingly vulnerable to the vagaries of anthropogenic climate change, manifesting as erratic precipitation patterns, rising average temperatures, and localized water scarcity (Zhang et al., 2023). In this context, greenhouse vegetable production has emerged as a critical solution for ensuring global food security. Unlike open-field systems, greenhouses offer a controlled environment where the microclimate can be manipulated to optimize crop growth regardless of external conditions (Abid et al., 2025). However, the transition from traditional, experience-based greenhouse management to high-tech, industrialized systems requires the integration of Precision Agriculture (PA) and the Internet of Things (IoT). These technologies facilitate a transition toward data-driven decision-making, where every drop of water and every gram of nutrient is applied with surgical precision, thereby maximizing resource use efficiency and minimizing environmental externalities (Puajpanda et al., 2024).

2. Theoretical Foundations of Precision Horticulture

Precision agriculture in the greenhouse environment represents a management strategy that utilizes Information and Communication Technologies (ICT) to observe, measure, and respond to inter- and intra-field variability in crops (Shafi et al., 2025). In the specific domain of vegetable production where crops such as tomatoes, cucumbers, and peppers are highly sensitive to

Figure 1. Conceptual Framewark of IOT-Based Precision Agriculture in Greenhoue Vegetable Production



physiological stressors precision management is not merely an optimization tool but a prerequisite for economic viability (Tripodi et al., 2018). The core mechanism of PA is the feedback loop: sensing the current state of the environment, processing that data through intelligent models, and executing precise interventions through automated actuators (Ahmed et al., 2024). This approach addresses the limitations of conventional farming, where managers often determine irrigation and fertilization schedules based on intuition or rigid timers, frequently leading to over-irrigation, nutrient leaching, or crop underperformance (Ray & Majumder, 2024).

The modern greenhouse serves as an ideal laboratory for these technologies due to its enclosed nature, which limits the number of stochastic variables compared to open fields. The integration of IoT transforms these structures into "Smart Greenhouses," capable of autonomous self-regulation (Cafuta et al., 2024). The primary objective is to maintain a state of homeostasis that aligns with the specific physiological requirements of the crop at each growth stage (Abid et al., 2025). This requires a nuanced understanding of the interactions between air temperature, relative humidity, light intensity (Photosynthetically Active Radiation), and root-zone moisture (Chen et al., 2025). The integration of sensing, communication, and intelligent decision systems forms the backbone of modern smart greenhouse management. The overall architecture of IoT-based precision agriculture in greenhouse vegetable production is illustrated in figure 1.

3. Hierarchical Architecture of Greenhouse IoT Systems

The implementation of a robust precision agriculture system is predicated on a well-defined architectural framework. Research across the domain suggests that a multi-layered approach is essential for ensuring the scalability and reliability of the system (Argento et al., 2024). This architecture typically consists of four distinct layers: perception, network, storage/processing, and application (Mrabet et al., 2020).

3.1. The Perception Layer: The Sensory Nervous System

At the foundational level, the perception layer comprises the hardware responsible for data acquisition. This layer acts as the sensory nervous system of the greenhouse, collecting real-time information on both abiotic factors (environmental conditions) and biotic factors (plant health) (Bicamumakuba et al., 2025). The hardware used in this layer has evolved from simple analog sensors to sophisticated digital modules capable of local pre-processing (Akbar et al., 2024).

Table 1: Common Environmental and Plant Health Sensors used in Greenhouse IoT

Category	**Specific Sensors**	**Parameters Measured**	**Unit of Measurement**
Atmospheric	DHT11/DHT22, DS18B20	Air Temperature, Relative Humidity	Celsius, %
Soil/Substrate	HL-69, VH400, Tensiometers	Volumetric Water Content (VWC), Matric Potential (MP)	%, kPa
Nutrient	NPK Sensors, pH, EC Sensors	Nitrogen, Phosphorus, Potassium, Acidity, Conductivity	mg/kg, pH scale, dS/m
Radiation	BH1750, Pyranometers	Light Intensity, Solar Radiation	Lux, W/m2
Plant Health	Infrared Thermometers, Cameras	Leaf Temperature, NDSI, NDVI	Celsius, Index (0-1)

In high-performance systems, the perception layer does not rely on raw data alone. For instance, low-cost sensors often generate signal noise that can lead to erroneous decision-making. To counter this, advanced signal processing algorithms, such as the Kalman filter, are implemented at the microcontroller level (e.g., Arduino Mega or ESP32) to smooth the data stream and ensure that the input to the higher-level models is accurate (Fei et al., 2024). Furthermore, the strategic spatial distribution of these sensors is vital. In a large greenhouse, micro-climates can develop; therefore, a mesh or grid of sensors is preferred over a single central station to capture localized variations in humidity or temperature (Fabre et al., 2024).

3.2. The Network Layer: Communication and Connectivity

The network layer facilitates the bidirectional flow of information between the perception layer and the cloud or local servers. The choice of communication protocol is a strategic decision influenced by the size of the greenhouse, the required data throughput, and the available energy budget (Qi et al., 2024). In recent years, Low-Power Wide-Area Network (LPWAN) technologies, particularly LoRaWAN and NB-IoT, have gained prominence due to their ability to provide long-range connectivity with minimal energy expenditure (Minew, 2024).

Table 2: Comparison of Wireless Communication Protocols for Greenhouse Monitoring

Protocol	Spectrum	Ideal Use Case	Max Range	Power Profile
LoRaWAN	Unlicensed (ISM)	Remote/Large-scale private networks	15-20 km	Ultra-low (10+ years)
NB-IoT	Licensed (LTE)	Dense urban/Operator-managed	1-10 km	Low to Moderate
Zigbee	Unlicensed (2.4 GHz)	High-density short-range mesh	100 m	Low
5G	Licensed	Real-time video/Robotic control	< 1 km	High
Wi-Fi	Unlicensed	Small greenhouses near infrastructure	50 m	Moderate

LoRaWAN is particularly favored for vegetable fields located at a distance from the farm's central hub, as it allows for the deployment of "set-and-forget" battery-powered sensors that can last for years (Aldhaheri et al., 2024). Its star topology where sensors communicate directly with a gateway simplifies the network structure and reduces the overhead associated with mesh routing protocols (Bicamumakuba et al., 2025). Conversely, in highly automated greenhouses where high-bandwidth data (such as high-resolution imagery for disease detection) is required, 5G or high-speed Wi-Fi is necessary to support the real-time processing needs of machine learning models (OdinS, 2024).

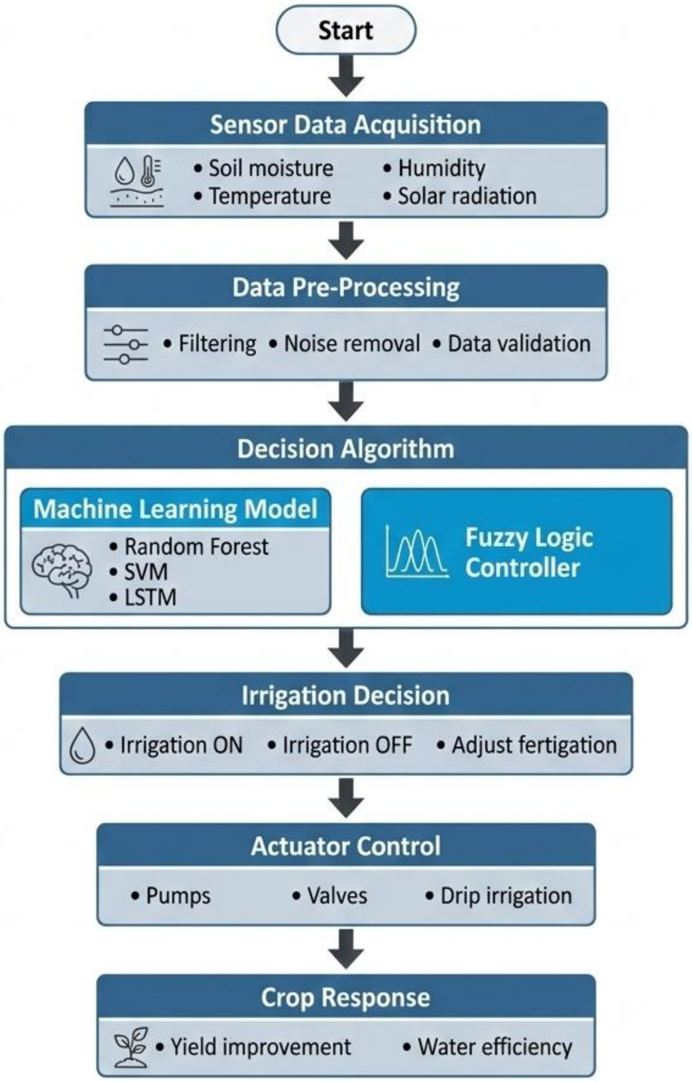
3.3. The Processing and Application Layers

The processing layer is where data is transformed into intelligence. This layer utilizes cloud-based platforms (e.g., Tago.io, Google Colab) or edge computing nodes to run complex algorithms (Hill, 2019). It is here that historical data is combined with real-time inputs to predict future states, such as soil moisture depletion or the onset of pest outbreaks. The final application layer provides the user interface often a mobile app or dashboard that allows growers to monitor their crops remotely and, if necessary, override automated systems (Oteyo et al., 2021). This decoupling of the physical process from management allows for the centralized control of multiple greenhouse units, a critical development given the increasing scarcity of skilled agricultural labor (Ariesen-Verschuur et al., 2022).

4. Precision Irrigation: Mechanisms and Physiological Impacts

Irrigation management is perhaps the most influential factor in greenhouse vegetable production. Vegetables, characterized by high water content, are exceptionally sensitive to both water deficit and waterlogging (Singh et al., 2021). Traditional irrigation methods based on fixed timers often result in substantial water waste and physiological stress (Di Gioia et al., 2022). Precision irrigation addresses this by using sensor feedback to match water delivery with actual plant demand (Nikolaou et al., 2019). Smart irrigation systems rely on real-time sensor feedback combined with intelligent decision algorithms to regulate water application. The operational workflow of an IoT-based irrigation decision system is illustrated in figure 2

Figure 2: Workflow of IoT-Based Smart Irrigation Decision System



4.1. Soil-Moisture vs. Evapotranspiration-Based Control

Two primary methodologies dominate the precision irrigation landscape: soil-moisture feedback and evapotranspiration (ET) modeling. Soil-moisture-based systems utilize sensors such as tensiometers (to measure matric potential, MP) or capacitive sensors (to measure volumetric water content, VWC) (Nemeskéri & Helyes, 2019). These sensors provide a direct measurement of the water available to the plant's root system. For instance, in tomato production, maintaining a matric potential threshold (e.g., -15 kPa to -25 kPa) has been shown to enhance biomass and leaf area compared to fixed-timer systems (Bhattacharya, 2021).

ET-based systems, on the other hand, utilize meteorological data (temperature, humidity, solar radiation, wind speed) to estimate the amount of water lost by the plant and soil (Abid et al., 2025). These models, often based on the Penman-Monteith equation, provide a top-down approach to irrigation management (Saha et al., 2025). Research indicates that ET-based smart irrigation can save up to 42% of water compared to traditional methods. However, the most effective modern systems are hybrid models that use ET to predict demand and soil sensors to verify and adjust the actual delivery (Puajpanda et al., 2024).

4.2. Impact on Vegetable Yield and Quality

The quantitative benefits of precision irrigation are well-documented across multiple vegetable varieties. By avoiding the cyclic stress of under- and over-watering, plants can allocate more energy to reproductive growth (fruit) rather than vegetative recovery (Van de Zande, 2023).

Table 3: Yield Improvements and Water Savings via Precision Irrigation

Crop	Yield Improvement	Water Savings	Quality Enhancement
Tomato	15% - 22%	10% - 30%	Higher Lycopene, Vit C, Sugars
Lettuce	25% - 30%	~50%	Higher Harvest Weight (Wet/Dry)
Blueberry	Increased Weight	30%	Improved 50-berry Weight
Cucumber	Significant	High	Better Uniformity, Reduced Bitterness

In a study of tomato production in Penn State, an IoT-based system utilizing LoRaWAN and soil matric potential sensors resulted in a marketable fruit yield 15.2% to 22.1% higher than ET-based controls, while maintaining significantly higher water use efficiency (iWUE) (Zhang et al., 2022). Furthermore, precision water management directly influences the secondary metabolite profile of vegetables. For tomatoes, the D3N3 treatment (drip irrigation with specific nitrogen levels) increased lycopene content by 41.3% and vitamin C by 39.2% (MDPI, 2023).

5. Intelligent Decision Support: AI and Machine Learning

The true power of IoT in the greenhouse is unlocked through Artificial Intelligence (AI) and Machine Learning (ML). These technologies enable the system to move from reactive control (e.g., "turn on pump if moisture is < 10 %") to proactive and predictive management (Wang & Gong, 2024).

5.1. Algorithmic Performance and Accuracy

Various ML models have been tested for their ability to predict crop needs and optimize environmental variables. Random Forest (RF) and Support Vector Machines (SVM) are frequently cited as high-performing algorithms for irrigation decision-making (Kok et al., 2021).

Table 4: Performance Comparison of Machine Learning Algorithms in Greenhouse Management

Algorithm	Metric	Performance	Application

Random Forest	Accuracy	99.3%	Automated Irrigation Decisions
Random Forest	Prediction	97.35%	Crop Recommendation based on soil NPK
SVM	Precision	High	Reducing False Positives in Irrigation
Linear Regression	Accuracy	93.49%	Yield Forecasting
LSTM	Accuracy	High	Time-series prediction of soil moisture

The "GAIA system" represents a sophisticated implementation of these concepts, utilizing a combination of data-driven AI, model-based prediction, and a knowledge base of expert rules to find an intermediate solution between contradictory objectives, such as maximizing yield while minimizing energy use (Verhoosel et al., 2022). For example, a grower might want to increase the temperature to accelerate growth, but this increases energy costs and water demand. AI models can simulate thousands of set-point combinations to find the "Pareto optimal" configuration for the specific crop variety and market price (Gaia Consortium, 2023).

5.2. Fuzzy Logic for Nuanced Control

While ML models are powerful, they often require significant computational resources and large datasets. Fuzzy Logic (FL) provides a robust alternative for real-time control (Patale et al., 2025). Fuzzy logic operates on the principle of "degrees of truth" rather than binary (0 or 1) logic. It allows the system to process inputs like "slightly dry" or "very bright" and produce a nuanced output, such as "low-flow irrigation for 5 minutes" (Saha et al., 2025).

Experimental results have demonstrated that fuzzy logic controllers can achieve a faster calibration rate of 66.23% and save approximately 61% more water compared to standard "average logic" algorithms. This efficiency is critical for maintaining the delicate balance of the greenhouse ecosystem, where over-correction can lead to fungal diseases or nutrient imbalances (Elnaghi et al., 2025).

6. Nutrient Use Efficiency and Precision Fertigation

Fertilization in greenhouse vegetable production is increasingly delivered via "fertigation" the simultaneous application of water and fertilizers through the irrigation system. This allows for the precise management of nutrient concentrations in the root zone, which is vital for crops like tomatoes that have varying nitrogen requirements throughout their growth cycle (Halitligil et al., 2002).

6.1. Metrics and Benchmarking for NUE

Nutrient Use Efficiency (NUE) is a key metric for sustainable farming, defined as the ratio of nutrients taken up by the plant to the total nutrients applied. In traditional soil application, nitrogen use efficiency is often as low as 34% due to leaching, volatilization, and runoff (EU Nitrogen Expert Panel, 2023)

Table 5: Nitrogen Use Efficiency (NUE) Improvement: Fertigation vs. Traditional Soil Application

Crop	Fertigation NUE (%)	Traditional NUE (%)	Net Improvement
Cucumber	63.4	34.0	+29.4%
Tomato	53.9	34.0	+19.9%
Eggplant	50.8	18.8	+32.0%
Pepper	49.2	33.9	+15.3%
Melon	21.4	11.0	+10.4%

Precision fertigation systems utilize electrical conductivity (EC) and pH sensors to monitor the nutrient solution in real-time. By adjusting the concentration of the fertigation stream based on the plant's actual uptake (measured via drainage sensors in soilless systems), growers can avoid "nutrient mining" or excessive accumulation of salts in the substrate (Oguntoye et al., 2024). This level of control is particularly important for mitigating environmental pollution, as excess nitrogen is a primary source of groundwater contamination and atmospheric nitrous oxide (N2O) emissions (Toselli et al., 2023).

6.2. Environmental Impact of Precise Nitrogen Management

The intersection of irrigation frequency and nitrogen application has a profound effect on the greenhouse carbon footprint. Research has shown that an "F2I2" treatment (moderate irrigation frequency and amount) can significantly improve tomato yield without causing a rise in soil N2O emission flux (Sapkota et al., 2020). Conversely, improper irrigation can reduce soil aeration, triggering denitrification and increasing N2O emissions a potent greenhouse gas (Qin et al., 2024). By using IoT to monitor soil aeration and moisture levels, precision systems can keep the root zone within the aerobic range, supporting beneficial microbial communities that aid in nitrogen fixation and root health (Frontiers, 2025).

7. Robotics and Autonomous Systems in Protected Cultivation

The final evolution of precision agriculture is the integration of autonomous robotics. As greenhouses scale in size and complexity, the ability of human workers to monitor every plant becomes impossible. Robots and drones are stepping in to fill this gap, performing tasks that are labor-intensive, repetitive, or hazardous (Biobest et al., 2020).

7.1. Autonomous Mobile Robots (AMRs) for Monitoring and Treatment

Modern greenhouse robots are modular platforms equipped with computer vision, LiDAR, and specialized actuators. Systems like "HERMAI" and "RAINOS" exemplify the versatility of these technologies (Bagagiolo et al., 2022).

- **Scouting and Yield Prediction:** Robots like "ROYA" or the "HERMAI Scout" use high-resolution 360-degree cameras and vision AI to monitor individual plants. They can predict yields up to six weeks in advance by analyzing cumulative light data and fruit counts, achieving a classification accuracy of over 97% for plant health status (Anderson et al., 2021).
- **Targeted Spraying:** Integrated Pest Management (IPM) is revolutionized by robots that can identify specific pest "hotspots" and apply localized treatments. This "spot-spraying" approach can reduce pesticide costs and time by focusing only on infested zones, rather than blanket-spraying the entire greenhouse (Lochan et al., 2024).
- **Precision Irrigation and Maintenance:** The "RAINOS" robot is designed for 24/7 autonomous irrigation. It can navigate complex greenhouse layouts, memorize the specific water requirements of different sections, and independently return to a refueling station when its tank is empty (Sethi, 2025). This autonomy ensures continuous care even during nights or holidays, optimizing the water supply based on night-time transpiration rates which reduce evaporation losses (Zou et al., 2025).

7.2. The Role of Drones in Infrastructure Management

While ground robots handle the plants, Unmanned Aerial Vehicles (UAVs) or drones are increasingly used for greenhouse maintenance. The high-risk task of cleaning greenhouse roofs necessary to maintain optimal light transmission has traditionally been a manual process prone to accidents (Galar et al., 2020). Drones equipped with specialized sprayers can now apply sun-blocking coatings or cleaning solutions to roofs with surgical precision (Kishor et al., 2025). A drone can cover 1.25 hectares in a fraction of the time required for manual cleaning, eliminating human risk and ensuring even application of cleaners (VSI Aerial, 2023).

8. Digital Twins and Edge Computing: The Virtualization of Horticulture

The cutting edge of greenhouse precision agriculture is the "Digital Twin" (DT) a virtual equivalent of the physical greenhouse that mirrors its behavior in real-time (Ariesen-Verschuur et al., 2022).

8.1. Bidirectional Flow and Simulation

A true Digital Twin involves a bidirectional data flow: the physical greenhouse sends data to the virtual twin, and the twin, after running simulations, sends control signals back to the physical actuators (Játiva et al., 2024). This allows growers to:

1. **Simulate Interventions:** Test the impact of a 2 Celsius temperature increase or a change in the light spectrum on plant growth before actually changing the greenhouse set-points (Chimankare et al., 2023).
2. **Predictive Maintenance:** Identify a failing pump or a clogged emitter in the virtual twin before it causes crop loss in the physical world (Shamshiri et al., 2021).
3. **Optimize Production Flows:** Align greenhouse production schedules with market demands and energy pricing in real-time (Georgiadis et al., 2025).

8.2. Edge Computing for Low Latency

The massive volume of data generated by Digital Twins and high-resolution imaging robots requires high-speed processing. Edge computing addresses this by processing data at the "edge" of the network (locally) rather than sending it to a distant cloud server (Sharma et al., 2024). This reduces latency, which is critical for autonomous robots navigating tight greenhouse rows where a delay of a few milliseconds could lead to a collision (Huang et al., 2021). While processing on edge devices may see a slight decrease in model accuracy (10-15%) compared to high-power cloud servers, the trade-off in speed and reliability for real-time control is often superior (Ajiboye et al., 2025).

9. Socio-Economic Viability and Sustainable Transitions

The transition to IoT-based precision agriculture is not only a technical challenge but an economic and social one. While the initial capital expenditure (CAPEX) can be high, the reduction in operational expenditure (OPEX) often leads to a favorable Return on Investment (ROI) (Puajpanda et al., 2024).

9.1. Quantifiable Economic Benefits

Table 6: Economic Impacts and Efficiency Gains in Smart Greenhouses

Factor	Metric	Reduction/Increase	Economic Impact
Water	Consumption	50% Reduction	Lower utility costs, sustainability compliance
Energy	Consumption	40-50% Reduction	Lower heating/cooling bills, grid independence
Labor	Efficiency	High Increase	Addressing labor shortages and costs
Pesticides	Application	30% Reduction	Lower chemical costs, healthier produce
Yield	Marketable Fruit	15-30% Increase	Higher revenue per square foot

The reduction in energy costs is particularly noteworthy in greenhouses utilizing solar-powered irrigation. By integrating Photovoltaic (PV) systems with battery storage and MPPT (Maximum Power Point Tracking), these systems can operate independently of the grid, ensuring continuous care even during power outages (Aldhaheri et al., 2024). This independence is estimated to save tens of thousands of dollars over the lifespan of the equipment while simultaneously mitigating greenhouse gas emissions (Bicamumakuba et al., 2025).

9.2. Social and Labor Implications

The automation of greenhouse tasks changes the nature of agricultural work. Instead of performing back-breaking manual labor in uncomfortable, high-humidity conditions, workers transition into "farm technicians" who oversee the robotic and IoT ecosystems (Singh et al., 2021). This shift can make agriculture more attractive to a younger, tech-savvy generation, helping to revitalize rural communities and address the global aging farmer population (Zhang et al., 2023). However, this transition requires significant investment in workforce training and digital literacy (Qi et al., 2024).

10. Barriers to Adoption and Future Horizons

Despite the demonstrable benefits, several challenges remain for the widespread adoption of precision agriculture in greenhouses.

1. **Cost and Complexity:** For small-scale farmers, the upfront cost of sensors, robots, and cloud subscriptions can be prohibitive. The complexity of integrating hardware from different vendors into a unified system also presents a significant hurdle ((Nikolaou et al., 2019).
2. **Trust and Education:** Many farmers remain skeptical of AI-driven recommendations, preferring to rely on traditional experience. Building trust requires "explainable AI" that can show the reasoning behind its decisions (Gaia Consortium, 2023).
3. **Data Ownership and Privacy:** As agricultural data becomes a valuable commodity, questions regarding who owns the data collected by sensors and how it can be used by technology providers are becoming central to policy discussions (Wang & Gong, 2024).

Looking forward, the future of precision horticulture lies in "Autonomous Greenhouses" systems that can not only monitor and respond to the environment but also perform complex tasks like plant training, pruning, and harvesting without any human intervention (Oteyo et al., 2021). The integration of "Digital Phenotyping" will allow systems to recognize the genetic potential of each individual plant and tailor its environment accordingly, pushing the boundaries of what is possible in crop production (Ariesen-Verschuur et al., 2022).

11. Conclusion

The synergistic application of precision agriculture and IoT-based smart irrigation in greenhouse vegetable production marks a paradigm shift toward efficient, sustainable horticulture, capable of mitigating water scarcity and enhancing food security amid escalating global demands. By leveraging real-time sensing, advanced analytics (e.g., ML-driven ETc models), and automated controls, these technologies achieve substantial reductions in resource consumption (20–50% water savings) and improvements in crop quality/yield, as evidenced in diverse regional case studies. Despite barriers like implementation costs and cybersecurity risks, emerging innovations such as edge computing, blockchain traceability, and AI-optimized digital twins promise to overcome these hurdles, fostering energy-efficient, climate-adaptive systems. Ultimately, widespread adoption requires policy support, interdisciplinary collaboration, and scalable solutions to democratize these tools, ensuring resilient vegetable supply chains and environmental stewardship in a resource-constrained future.

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