
Artificial intelligence and the internet of things for enhancing agricultural production: an analytical study of international experiences

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Abstract:

This study aims to address the central problem of the significant gap between the high potential of AI and IoT in agriculture and their limited real-world application. It investigates how these technologies can be effectively leveraged for productivity and sustainability, adapting international models to local contexts.

The research employed a multiple case study methodology, analyzing leading international experiences alongside secondary data from reports and global statistics to extract common patterns. Key findings indicate that institutional support outweighs mere technical advancement, with no universal solution. Success requires local adaptation, noting a trade-off between efficiency and digital inclusion, and a redefined role for farmers as data-driven system managers.

Keywords: Artificial Intelligence; Internet of Things; Smart Agriculture; Precision Agriculture; Agricultural Digital Transformation.

Jel Classification Codes: O33, Q16, Q55, O13.

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1. Introduction :

The global food system in the 21st century faces unprecedented challenges that threaten global food security and societal stability. On one hand, food demand is steadily increasing due to accelerating population growth, projected to reach 9.7 billion people by 2050. On the other hand, agricultural resources are under immense pressure manifested in soil degradation, escalating water scarcity, and the contraction of arable land due to urbanization. Compounding these chronic challenges is the existential threat of climate change, evident through extreme phenomena such as prolonged droughts, devastating floods, unprecedented heatwaves, and the spread of pests and plant diseases into new regions.

Reports from the Food and Agriculture Organization (FAO) indicate that the world needs to increase food production by up to 70% to meet projected demand, while approximately one-third of the food produced globally is wasted due to problems in harvesting, transportation, and storage. In the poorest regions, these challenges are exacerbated by limited access to modern technologies, inefficient agricultural value chains, and weak supportive infrastructure. All these factors create a state of urgent necessity to seek new, more efficient, and resilient agricultural models capable of producing more with fewer resources—a principle known as "more from less."

Within this critical context, the Fourth Industrial Revolution emerges as a potentially transformative force capable of fundamentally reshaping the agricultural sector. Having undergone transformative revolutions—from primitive agriculture, through the agricultural revolution that introduced steam-powered machinery, to the Green Revolution that relied on fertilizers, pesticides, and genetic engineering—we now enter the era of "Agriculture 4.0" or Smart Agriculture. In this era, advanced digital technologies converge with agricultural processes to create a more intelligent, precise, and efficient production system.

The digital transformation in agriculture represents a qualitative shift from reliance on intuition and traditional experience to data-driven, scientifically precise farming. Today, a farmer can obtain real-time information about the health of every plant in their field, soil moisture at a specific depth, nutrient concentrations in different field zones, and even predict the likelihood of crop diseases days or even weeks before symptoms appear. This transition is no longer a technical luxury; it has become a strategic imperative to ensure the sustainability of agricultural systems in the face of growing complexities.

At the heart of this digital transformation lie two complementary technologies that form the backbone of smart agriculture: the Internet of Things (IoT) and Artificial Intelligence (AI). On one hand, IoT provides the "eyes and ears" for the smart agricultural system through a vast network of intelligent sensors deployed across fields, greenhouses, storage facilities, and transportation mechanisms. These sensors gather instantaneous and

accurate data on environmental conditions, crop status, water resources, soil, and agricultural machinery. This continuous stream of big data creates a dynamic, living digital representation of the entire agricultural operation.

Artificial Intelligence, on the other hand, represents the "mastermind" that transforms this raw data into actionable insights and intelligent decisions. Through machine learning algorithms, image analysis, and predictive analytics, AI can uncover hidden patterns in data, forecast disease probabilities, determine optimal timings for irrigation, fertilization, and harvest, and even guide autonomous agricultural machinery with centimeter-level precision. The synergistic pairing (AI + IoT) creates an ideal interactive loop: IoT collects the data, AI analyzes it, the resulting decisions are sent to actuators (such as automated irrigation systems or self-driving tractors) for precise execution, and then sensors gather new data on the outcomes of that execution. This continuous cycle of improvement is self-reinforcing.

— The research' Problem :

Despite the immense potential offered by Artificial Intelligence (AI) and Internet of Things (IoT) technologies, their application within the agricultural sector faces a significant gap between theory and practice, as well as a disparity between successful experiments in leading nations and the reality of the agricultural sector in many developing countries. This presents the central research problem:

How can Artificial Intelligence and Internet of Things technologies be effectively employed to enhance agricultural productivity and achieve sustainability, while taking into account the lessons learned from leading international experiences and the possibility of adapting these models to the specific contexts of developing nations?

This primary problem branches into several subsidiary questions:

- What are the most impactful applications of AI and IoT for improving agricultural productivity and sustainability?
- How have leading nations successfully integrated these technologies into their agricultural systems, and what are the critical success factors in their experiences?
- What are the common obstacles and challenges encountered in applying these technologies, and how were they overcome?

— Study Hypotheses :

To address the research problem, the following hypotheses can be tested:

- The effectiveness of implementation depends on the degree to which the technology is adapted to local specificities, rather than on its absolute technical superiority.
- Governmental and institutional roles are the decisive factors in transitioning from the experimental phase to a phase of systemic transformation.

- A fundamental contradiction exists between the goal of achieving maximum productive efficiency and the goal of achieving broad digital inclusivity.

— **Research’ Objectives and Significance :**

This research aims to achieve the following objectives:

- To analyze the theoretical framework for the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) within the agricultural sector.
- To survey and classify the diverse applications of these technologies across the entire agricultural value chain.
- To construct a comparative analytical model for understanding adoption patterns and the factors influencing the success of international experiments.
- To extract key lessons learned and critical success factors from leading international experiences.
- To identify practical obstacles and challenges, along with strategies for addressing them.
- To propose an adaptation framework for the tailoring and application of these technologies within developing contexts.
- To formulate strategic recommendations for policymakers, investors, and farmers.

The significance of this research lies in its contribution to bridging the gap between technological potential and practical application in global agriculture. By systematically analyzing successful models and their underlying conditions, it provides actionable insights for enhancing productivity, resource efficiency, and sustainable intensification. The proposed adaptation framework offers a vital roadmap for tailoring advanced agricultural technologies to the diverse socioeconomic and infrastructural realities of developing nations, thereby supporting informed decision-making for stakeholders aiming to foster innovation, improve food security, and enhance economic viability within the agricultural sector

2. Theoretical Framework of the Study

2.1 First The Concept of the Internet of Things (IoT):

The Internet of Things (IoT) represents the transformation of the physical world into a vast information system. In agriculture, this translates into converting soil, plants, climate, and machinery into continuous streams of data (Atzori, Iera, & Morabito, 2017). Sensors constitute the fundamental building block: small devices that test the world around them. They have evolved from rudimentary instruments into intelligent, wirelessly connected, solar-powered units, capable of withstanding environmental factors to transmit precise data about everything (Jawad et al., 2017).

However, isolated sensors are of little value. This is where networks come into play, serving as the arteries for data transmission. Ranging from short-range technologies for limited areas to long-range, low-power wide-area networks (LPWAN) such as LoRaWAN, these networks cover vast agricultural expanses with high reliability and low energy consumption (Mekki, Bajic, Chaxel, & Meyer, 2019). These networks create the digital fabric of the smart field.

The third layer comprises analytical platforms. These function as the "control room." They are integrated software systems that ingest data from all sources—ground sensors, satellites, weather stations, historical records—and fuse them in a single crucible to produce actionable insights (Wolfert, Ge, Verdouw, & Bogaardt, 2017). They are the converters that transform electrical signals into agricultural decisions..

2.2 The Concept of Artificial Intelligence (AI)

If sensors are the senses, then Artificial Intelligence (AI) is the mind that interprets what these senses perceive. It is a system's ability to learn from data, reason, adapt, and solve problems in a manner that resembles—and sometimes surpasses—human intelligence (Goodfellow, Bengio, & Courville, 2016).

2.3 The types used in agriculture are varied :

- **Machine Learning (ML):** At its core is pattern discovery. It analyzes vast quantities of historical and real-time data to predict potential events: crop yield, disease outbreak, or water requirements (Chlingaryan, Sukkariéh, & Whelan, 2018).
- **Image Processing and Computer Vision:** Here, the machine "sees." It examines crop images captured by drones or satellites, detecting plant stress, weeds, or ripeness levels with an accuracy that often exceeds the human eye (Mohanty, Hughes, & Salathé, 2016).
- **Expert Systems:** These emulate the knowledge of a seasoned agronomist. A vast knowledge base of rules and relationships allows the system to diagnose a problem through symptoms and provide precise recommendations, as if a human expert were surveying the field .

2.4 Smart Agriculture and Precision Farming

- **Smart Agriculture (Smart Agriculture):** This is a broad and comprehensive concept. It signifies the holistic digital transformation of the sector. It is an integrated system that employs digital technologies (IoT, AI, Big Data) to monitor, analyze, and automate agricultural processes in their entirety, aiming to enhance efficiency, productivity, and sustainability in real-time (Zhang, Wang, & Li, 2021).
- **Precision Farming (Precision Farming):** This is the most tangible practical application of Smart Agriculture. Its philosophy is simple yet profound: a field is not a single, homogeneous unit. Soil varies, sunlight varies, and needs vary. Therefore, instead of treating it as a whole, we manage each small plot

according to its specific requirements (McBratney, Whelan, & Ancev, 2005). We apply water where there is thirst, fertilizer where there is hunger, and pesticide where there is disease. In essence: the right input, in the right place, at the right time, in the right amount (Gebbers & Adamchuk, 2010).

3. Implementation Mechanisms - The Interactive Synergy between Artificial Intelligence and the Internet of Things in the Agricultural Sector

3.1 Intelligent Monitoring and Predictive Analytics:

This is achieved through:

- **Crop Monitoring:** Drones equipped with multispectral cameras fly over the field. They measure indices such as the Normalized Difference Vegetation Index (NDVI), which reveals plant health and photosynthetic efficiency. AI algorithms analyze these images to identify areas of water stress, nitrogen deficiency, or the initial foci of pest infestation, often before the naked eye can detect them (Liakos et al., 2018).
- **Soil and Irrigation Management:** Sensors buried at different depths monitor soil moisture and nutrient concentrations. This data is integrated with precise weather forecasts. The result? An intelligent predictive model that determines exactly when and how much to irrigate each zone, potentially reducing water waste by up to 30% (Zhang et al., 2021).
- **Livestock Care:** Wearable sensors (collars, tags) are placed on animals. They monitor body temperature, heart rate, and activity levels. AI detects any deviation in established patterns that may indicate early-stage illness, heat stress, or even the optimal time for insemination (Neethirajan, 2017). Intervention becomes rapid, losses are minimized, and animal welfare improves.

3.2 Automation and Robotics

- **Autonomous Machinery:** Tractors and harvesters guide themselves with centimeter-level precision using high-accuracy GPS and computer vision systems. Perhaps most innovatively, weed control robots utilize cameras and AI to distinguish between desirable crops and invasive weeds. They then intervene with surgical precision, either mechanically removing the weed or applying a micro-dose of herbicide only where needed. This targeted approach can reduce the use of chemical herbicides by up to 90% (Saiz-Rubio & Rovira-Más, 2020).
- **Harvesting Robots:** A task that is arduous and labor-intensive when performed manually is now executed with remarkable skill by robots. Their cameras identify ripe produce (e.g., strawberries, tomatoes), and gentle robotic arms then harvest the fruit without damaging the plant. This represents a significant technical challenge in pattern recognition and fine motor coordination.

3.3 Smart Supply Chains: From Farm to Fork with Confidence.

The technology's reach extends far beyond the farm gate. Sensors monitoring temperature, humidity, and shock accompany the product in refrigerated transport vehicles, streaming data throughout the journey. AI analyzes this data to predict remaining shelf life, thereby optimizing inventory management and drastically reducing the immense post-harvest losses prevalent in the industry.

Furthermore, AI models process vast quantities of market data—including supply, demand, global weather patterns, and economic trends—to provide farmers with forecasts of future crop prices. This empowers them to make more profitable planting and marketing decisions.

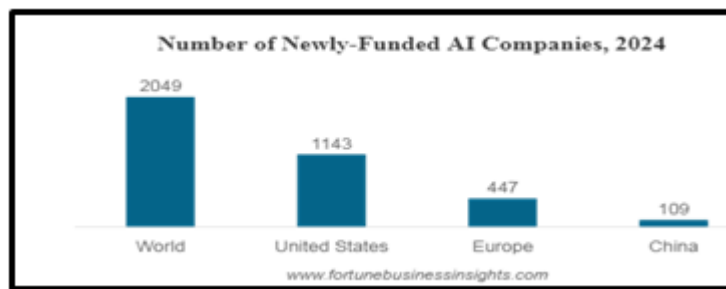
4. The Current State of Artificial Intelligence and Internet of Things Adoption in Agriculture

4.1 The Artificial Intelligence Market Size and Future Projections

The global artificial intelligence (AI) market was valued at an estimated \$294.16 billion USD in 2025 and is projected to grow from \$375.93 billion USD in 2026 to \$2,480.05 billion USD by 2034, achieving a compound annual growth rate (CAGR) of 26.60% during the forecast period. North America dominated the global market with a 31.80% share in 2025.

Artificial Intelligence is defined as the use of machines to simulate human cognitive processes. It involves the development of intelligent software and hardware to emulate human capabilities such as learning and problem-solving. A growing number of corporations are leveraging AI to analyze their data for informed decision-making, with nearly 35% of companies having embedded AI and 9 out of 10 organizations utilizing this technology to maintain competitive advantage. Governments worldwide are making substantial investments in AI research and development. The following illustrates global AI usage trends:

Figure 1: Number of Newly –Funded AI Companies, 2024



Source: Mordor Intelligence ,2024

The machine learning segment held a 40% market share in 2025 and is projected to grow at the highest CAGR of 32.6% during the forecast period. This growth is driven by its unique capability to enhance accuracy, process vast data volumes, and identify critical patterns and anomalies that inform superior data-driven decisions (Fortune Business Insights, 2024).

Natural Language Processing (NLP) is also poised for significant growth. Powered by technologies like Interactive Voice Response (IVR), virtual assistants, and chatbots, NLP increases operational efficiency. It facilitates direct AI-

customer interaction for seamless data collection, enhances big data synchronization, reduces costs, and boosts overall business productivity.

Figure 2: Market Trends in AI Sub-sectors / Impact of NLP on Business Operations,2024.



Source: Fortune Business Insights. (2024)

4.2 Analysis of the Size and Share of the Artificial Intelligence in Agriculture Market a. Growth Trends and Forecasts (2025 – 2030) :

The AI in agriculture market is estimated to be valued at USD 2.55 billion in 2025 and is projected to reach USD 7.05 billion by 2030, registering a compound annual growth rate (CAGR) of 22.55% during the forecast period (2025-2030).

- This momentum stems from the convergence of precision farming practices, national mandates for digital agriculture, and the increasing availability of cloud-based AI tools that lower entry barriers for farms of all sizes. The pressure to increase food production for a global population projected to reach 10 billion by 2050 is intensifying adoption. Simultaneously, the declining costs of sensors, connectivity, and AI-as-a-Service subscriptions are positioning the AI in agriculture market for accelerated expansion. Strategic alliances between technology leaders and agricultural equipment manufacturers are fostering comprehensive platforms that integrate hardware, software, and advisory services into a single ecosystem.
- However, volatility in semiconductor supply chains and fragmented data standards remain significant barriers to adoption, particularly for the 80% of the world's farms that are smaller than two hectares.
- Within the market, precision agriculture applications dominated, holding a 46% share of the AI in agriculture market in 2024, while drone-based analytics are expected to register the fastest CAGR of 25.8% through to 2030
- By technology, Machine Learning maintained a 41.3% share of the AI in agriculture market volume in 2024, while Computer Vision is on track for a Compound Annual Growth Rate (CAGR) of 23.6% until 2030.
- By component, Hardware accounted for 48.5% of the AI in agriculture market volume in 2024; Services are expected to expand at a CAGR of 25.1% until 2030.

— By deployment mode, Cloud-based models dominated with 63.2% of the AI in agriculture market volume in 2024 and are still growing at a CAGR of 24.8%.

— By geography, North America dominated with a 34.7% share of the AI in agriculture market in 2024, while Asia-Pacific is projected to register the highest CAGR of 24.4% until 2030.

- **Rapid Adoption of Precision Agriculture Platforms :**

Precision agriculture uses IoT sensors, GPS, and AI analytics to provide field-specific insights that cut fertilizer, water, and chemical use. In 2024, John Deere invested \$20 billion in AI machinery, which reduces input waste by up to 25%, while solutions like Trimble's See & Spray system lower herbicide use by 90%. Adoption is highest where labor costs and environmental regulations incentivize data-driven farming, making AI a key driver for sustainable intensification.

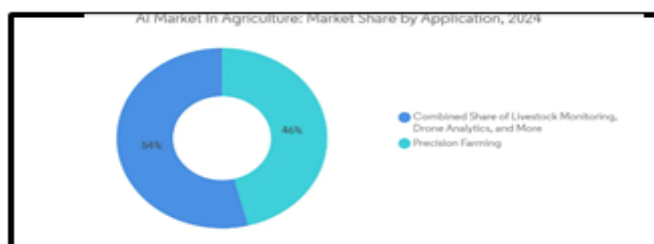
- **Expansion of Drone and High-Resolution Satellite Imagery Services :**

Multispectral sensors and AI analytics detect plant stress weeks before it is visible, with solutions like EOS Data Analytics helping African farmers double maize yields. Supported by real-time 5G data transfer, this reduces scouting costs and expands market reach.

Precision agriculture formed the market foundation in 2024, holding a 46% share. It enables targeted interventions like weed control and variable-rate application, translating data into savings and higher yields. Drone analytics is growing rapidly at a 25.8% CAGR, aided by lower costs and relaxed BVLOS regulations.

The next innovation wave includes livestock monitoring (with 95% accuracy in behavior detection), smart greenhouses (improving resource efficiency by 32%), and supply chain optimization. These new applications are creating additional revenue streams, as shown in the following figure .

Figure 4: AI Market Agriculture : Market share by Application 2024



Source: Fortune Business Insights. (2024).

5. Comparative Analysis of Adaptive Strategies - Leading International Experiences Study

5.1 The Netherlands: The "Precision Agriculture" Model - An Analysis of Responding to Geographical Constraints :

The Netherlands presents a unique case study in agricultural transformation. Despite its limited area of just 41,543 km², the country ranks as the world's second-largest agricultural exporter, with revenues exceeding €104.7 billion in 2021 (CBS, 2022). This apparent paradox was achieved through the adoption of a "precision

agriculture" strategy as a systematic response to constraints in land and resources. This transformation was not spontaneous; it resulted from political will and strategic planning that turned limitations into drivers for innovation.

- **Technical Infrastructure:**

The Dutch model is founded on the integration of four advanced technical components:

A Comprehensive Monitoring Network: This network integrates centimeter-accurate GPS systems, ground and aerial sensors, fleets of drones, and satellite data. This integration provides a quantitative and real-time visualization of the field in all its dimensions.

- **Smart Greenhouses:** The 10,000 hectares of advanced greenhouse facilities represent a near-complete closed-loop system. Here, sophisticated algorithms control every internal climatic variable (temperature, humidity, CO₂ concentration), while vertical farming techniques and subsurface drip irrigation maximize production within the minimal spatial footprint.

- **Advanced Data Management:** Platforms such as Acre and Factor-X function as digital brains, integrating sensor data with disease prediction models and plant nutritional requirement algorithms, creating a continuous improvement cycle.

- **Closed-loop Recycling Systems:** The system achieves up to 90% efficiency in irrigation water recycling, complemented by rainwater harvesting and nutrient recirculation, drastically reducing dependence on external inputs.

- **Measurable Outcomes:**

Furthermore, the success of this model is not hypothetical but is substantiated by tangible performance indicators:

- **Resource Efficiency:** 90% reduction in water usage, 97% reduction in pesticides for crops like tomatoes, and up to a 60% decrease in chemical fertilizer use compared to traditional open-field agriculture.

- **Unprecedented Productivity:** Tomato yields reach 70 kg/m² compared to a global average of 3.5 kg/m², and potato yields achieve 47 tons/hectare versus a global average of 21 tons/hectare. This explains the Netherlands' dominance in one-third of the global trade in vegetable seeds.

- **Environmental Sustainability:** A 40% reduction in greenhouse gas emissions from the greenhouse sector between 1990-2020, alongside a steady increase in the use of renewable energy.

- **The Success Framework: Beyond Technology**

Without a doubt, this exceptional performance would not have been achievable without a supportive institutional framework. The Triple Helix collaboration between leading research universities (such as

Wageningen University), private agri-tech companies, and a government that provided enabling policies and funding, created an exceptional innovation ecosystem. Furthermore, investment in research and development reaching 1.5% of the agricultural sector's GDP, alongside the collaborative culture among farmers fostered through cooperatives and field trial clubs, formed a cohesive socio-technical fabric.

- **Economic and Social Impacts:**

Precision agriculture has instigated a fundamental transformation within the Dutch economy and labor market. The contribution of the agricultural and food sector to the national GDP stands at 10.2%, and agricultural exports represent 17.5% of total exports. Strong parallel industries have emerged, such as Food Valley as a global hub for agricultural innovation, and the AgriTech sector which generates annual revenues exceeding €9 billion.

On the labor market front, job roles have shifted from manual labor to high-skill technical positions such as agricultural data analysts and smart greenhouse systems engineers, raising the average wages of specialized workers by 30–40%. However, this transformation has introduced parallel challenges, most notably a digital divide between generations and an annual labor market deficit of approximately 7,000 qualified professionals in technological specializations.

- **Persistent Challenges:**

Despite its successes, the Dutch model faces both internal and external challenges:

- High capital investment costs, which act as a prohibitive barrier to entry for new farmers.
- Technical complexity, necessitating continuous training and upskilling programs.
- Issues of data privacy and cybersecurity related to the management of sensitive agricultural data.
- Adaptation to the accelerating pace of climate change and rising temperatures.

The Dutch have not merely invented new technologies; they have crafted an integrated innovation ecosystem in which policy, research, innovation, and business synergize. They understood that geographical constraints are not overcome by expanding land area, but by intensifying knowledge per square centimeter. In conclusion, the Netherlands demonstrates that the future of agriculture is not necessarily tied to the scale of land, but to a system's ability to transform data into decisions and limitations into opportunities. This lesson, while specific to the Dutch context, offers fundamental principles that can be extrapolated regarding the importance of integrated governance and long-term investment in research and development as strategic preconditions for any genuine smart agricultural transformation.

5.2. United States: The "Large-Scale Agriculture and Big Data" Model – An Analysis of Economies of Scale

The United States stands in logical contrast to the Netherlands, adopting a strategy of improving efficiency through vast scale rather than intensification. As the world's largest exporter of corn and soybeans, producing

approximately 40% of global corn and 35% of global soybeans, its true achievement lies in how it manages this immense volume through data (USDA, 2023). The expansive plains have been transformed from mere farmland into open data platforms, where every hectare is a data point in a massive analytical model.

- **Technical Infrastructure:** The Power of Aggregation and Automation

Comprehensive Sensing Network: The number of installed agricultural sensors exceeds 50 million units (2023), constituting the largest agricultural Internet of Things (IoT) network in the world. This is complemented by a fleet of over 200,000 drones and dedicated satellites (e.g., Landsat, Sentinel-2) providing exhaustive coverage.

- **Proprietary Data Platforms:** Near-total market dominance is held by a limited number of vertically integrated platforms. The Climate FieldView platform (owned by Bayer) covers 180 million acres globally, and the John Deere Operations Center serves 200,000 clients. This creates a powerful network effect and makes data a commodity that can be aggregated and analyzed on an unprecedented scale.

- **Advanced Automation:** Yield prediction algorithms achieve accuracy rates of up to 95%, while AI systems process decades of historical data to extract patterns invisible to the human .

- **Economic Outcomes:** The Logic of Profitability on a Massive Scale

There is no doubt that the primary driver here is purely economic. The figures indicate that:

- The market value of precision agriculture in the United States is USD 12.9 billion (2024), projected to reach USD 23.1 billion by 2030.

- 80% of large farms utilize some form of data analytics.

- Corn yield has increased from 100 bushels/acre (1970) to 177 bushels/acre (2023), while smart irrigation systems have reduced water use by 20–50% and pesticides by 30–50%.

- **Practical Applications:**

- **Variable Rate Technology (VRT):** In the Corn Belt, areas of up to 10,000 acres are managed digitally, with VRT applied to 70% of the area, yielding an average additional return of USD 30–50 per acre.

- **Predictive Supply Chains:** Analytics extend beyond production to price forecasting and inventory management through models integrating global market and weather data.

- **Regional Specialization:** In California, lettuce farm automation reaches 85%, and soil sensors are installed in 90% of almond orchards, saving an equivalent of 1.2 million acre-feet of water annually.

- **Regulatory Framework and Support:** A Public-Private Partnership Alliance

This transformation is supported by clear structural policies:

- **The Farm Bill:** Allocates \$3 billion to agricultural research and development.

- **The Climate-Smart Agriculture Initiative:** Provides incentives for technology-supported sustainable practices.
- **Bold Investment Partnerships:** John Deere alone invested \$20 billion in agricultural technology in 2024.

- **Structural Challenges:**

Despite its apparent strength, the American model suffers from profound internal contradictions:

- **Digital Polarization:** A vast gap between large farms (capable of investment) and small farms (technologically marginalized).
- **Data Monopoly Issues:** The control of farm data by a handful of corporations raises serious governance and transparency concerns.
- **Social Erosion:** The decline of traditional rural communities alongside the loss of manual jobs and increasing technological dependency.

The American model proves that data is the new crop. It has successfully transformed agriculture from a production activity into an intensive knowledge industry. Furthermore, it demonstrates how scale can become a tool for lowering marginal costs and maximizing efficiency to the utmost degree. However, this quantitative success comes at the expense of agricultural system diversity and resilience. In conclusion, the United States offers a lesson in the power of aggregation and targeted investment but poses a profound ethical question: Who owns the future of food—the farmer or the data platform?

5.3. Singapore and Japan: The "Urban and Vertical Agriculture" Model – An Analysis of Responding to Population Density.

Singapore and Japan represent models of forced innovation. With a population density reaching 8,358 persons/km² and a 90% dependency on food imports, Singapore launched the "30×30" initiative to produce 30% of its nutritional needs locally by 2030. Japan, with a 20% decline in agricultural land since 2000 and an aging farming population (67% over 65 years old), strives to maintain food self-sufficiency amidst challenging demographic shifts. Here, technological creativity is not a choice but a survival strategy.

- **Technical Infrastructure:** Vertical Intensification and Absolute Control
- **Multi-story Vertical Farming:** The A-Go-Gro system at Singapore's "Sky Greens," the world's first commercial rotating vertical farm, produces 10 times the output of traditional farming while saving 95% of water. In Japan, the "Spread" farm in Kyoto produces 30,000 heads of lettuce daily using "plant gene expression" technology that analyzes 10,000 variables, reducing labor by 50% and water use by 98%.

- **Extreme Urban Integration:** From Singapore's "Campbell Crescent" rooftop farm (1,800 m² producing 5 tons monthly) to the "Pasona" underground farm in a Tokyo skyscraper basement (4,000 m² underground, 100 plant species). These models have redefined the very concept of "farmland."
- **Robotics and Precise Environmental Control:** In Japan, fully automated harvesters and AI-driven smart climate control. In Singapore, dynamically adjustable LED lighting systems tailored to specific plant growth stages.
- **Supportive Framework: Proactive Policies and Partnerships :**
 - **Singapore:** The Singapore Food Agency (SFA) allocated SGD 40 million to an urban agriculture fund, with research and development grants covering up to 70% of costs.
 - **Japan:** Enacted the world's first Plant Factory Promotion Law (2011), with the Ministry of Agriculture, Forestry and Fisheries (MAFF) subsidizing 50% of initial capital costs and investing 4 billion yen annually in its "Smart Agriculture" program.
- **Results and Impacts:** Towards an Urban Food Ecosystem

These models have achieved tangible progress:

 - Increased the share of locally produced leafy vegetables in Singapore from 8% (2019) to 14% (2023).
 - Reduced the carbon footprint by minimizing food transportation distances.
 - Created over 300 new technical jobs annually in Singapore alone.
- **Ongoing Challenges**
 - High energy costs for powering artificial lighting and climate control systems.
 - Price competition with traditionally farmed, imported produce.
 - Technical complexity, which requires rare, specialized skills.

What Singapore and Japan are achieving is a radical reimagining of the relationship between the city and its food. They have transformed their structural weaknesses—scarcity of land and labor—into an impetus for inventing production models independent of traditional geography. Furthermore, they prove that agriculture can be an organic part of the urban fabric, not a separate activity confined to rural areas. There is no doubt that these models, despite their cost, offer a strategic solution for major global cities suffering from fragile food supply chains. In conclusion, they serve as an antidote to the notion that agriculture requires horizontal space and open horizons for food-independent cities.

5.4. India and China: The "Locally-Adapted Innovative Solutions" Model – An Analysis of Digital Inclusion

India and China grapple with unparalleled complexity: together, they represent 35% of the world's population and 25% of its agricultural land, yet under radically different conditions. India: 146 million farms (86% are small or marginal), fragmented landholdings (average 1.08 hectares), and acute water stress. China: Achieving 95% self-sufficiency in grains with only 9% of the world's agricultural land, yet facing challenges of an aging farmer population and soil contamination. The solution here must be multi-layered and scalable.

- **India's Strategy: Bottom-Up Innovation :**

India has adopted a digital inclusion approach through:

- **Simple Advisory Platforms:** The government's Kisan Mitra app serves 15 million farmers with localized advice in native languages. The Plantix app for visual disease diagnosis serves 15 million users.
- **Low-Cost Smart Water Solutions:** IoT-based soil moisture sensors have reduced water use by 30-40% across 50,000 farms.
- **Comprehensive Digital Marketplaces:** The national e-NAM platform connects 1,000 markets across 18 states, with a trading volume of 2.5 trillion rupees.
- **Massive Institutional Framework:** The Digital India program aims to digitally enable 100 million farmers, supported by 25 agricultural AI labs.

- **China's Strategy: Centralized Planning and Widescale Application (Top-Down)**

China has taken the path of comprehensive automation and central control:

- **Unified Large-Scale Projects:** The "Dongping" smart rice farm (667 hectares) increased productivity by 15% and reduced chemical inputs by 30%. JD.com's smart pig farms have reduced labor requirements by 90%.
- **Big Data Platforms:** Baidu's agricultural platform monitors 50 million hectares using deep learning algorithms to predict pest outbreaks.
- **National Digital Infrastructure:** The 5G network covers 98% of villages, supported by 300 regional agricultural data centers.
- **Clear Strategic Framework:** The 14th Five-Year Plan (2021-2025) invests \$5 billion in agricultural artificial intelligence, aiming for 20% of farms to be "smart" by 2025.

6. Conclusion

The research makes it clear that the digital transformation in agriculture is no longer a technological luxury but has become a strategic necessity, which nations approach through two complementary perspectives: a technical perspective focused on integrating the dual forces of the Internet of Things (IoT) as comprehensive sensory infrastructure and Artificial Intelligence (AI) as analytical intelligence, and an institutional perspective that investigates the conditions for converting technical potential into productive reality. The analysis of the four models (Netherlands, United States, Singapore/Japan, India/China) revealed a remarkable diversity in strategic

responses to local challenges, with each nation adopting a pathway that reflects a precise diagnosis of its agricultural structure and its economic and social capabilities. This confirms that the success of the technology is contingent upon the degree to which it is integrated into a supportive political, economic, and social fabric, not on its abstract technical superiority.

— Testing Research Hypotheses

Based on the central research problem, the following hypotheses can be tested:

- The effectiveness of implementation depends on the degree to which the technology is adapted to local specificities, not on its absolute superiority. This hypothesis is fully confirmed. The success of India in adopting simple, phone-based applications in local languages, contrasted with the Dutch focus on complex, closed systems, proves that "contextual suitability" outweighs "technical sophistication" as a success factor in developing nations.
- The governmental and institutional role is the decisive factor in transitioning from the experimental phase to a phase of systemic transformation." All models affirm this hypothesis. The Triple Helix cooperation in the Netherlands, the supportive legislation in Singapore and Japan, and the massive national initiatives in China and India all constitute an indispensable, prerequisite institutional framework for achieving widespread adoption.
- A fundamental contradiction exists between the goal of achieving maximum productive efficiency and the goal of achieving broad digital inclusivity. This hypothesis is partially confirmed. While the Netherlands and the United States achieved high efficiency, which may hinder inclusivity due to cost and complexity, India demonstrates a path towards inclusivity that might reduce the level of individual farm efficiency in the short term. Successful models (like some in China) seek to reconcile the two through scalable solutions.

— Key Research Findings

- The gap between leading and developing nations is not primarily a technical gap but rather a gap in integrated governance. Success is linked to the existence of a supportive system that connects enabling policies, targeted financing, context-specific R&D, and farmer capacity building.
- There is no single "silver bullet" solution. Precision agriculture on vast farms (USA) differs technically and managerially from vertical farming in cities (Singapore) or advisory systems for smallholders (India). Decomposing the agricultural process into separately digitizable units (irrigation, monitoring, fertilization) offers a more practical entry point than seeking a comprehensive solution.

- The digital transformation is altering the nature of agricultural labor from manual jobs to supervisory and technical roles. This necessitates a radical restructuring of agricultural vocational education and training systems to address the accelerating skills gap.
- The models most resilient in the face of climate change are those that combine precise resource control (like the closed-loop systems in the Netherlands) with diversified production sources (like dispersed urban farms). Focusing on system resilience has become as important as increasing its productivity.
- The evidence leads to the conclusion that the future of global food security will not be forged in a single field, by a single farmer, or with a single technology. It will be built within integrated ecosystems that know how to select suitable technologies from the global toolkit, design policies to support them, and invest in the human capital that will operate them. The greatest challenge is no longer developing the most accurate sensor or the fastest algorithm, but building the collective intelligence that enables societies to transform data into wisdom and technology into broad-based prosperity.

- Research Recommendations

- Launch a national digital agricultural advisory platform via mobile phone, focusing on irrigation advice and combating common pests and diseases.
- Develop a central repository for foundational climate and soil data as a starting point for future analytics.
- Introduce a core curriculum on "Concepts of Digital Agriculture" into technical and university-level agricultural education programs.
- Encourage the establishment of local startups (AgriTech Startups) that offer solutions to local problems through "Farming as a Service" models.
- Implement pilot projects for precision agriculture in strategic, high-value crops, meticulously documenting the economic and environmental return on investment.
- Enact legislation governing agricultural data ownership and exchange, balancing the need to stimulate innovation with the protection of producers' rights.
- Direct research and development towards "integrative predictive agriculture," which combines genomics, climate modeling, and big data management to forecast crop behavior under various climate scenarios.
- Export institutional models, not just technology: share expertise in policy design, research cooperatives, and innovative financing mechanisms.
- Develop open global standards for device and data interoperability to lower entry costs for farmers everywhere.

- Redirect a portion of traditional agricultural subsidies towards creating dedicated venture capital funds for digital agricultural innovation in developing countries.
- Support the establishment of South-South alliances for exchanging expertise and appropriate technologies among nations with similar conditions (e.g., arid regions, rice cultivation, etc.).
- Adopt a composite index to measure "Smart Agriculture Readiness" that considers digital infrastructure, policies, skills, and the state of local innovation, to help countries accurately diagnose their gaps.

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