
Empowering Sustainable Vertical Farming Through IoT and AI-Driven Technologies: A technical Blueprint with insights from the UK and India

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ABSTRACT

Rapid urbanisation and shrinking arable land have necessitated the exploration of alternative agricultural paradigms to ensure food security under space and resource constraints. Conventional ground-based agriculture is challenged by population growth and climate uncertainty, accelerating the need for alternatives, including controlled cultivation technologies. Hence, vertical farming and Internet of things (IoT)-enabled Artificial Intelligence (AI) approaches have emerged as viable and sustainable solutions. The study aims to create a roadmap for next-generation vertical farming systems and bridge the gap between technology and policies by providing a technical blueprint that supports scalable and sustainable agricultural transformation. The pillars around which the paper is structured are i) Infrastructure & Systems: A detailed analysis of hydroponic, aeroponic, aquaponic, and hybrid technologies, analysing their operational parameters, environmental requirements, and sustainability metrics (ii) Digital Integration using IoT and AI: An architectural breakdown of multilayered IoT frameworks, integrating sensor networks, robotics, and automation with advanced Machine Learning, Deep Learning, and Digital Twin technologies for precise environmental control (iii) policy and techno-economic frameworks: A comparative analysis of the UK and Indian landscapes, assessing how their respective regulatory frameworks, energy infrastructures, and market structures can be harmonised to support large-scale adoption. A comparative techno-economic and policy analysis of vertical farming adoption in the United Kingdom and India is presented, considering climatic conditions, energy infrastructure, market structures, and regulatory frameworks. It also integrates UK's high-tech agricultural innovation with India's massive scale and policy frameworks to develop an adaptable, sustainable solution. The paper also proposes a next-generation cyber-physical vertical Farming architecture and outlines the policy roadmaps that must be rolled out to support scalable, resilient, and climate-adaptive agricultural systems. This review follows the PRISMA framework, with 246 studies included after systematic screening. The significance of the proposed framework is that it offers actionable and impactful guidance for vertical farming design, digital integration, and policy alignment that supports resilient and climate-adaptive food systems

INDEX TERMS Vertical farming, IoT, Artificial Intelligence, controlled environment agriculture, precision farming

I. INTRODUCTION

Approximately 45% of the world's population lives in urban areas, according to the World Urbanisation Prospects report [1]. By 2050, it is projected that roughly two-thirds of the global population will live in urban areas, as seen in Figure 1, based on the United Nations estimates [2]. This shift re-

quires the agricultural sector to develop strategies that balance food production with addressing key challenges: rising caloric demands, diminishing arable land, and unpredictable climate change. Urban migration has created challenges for cities in meeting residents' needs. Adopting modern agricultural methods is essential to address these issues and ensure urban

sustainability. Integrating agriculture into urban lifestyles can facilitate local food production. While this transition depends on increased awareness of urban needs, the industry has developed multiple solutions for farming in limited spaces and for optimising resources such as water and nutrients.

This paper provides a comprehensive overview of the challenges and limitations of deploying conventional agricultural practices in urban society and the rise of modern agricultural methods like CEA (Controlled Environment Agriculture) and Vertical Farming, augmented by IoT infrastructures and AI enabled systems. Additionally, emphasis is placed on vertical farming methodologies adopted in India and the UK. Concise discussions of the techniques employed in both countries are presented in dedicated subsections in this paper and future work will extend this comparison to large-scale deployment, including experimental validation and economic evaluation.

With the increasing urbanisation, industrialisation, rapid population growth, and climate uncertainty, diminishing natural resources have placed an excessive burden on food supply chains. As the demand for pesticide-free and locally produced food increases, vertical farming in urban areas and controlled agriculture prove to be a saviour to mitigate potential food shortages.

A. CHALLENGES IN CONVENTIONAL AGRICULTURE EVOLUTION AND EVOLUTION OF CEA

Conventional agricultural techniques face challenges, including a reduction in the availability of arable land, population growth, climatic disruptions such as natural disasters, water scarcity, and soil degradation. According to global projections, the world population is expected to reach 9.7 billion by 2050, significantly increasing pressure on food production systems that are already strained by unpredictable environmental conditions and monsoon cycles [3], [4]. Countries with dense populations, such as India, face even sharper declines in per-capita cultivable land, leading to innovation in controlled food production methods.

In very simple words, CEA means growing plants in an environment where everything they need to grow is managed and controlled automatically. CEA encompasses greenhouses, hydroponics, aeroponics, aquaponics, and climate-regulated indoor farms. This provides controlled and regulated growing environments where microclimate challenges such as temperature, humidity, CO₂, vapor pressure deficit (VPD), and nutrient delivery can be controlled with high precision. This supports year-round production without being dependent upon climate and seasonal variations. Recent innovations in IoT and AI have strengthened the CEA landscape, enabling automated systems that optimise lighting, controlled fertilisation, pest monitoring, and energy management [10], [11] through data-driven techniques monitored by humans.

The trajectory of CEA traces back to the 19th century, where passive greenhouse structures relied heavily on natural sunlight and conventional combustion-based heating. Over the decades, the materials used for building greenhouses with glazing materials, nutrient management fertilisation

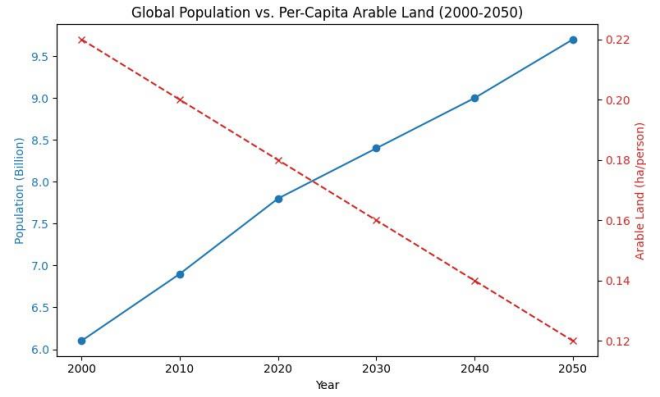


FIGURE 1: Projected global population growth (2000–2050) with declining per-capita arable land.

techniques, automated illumination, and ventilation have progressively enhanced environmental regulation requirements [4]. The introduction of LED lighting proves to be highly efficient, providing energy-efficient, spectrum-tunable illumination that directly influences photosynthesis and plant morphology. This was followed through innovation of programmable controllers and sensor networks that transitioned CEA from semi-manual operations to cyber-physical systems capable of autonomous decision-making. Vertical farming represents the most advanced stage of this evolution [15]. By stacking multiple crop layers within enclosed, climate-controlled spaces, Vertical farming maximises land-use efficiency while enabling precise environmental reproducibility. Recent innovations in vertical farming include:

- Real-time sensor fusion that integrates information from multiple sensors to maintain microclimate stability
- AI-assisted automated nutrient dosing and disease prediction
- Digital twins that generate virtual models of vertical farming structures for simulation-driven crop cycle planning with fluctuating weather and climatic conditions
- cloud-edge hybrid analytics for operational intelligence and data-driven decision making [11], [14].

B. VARIANTS OF FARMING TYPES: NOMENCLATURE AND TECHNICAL DISTINCTIONS

With evolving digital and soilless agriculture, multiple farming paradigms have emerged, each with its own technical boundaries and objectives. These include:

- **Smart farming** leverages IoT systems, cloud analytics, and decision-support tools to enhance food productivity [39].
- **Precision farming** relies on spatially targeted interventions using geographic information systems (GIS), drones, and sensor networks across diverse landscapes [10], [44].
- **Vertical farming** is a form of indoor agriculture in which crops are grown in vertically stacked layers within fully enclosed, automated, controlled environments [26], [85].
- **IoT-controlled farming** uses networked sensors and actuators to monitor and regulate climatic conditions, fertigation, and operational oversight [10], [44].
- **Closed/indoor farming** grows crops indoors, protecting them from external weather, biological contamination, and other threats [86], [233].
- **Open/ground farming** is conventional soil-based cultivation in which crops are exposed to natural cycles and weather variability [5], [55], [108].

These categories often overlap and form a comprehensive taxonomy that informs research direction, technological integration, and deployment strategies for future agricultural systems.

C. VERTICAL FARMING AND THE IOT

Vertical farming is a technology-augmented agriculture, where IoT serves as the central nervous system [24]. This facilitates real-time environmental monitoring, fault detection, and resource-efficient actuation. For instance, IoT sensors monitor critical factors such as light intensity, nutrient conductivity, dissolved oxygen, CO₂ levels, pH, temperature, and humidity. The data generated from these sensors is transmitted to edge devices or cloud servers, where it is processed by AI models enabling automated decision-making. The automated decisions include adaptive LED dimming to optimise photosynthetic efficiency, automatic nutrient solution balancing and recirculation, predictive operations for Heating, Ventilation, and Air Conditioning (HVAC) adjustments to maintain ideal VPD, early detection of pathogen or nutrient stress through imaging and time-series analysis, etc. [10], [16], [20].

Advances in AI further enhances IoT capabilities through specialised techniques such as Reinforcement Learning (RL) which enables climate control [11], computer vision-based disease detection [20], and privacy-preserving federated learning frameworks enabling collaborative model improve-

ments across farms [21]. Figure 2 depicts the projected growth of the urban population and the rising demand for crops grown through vertical farming, while clearly indicating that arable land remains largely unchanged, resulting in a widening imbalance between food demand and agricultural capacity [22], [226].

This imbalance highlights the need for the convergence of IoT, AI, and automated subsystems that transform VF from a labor-intensive approach into a data-driven and autonomous food production paradigm capable of meeting urban requirements. This transformation is achieved through a closed-loop cyber-physical architecture where IoT sensor networks continuously monitor environmental parameters such as temperature, humidity, CO₂ concentration, and nutrient levels, transmitting real-time data to cloud-based or edge-processing platforms. AI algorithms including machine learning models, genetic algorithms, and predictive analytics process this data to make intelligent decisions, such as dynamically optimising lighting spectra, adjusting irrigation schedules, and predicting crop growth trajectories. Automated actuators then execute these decisions without human intervention. Furthermore, the system's predictive capabilities enable proactive interventions such as early disease detection and yield forecasting that eliminate manual guesswork and reduce labor dependency. Through this synergy of perception, analysis, decision-making, and execution, the integration of these technologies is essential for addressing the sustainability and efficiency challenges inherent in vertical farming systems.

The integration of these technologies has been validated in recent studies at [5]–[9].

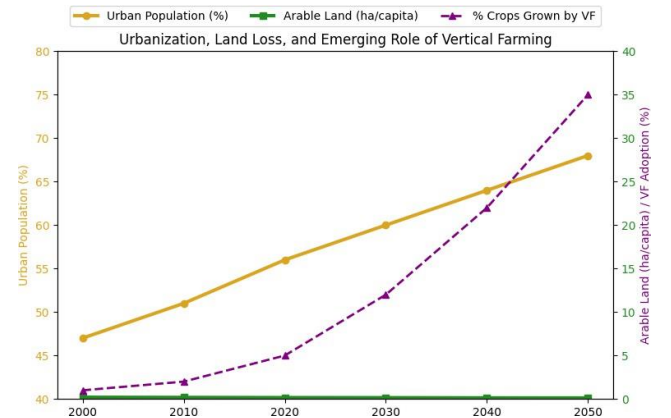


FIGURE 2: Emerging role of vertical farming: resource-adaptive food production in urban and peri-urban settings.

D. FUNDAMENTALS OF VERTICAL FARMING SYSTEMS

A fully functional VF system integrates multiple interdependent components that collectively create a controlled microclimate supporting the plant growth:

- **Modular racks or towers** for vertical space optimisation and airflow management [126],
- **Environmental control subsystems** including HVAC, humidifiers, dehumidifiers, and CO₂ injectors [145], [155],
- **IoT-enabled sensor–actuator networks** that continuously monitor and regulate system variables [121], [150],
- **Automated nutrient dosing and recirculation systems** with real-time pH and EC balancing [49], [51],
- **Edge–cloud architectures** enabling data visualisation, anomaly detection, and AI-powered decision-making [11], [14].

These subsystems must operate in synergy to provide a stable and high-precision environment suitable for the needs of the crop [19].

E. PAPER CONTRIBUTIONS AND ORGANISATION

1) Tri-Dimensional Framework

This manuscript makes three distinct novel contributions to the existing body of knowledge on vertical farming. First, unlike existing review articles that typically focus on a single aspect of vertical farming—either technology, IoT, or policy in isolation—our manuscript provides a comprehensive tri-dimensional framework that synthesises: (i) infrastructure and system-level requirements for soilless cultivation technologies with detailed operational parameters, (ii) digital integration through multi-layer IoT architectures and AI-driven optimisation, and (iii) policy and techno-economic frameworks through comparative analysis of UK and Indian Landscape. This holistic integration across technological, digital, and regulatory dimensions represents a novel contribution that addresses the interconnected nature of vertical farming implementation challenges, providing readers with a complete understanding of how these three dimensions interact and influence each other. (as shown in quarter 1 of Figure 3)

While previous review articles have examined vertical farming in developed or developing contexts in isolation, our manuscript provides a novel comparative analysis between the UK (representing a mature, high-technology agricultural economy with advanced automation, strong policy frameworks, and premium market positioning) and India (representing a rapidly developing economy with infrastructure limitations, diverse market segments, and acute resource constraints) (as shown in quarter 2 of Figure 3). This comparative perspective generates unique insights into how the same technological foundation must be adapted to vastly different economic, environmental, and policy contexts. Our analysis reveals that while technology transfer is feasible, adaptation to local conditions remains essential for economic viability—a finding that has not been systematically addressed in previous literature.

Our proposed cyber-physical system (CPS) architecture (as shown in quarter 3 of Figure 3) and edge-cloud continuum framework provide specific, quantifiable performance improvements that differentiate our contribution from previous conceptual frameworks. Unlike prior work that has offered qualitative architectural descriptions without performance validation, we demonstrate through comparative analysis that the quantitative performance estimates derived from the PRISMA-based literature review indicate potential improvements in energy efficiency (40–60%), reductions in control system latency (80–90%), improvements in nutrient utilisation efficiency (10–20 percentage points), and increases in system uptime (1.5–4.9 percentage points) for CPS-based vertical farming systems compared with conventional systems. These values represent indicative benchmarks synthesised from the reviewed literature. These quantified performance metrics provide actionable guidance for system designers and operators, moving beyond qualitative recommendations to provide specific, measurable targets for system implementation. The quantitative evidence used in the manuscript was incorporated through two complementary approaches: direct extraction of reported quantitative findings from the literature, with the corresponding sources cited wherever required, and structured processing and synthesis of quantitative evidence across multiple studies. For the second approach, the extracted quantitative evidence was further processed through a systematic synthesis and comparative analysis through aggregating findings from multiple independent studies that have evaluated the performance improvements attainable through IoT-enabled and AI-driven controlled environment agriculture systems. The values were obtained through a rigorous four-stage synthesis process: (i) extraction of performance improvement percentages from studies that conducted direct comparisons between traditional and IoT/AI-enhanced systems, (ii) cross-validation of these figures against multiple independent sources to ensure consistency and reliability, (iii) standardisation of metrics to common units and methodologies to enable meaningful comparison, and (iv) calculation of weighted averages based on sample sizes and study quality as reported in each source. The figures plotted in the proposed review serve as indicative benchmarks for the potential performance gains achievable through the integration of these technologies, providing evidence-based targets for system design and optimisation rather than representing direct experimental validation of the proposed architecture.

While previous review articles have discussed policy challenges in general terms, our manuscript provides a detailed, actionable policy roadmap with concrete recommendations across three dimensions as shown in quarter 4 of Figure 3): financial incentives (capital subsidies of 30–50%, tax benefits through accelerated depreciation and R&D credits, grant programs for energy-efficient technologies), regulatory support (zoning amendments for agricultural use in industrial zones, building code adaptations for indoor

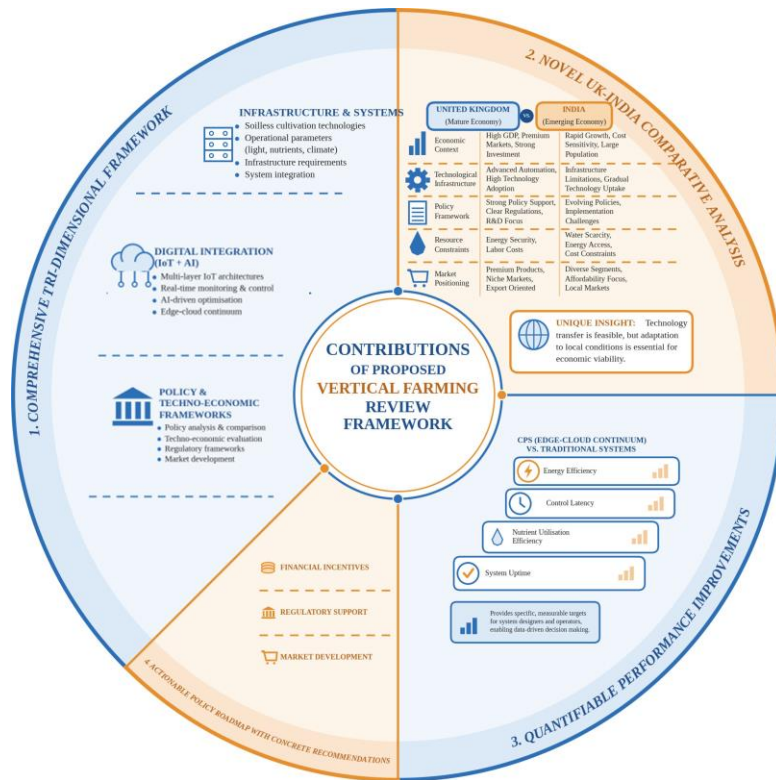


FIGURE 3: Comprehensive framework for vertical farming integrating Infrastructure & Systems, Digital Integration, and Policy & Techno-Economic Frameworks. The figure summarises the contributions of the proposed vertical framing review framework through four linked quadrants: (1) a comprehensive tri-dimensional framework, (2) a novel UK–India comparative analysis, (3) quantifiable performance improvements, and (4) an actionable policy roadmap with concrete recommendations.

farming facilities, water rights prioritisation for recirculating systems), and market development (government procurement policies sourcing from vertical farms, labeling standards for premium positioning, export support for international market entry). These concrete recommendations are grounded in our comparative UK-India analysis and provide clear guidance for policymakers in both developed and developing contexts.

The review was guided by four research questions:

- (RQ1) What are the core technologies and architectural designs for vertical farming systems?
- (RQ2) How are IoT and AI technologies integrated to enable automated and data-driven vertical farming?
- (RQ3) What are the policy and techno-economic frameworks enabling vertical farming adoption in different geographical contexts?
- (RQ4) What are the quantifiable performance improvements achievable through CPS-based vertical farming systems?

2) Search Methodology, Inclusion/Exclusion Criteria, Review Strategy using PRISMA framework

Search Methodology: We conducted a comprehensive literature search across four major academic databases: Scopus,

Web of Science, Google Scholar, and ScienceDirect. The search was conducted between January 2023 and December 2025 using the following keywords and Boolean operators: "vertical farming" OR "controlled environment agriculture" OR "CEA"; "soilless cultivation" OR "hydroponics" OR "aeroponics" OR "aquaponics"; "Internet of Things" OR "IoT" OR "sensors" OR "automation"; "artificial intelligence" OR "machine learning" OR "deep learning" OR "digital twin"; "policy" OR "regulatory framework" OR "techno-economic analysis"; "United Kingdom" OR "UK" OR "India." We also manually searched reference lists of identified articles and included grey literature from the FAO and government reports [5].

Inclusion criteria required that studies be: (i) peer-reviewed journal articles, conference proceedings, or systematic reviews; (ii) published in English between 2010 and 2025; (iii) addressing vertical farming, soilless cultivation, IoT/AI integration, or policy frameworks; and (iv) providing empirical data, techno-economic analysis, or comparative policy analysis. Exclusion criteria excluded: (i) studies not directly related to vertical farming or CEA; (ii) studies lacking technical or policy analysis; (iii) non-English publications; and (iv) opinion pieces without empirical or analytical content.

Review Strategy: The study selection followed a multi-stage

screening process following the PRISMA framework [162] (shown in Figure 4). Initial database searches yielded 1,847 articles. After removing 387 duplicates, 1,460 articles were screened by title and abstract, excluding 894 that did not meet the inclusion criteria. Full-text review of the remaining 566 articles led to the exclusion of 320 articles, resulting in a final set of 246 articles included in the review. From each included article, we extracted: author(s), year of publication, research focus, vertical farming technology type, IoT/AI methodology, key findings, and performance metrics. Data synthesis was conducted using thematic analysis, with findings organised into three main themes: (i) infrastructure and system-level requirements, (ii) digital integration through IoT and AI, and (iii) policy and techno-economic frameworks [163].

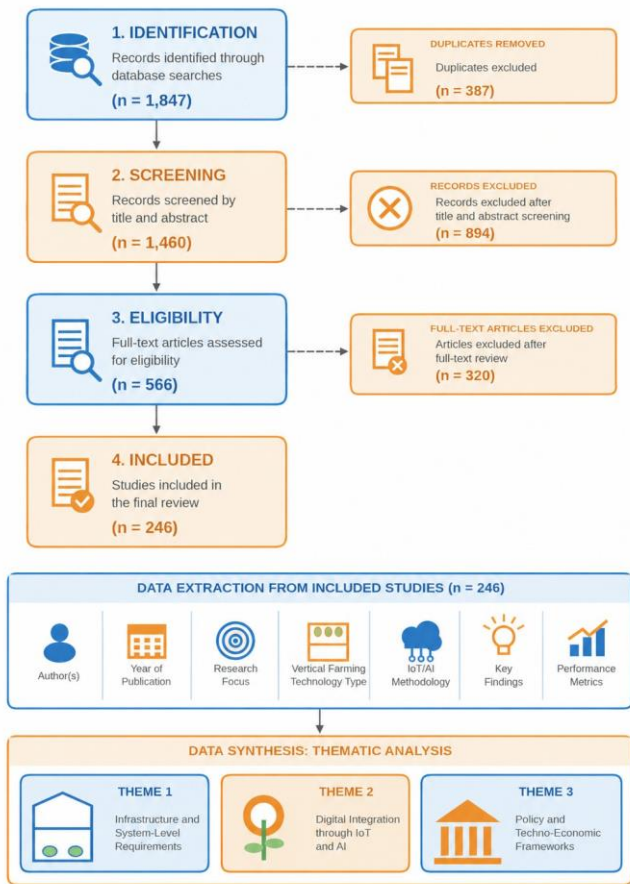


FIGURE 4: PRISMA-based study selection and data synthesis process followed in this review

3) Comparative Analysis of Related Work

Table 1 presents a systematic comparison of eight influential review papers on vertical farming against our comprehensive review. The evaluation criteria are derived from the tri-dimensional framework (Figure 3) and the PRISMA methodology (Figure 4) covering: (1) adherence to the PRISMA framework for systematic review, (2) inclusion of a UK-

India comparative analysis, (3) depth of IoT/AI integration coverage, (4) policy and techno-economic analysis, (5) quantifiable Cyber-Physical System (CPS) performance metrics, (6) financial incentives, and (7) regulatory support mechanisms. As shown in Table 1, while all related reviews follow the PRISMA framework and most cover IoT/AI integration to varying degrees, significant gaps exist across the other dimensions.

Our review uniquely fills these gaps by offering an integrated, multi-dimensional framework that bridges infrastructure, digital integration, and policy frameworks, supported by empirical evidences.

4) Referred Data Sources

The quantitative data in the tables and figures of this manuscript were compiled from three types of source: (i) peer-reviewed journal articles and conference proceedings published between 2010 and 2025, (ii) industry reports and market analyses from reputable sources including Market-sandMarkets, Grand View Research, and the FAO, and (iii) government and institutional publications including DEFRA (UK), NITI Aayog (India), and the European Commission. For each parameter, values were extracted from the source publications and converted to common units. Where more than one source was available, the values were compared across sources. Where reported values differed, the range is presented, as a weighted average or midpoint value. Values are indicative benchmarks drawn from the literature and not experimental results from this work. The sources for each value are cited in the corresponding table or figure caption or accompanying text.

This paper is organised as follows:

- 1) Section 2 provides a comprehensive survey of core vertical farming and CEA technologies including hardware frameworks, control systems, and AI-assisted analytics;
- 2) Section 3 presents a multi-layer IoT architecture for vertical farming, detailing perception, network, processing, and application layers with specific communication protocols and platform comparisons;
- 3) Section 4 reviews AI and machine learning applications including energy optimisation, intelligent lighting control, reinforcement learning for climate control, digital twins, yield prediction, and disease detection;
- 4) Section 5 provides a comparative techno-economic and policy analysis of vertical farming adoption in the United Kingdom and India;
- 5) Section 6 proposes a next-generation cyber-physical vertical farming architecture with quantified performance metrics;
- 6) Section 7 outlines policy roadmaps for scalable, resilient, and climate-adaptive agricultural systems.

II. LITERATURE REVIEW

A. CORE VERTICAL FARMING ARCHITECTURES

The architectural design of vertical farming systems has evolved significantly, with three predominant configurations

TABLE 1: Comparative Analysis of Related Review Papers on Vertical Farming

Reference	PRISMA Framework	UK-India Comparative Analysis	IoT/AI Integration	Policy & Techno-Economic Analysis	Quantifiable CPS Metrics	Financial Incentives	Regulatory Support
[207] Kaiser et al.	✓	✗	✓	✗	✗	✗	✗
[208] Alipio et al.	✓	✗	✓	✓	✗	✗	✗
[209] Zhang et al.	✓	✗	✓	✗	✓	✗	✗
[211] Gang et al.	✓	✗	✓	✗	✗	✗	✗
[212] Thomaier et al.	✓	✗	✗	✓	✗	✓	✓
[213] Liu and Wang	✓	✗	✓	✗	✗	✗	✗
[214] Lubna et al.	✓	✗	✗	✓	✗	✓	✗
[216] Richa et al.	✓	✗	✓	✗	✗	✗	✗
Proposed review	✓	✓	✓	✓	✓	✓	✓

emerging in both research and commercial implementations as listed below :

Stacked/Multi-Level Systems represent the most common approach, utilising vertically arranged growing shelves within buildings or repurposed urban structures. These systems maximise spatial efficiency while maintaining centralised environmental control [24], [25].

Warehouse-based VF configurations transform large industrial spaces into fully controlled agricultural environments, often employing advanced automation and robotics for planting, monitoring, and harvesting operations [26].

Containerised/Modular VF, a recent innovation which offers scalability and mobility advantages, particularly suitable for urban environments and regions with limited infrastructure [86].

TABLE 2: Comparison of Vertical Farming Architectural Types

Architecture Type	Key Features	Advantages	Limitations
Stacked VF	Vertical shelving, centralised control	High spatial efficiency, uniform environment	Limited scalability, fixed installation
Warehouse-based VF	Large-scale, robotic automation	High production capacity, full automation	High capital cost, energy intensive
Containerised VF	Portable, plug-and-play design	Scalable, mobile, rapid deployment	Limited growing area, higher per-unit cost

Table 2 data extracted from [24] provides a comprehensive comparison between the three primary vertical farming architectural types—Stacked VF, Warehouse-based VF, and Containerised VF. The table systematically addresses the key features, advantages, and limitations of each architecture to compare their relative strengths and weaknesses. This com-

parative analysis reveals that Stacked VF offers high spatial efficiency and uniform environmental conditions, though it faces limitations in scalability due to its fixed installation nature. Warehouse-based VF provides high production capacity through full automation and robotic integration, yet this comes with significant capital costs and high energy intensity. Containerised VF presents scalable, mobile, and rapidly deployable solutions suitable for urban environments, but these systems are constrained by limited growing areas and higher per-unit costs. The comparison highlights that the selection of an appropriate architectural type depends on specific operational requirements, available resources, and strategic objectives, with each architecture presenting distinct trade-offs between spatial efficiency, scalability, capital investment, and operational complexity.

B. SOILLESS CULTIVATION TECHNOLOGIES IN MODERN VERTICAL FARMING

Soilless cultivation technologies represent the fundamental pillar of modern vertical farming systems, enabling unprecedented precision in nutrient delivery, root zone environment management, and resource utilisation optimisation [25]. These advanced agricultural methods have revolutionised traditional farming practices by effectively eliminating soil-borne diseases, optimising resource efficiency through recirculating systems, and facilitating year-round production in completely controlled environments [85]. The transition from conventional soil-based agriculture to soilless systems marks a significant paradigm shift in food production methodology, particularly in urban and resource-constrained settings where traditional farming faces substantial limitations [26].

The technological evolution of soilless cultivation has progressed through several distinct phases, beginning with basic hydroponic systems in research settings and evolving into sophisticated commercial implementations integrating

IoT monitoring and AI-driven optimisation [233]. Contemporary soilless systems demonstrate remarkable improvements in water use efficiency, typically achieving 70-95% reduction in water consumption compared to conventional agriculture, while simultaneously enhancing nutrient use efficiency through precise delivery mechanisms and real-time monitoring capabilities [86]. The integration of digital technologies has further accelerated this evolution, enabling data-driven optimisation of plant growth parameters and predictive maintenance of cultivation infrastructure [48], and Table 3 lists all the soilless cultivation technologies. Table 3 provides a comprehensive overview of the global implementation status of various soilless cultivation technologies, comparing their adoption rates, water efficiency, and energy requirements. The Deep Water Culture (DWC) and Nutrient Film Technique (NFT) represent the most widely adopted technologies, with adoption rates of 80% and 75% respectively, indicating their commercial maturity and operational reliability. Aeroponics and substrate-based systems show moderate adoption at 45% and 60%, reflecting their specialised applications and specific crop suitability. Emerging technologies such as Fogponics (15%) and Bioponics (10%) demonstrate growing interest in advanced cultivation methods, though their commercial scalability remains limited. In terms of resource efficiency, Fogponics achieves the highest water efficiency at 92-97%, followed by Aeroponics at 90-95%, while substrate systems show the lowest water efficiency at 60-70%. Energy requirements vary significantly across technologies, with Fogponics and Aeroponics demanding very high to high energy inputs due to their sophisticated mist generation and high-pressure systems, whereas DWC and substrate systems operate with low to medium energy consumption. This comparative analysis highlights the trade-offs between adoption maturity, water conservation, and energy intensity, guiding technology selection based on specific operational priorities and resource constraints.

TABLE 3: Global Implementation of Soilless Cultivation Technologies

Technology	Adoption	Water	Energy
NFT	High (75%)	85-90%	Medium
DWC	High (80%)	70-80%	Low-Med
Aeroponics	Medium (45%)	90-95%	High
Aquaponics	Low (25%)	85-90%	Medium
Substrate	Medium (60%)	60-70%	Low
Hybrid	Growing (35%)	80-90%	Med-High
Fogponics	Emerging (15%)	92-97%	Very High
Bioponics	Exp. (10%)	75-85%	Medium

1) Hydroponic Systems Architecture and Performance Metrics
Hydroponic systems (Figure 5) form the backbone of commercial vertical farming operations, with multiple configurations developed to address specific crop requirements and operational constraints [40], [54], [147]. The Nutrient Film Technique (NFT) represents one of the most water-efficient

configurations, operating through continuous circulation of nutrient solution through precisely sloped channels [27]. This system maintains a thin film of nutrient solution that provides both hydration and aeration to plant roots while minimising water consumption. The technical specifications require setting up specific parameters like exact slope gradients between 1.5-3.0 degrees and flow rates maintained at 1-2 liters per minute to ensure optimal root zone conditions without waterlogging or oxygen deprivation,as mentioned in the research paper [105], and the data is condensed in Table 4 .

Deep Water Culture (DWC) systems operate on the principle of complete root submersion in oxygenated nutrient solutions, with commercial implementations maintaining dissolved oxygen levels above 6 mg/L through continuous aeration systems [106]. The system’s inherent robustness and simplicity make it particularly suitable for large-scale green leaf production, though it demands vigilant monitoring protocols to prevent pathogen outbreaks in the recirculating solution [107]. Table 5 details the operational parameters of hydroponic systems. DWC systems typically employ air stones or diffusers connected to commercial-grade air pumps to maintain adequate oxygen levels, with backup systems essential for commercial operations to prevent crop loss during power interruptions [50].

Ebb and Flow systems, also known as flood and drain systems, provide intermittent flooding and draining of grow trays, creating periodic saturation and aeration cycles that promote robust root development [108]. These systems combine beneficial aspects of both hydroponics and aeroponics, allowing flexibility in crop selection and growth stage management. Advanced implementations utilise sensor-driven automation to adjust flood frequency and duration based on real-time assessment of plant growth stage and environmental conditions, creating a responsive cultivation environment that dynamically adapts to plant physiological needs [56].

TABLE 4: Core Technical Parameters of Hydroponic Systems

Parameter	NFT	DWC	Ebb & Flow	Drip	Wick
Flow (L/min)	1-2	N/A	5-10	2-4	0.1-0.5
O ₂ (mg/L)	6-8	6-8	5-7	5-7	4-6
pH Range	5.5-6.5	5.5-6.5	5.5-6.5	5.5-6.5	5.5-6.5
EC (mS/cm)	1.8-2.5	1.8-2.5	1.8-2.5	1.8-2.5	1.8-2.5

2) Aeroponic System Implementation and Technical Challenges
Aeroponic technology represents the most advanced category of soilless cultivation, characterised by complete root suspension in air as shown in Figure 6 with periodic application of nutrient-dense mist [28], [79]. High-pressure aeroponic

TABLE 5: Operational Parameters of Hydroponic Systems

Parameter	NFT	DWC	Ebb & Flow	Drip	Wick
Temp (°C)	18-22	18-22	18-22	18-22	18-22
Energy (kWh/m ²)	15-25	10-20	20-30	25-35	5-10
Maintenance	Medium	Low	Medium	High	Very Low

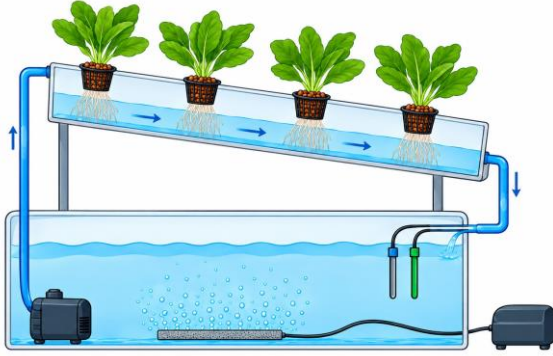


FIGURE 5: Overview of hydroponic system.

systems operating at 60-80 psi achieve a remarkable 95% water use reduction while enhancing growth rates by 25-30% compared to hydroponic controls [97]. The fine mist droplets, typically ranging from 5-50 microns in diameter, create an optimal environment for nutrient absorption and gas exchange, facilitating enhanced metabolic activity and accelerated growth rates [109]. The aeroponic crop performance is shown in Table 6 and the data values are extracted from

[28], [109].

The technical sophistication of aeroponic systems introduces several critical implementation challenges that require sophisticated engineering solutions, as shown in Table 7 [110]. Nozzle clogging prevention demands multi-stage filtration systems, typically employing 5-10 micron filters combined with regular maintenance protocols to ensure consistent mist distribution across the entire root zone [113]. High-pressure pump requirements, typically operating between 40-100 psi, significantly increase energy consumption compared to other cultivation systems, impacting operational economics and sustainability metrics [87]. Precise misting intervals, typically calibrated to 15-30 seconds every 3-5 minutes, must be carefully programmed to prevent root desiccation while avoiding oversaturation conditions that could lead to oxygen deprivation [114].

Low-pressure aeroponic systems have emerged as an alternative approach, operating at 15-30 psi with larger droplet sizes but reduced energy requirements [115]. While these systems offer improved reliability and lower operational costs, they typically achieve slightly lower growth rates and water efficiency compared to high-pressure implementations [116]. The emergence of ultrasonic aerponics, utilising piezoelectric transducers to generate micron-sized droplets at minimal operational pressures, represents the latest advancement in mist-based cultivation technology, though commercial scalability remains limited to specialised applications [117].

TABLE 6: Aeroponic Crop Performance

Crop	Days	kg/m ²	Q/10	Market
Lettuce	28-35	12-15	8.5	Prem
Basil	42-49	8-10	8.0	High
Strawberry	75-90	15-20	8.8	Prem
Tomato	95-110	25-30	8.2	Med
Pepper	100-120	18-22	8.1	Med
Microgreens	14-21	4-6	9.0	High
Medicinal	60-90	6-8	8.7	Prem

TABLE 7: Aeroponic Resource Use

Crop	L/kg	Nut. %	Profit %	ROI
Lettuce	8-12	85-90	25-35	High
Basil	10-15	80-85	30-40	High
Strawberry	15-20	75-80	35-45	V.High
Tomato	20-25	70-75	20-30	Med
Pepper	18-22	72-78	25-35	Med
Microgreens	5-8	90-95	40-50	V.High
Medicinal	12-18	80-85	45-60	Prem

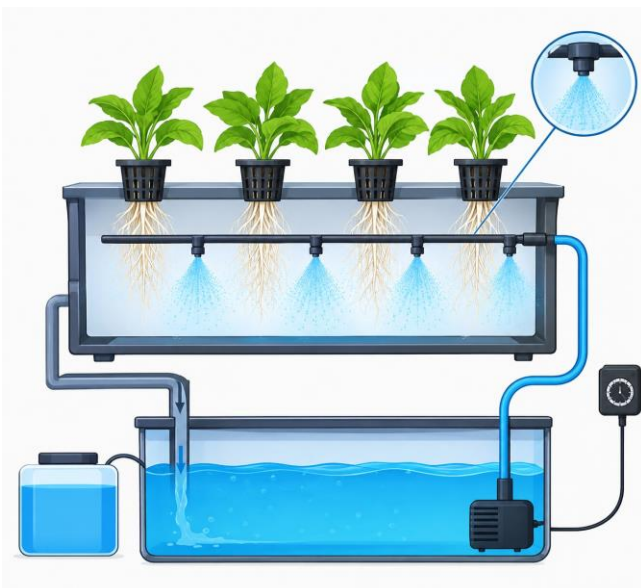


FIGURE 6: Schematic of an aeroponics system.

3) Aquaponic Systems: Integrated Ecosystem Approach

Aquaponics (schematic representation shown in Figure 7) represents a sophisticated synergistic integration of recirculating aquaculture systems (RAS) [30] with hydroponic cultivation, creating a closed-loop ecosystem where fish waste provides organic nutrients for plant growth while plants function as natural biofilters to purify water for aquatic organisms [118]. This

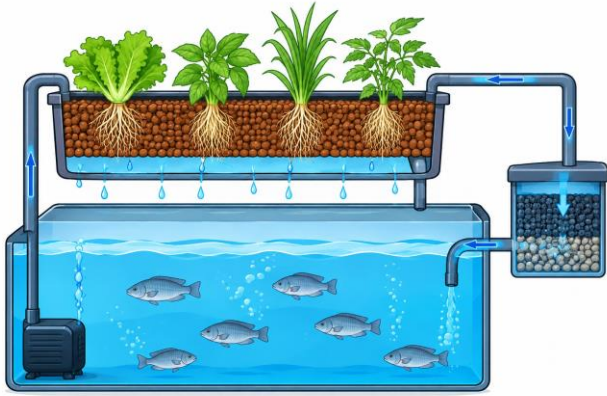


FIGURE 7: Schematic of an aquaponics system.

symbiotic relationship embodies circular economy principles and offers unique sustainability advantages by converting waste streams into valuable agricultural inputs [119]. The approach has gained significant attention for its potential to create integrated food production systems that yield both plant and animal products while minimising environmental impact and resource consumption [120].

The nitrogen cycle forms the biochemical foundation of aquaponic systems, where fish excreta, primarily in the form of ammonia, undergo bacterial nitrification processes to form nitrites and subsequently nitrates, which serve as the primary nitrogen source for plants [125]. The biological components of the aquaponic system are shown in Table 8 [126]. Successful system operation requires meticulous balancing of three interconnected biological components: fish stocking density typically maintained at 10-20 kg/m³ depending on species and system maturity; plant growing area generally requiring 3-5 m² of grow bed per m³ of fish tank volume; and biofilter capacity sized to handle daily ammonia production rates of 0.5-1.0 g per kg of fish feed. This delicate balance demands continuous monitoring and adjustment to maintain system stability and optimise productivity [127].

Commercial aquaponic implementations face several significant operational challenges that require specialised expertise in multiple domains [128]. System balancing complexity necessitates simultaneous optimisation of fish health parameters, bacterial activity levels, and plant nutrition requirements, creating a multi-dimensional management challenge that demands integrated approaches [129]. The environmental parameters of aquaponic systems extracted from [129] and [130] are shown in Table 9. Disease management must address both piscine and botanical pathogens within the shared water environment, requiring comprehensive strategies that consider impacts across multiple organism types and life stages [18]. Market diversification necessitates the development of dual revenue streams from both fish and plant products, complicating business planning, marketing strategies, and supply chain management [130].

TABLE 8: Aquaponic System Biological Components

System Type	Fish Species	Stock Density (kg/m ³)	Plant Ratio
Media Bed	Tilapia, Trout	15-20	4:1
Deep Water	Catfish, Carp	20-25	5:1
NFT Hybrid	Ornamental	10-15	3:1
Vertical Tower	Tilapia, Perch	15-18	6:1
Commercial Scale	Multiple	25-30	7:1

TABLE 9: Aquaponic System Environmental Parameters

System Type	Water Exchange	pH Range	Temperature
Media Bed	1-5% daily	6.8-7.2	22-26°C
Deep Water	1-3% daily	6.8-7.2	20-24°C
NFT Hybrid	5-10% daily	6.5-7.0	18-22°C
Vertical Tower	2-5% daily	6.8-7.2	22-26°C
Commercial Scale	1-2% daily	6.8-7.2	24-28°C

4) Emerging Soilless Technologies and Hybrid Approaches

Fogponics represents the latest evolution in aeroponic technology, utilising ultrasonic foggers to generate nutrient-rich fog with droplet sizes below 10 microns [131]. This approach offers even greater oxygen availability to root zones and potentially higher nutrient absorption efficiency, though commercial implementation remains limited due to technical complexity and higher energy requirements [132]. Fogponic systems typically achieve water efficiency exceeding 95% and can enhance growth rates by 35-55% compared to traditional hydroponics, positioning them as a promising technology for high-value crop production [133].

Bioponic systems integrate organic nutrient sources and biological processes into soilless cultivation, combining the precision of hydroponics with the sustainability principles of organic agriculture [134]. These systems utilise compost teas, vermicompost extracts, and other organic amendments to create living nutrient solutions that support complex microbial communities [135]. While bioponics offers potential benefits for soil health and environmental sustainability, it presents significant challenges in nutrient consistency and system stability that require advanced management approaches [136].

Hybrid cultivation systems combine multiple soilless technologies to leverage their respective advantages while mitigating limitations [137]. Common hybrid approaches include aeroponic propagation followed by hydroponic finishing phases, substrate-based systems with integrated drip irrigation, and aquaponic systems incorporating aeroponic components for specific crop types [138]. These integrated approaches enable optimisation across different growth stages and crop requirements, though they increase system complexity and require sophisticated control systems [139]. Table 10 (

[139]) and Table 11 ([138]) present the performance metrics and practical applications of the aforementioned soilless cultivation technologies, respectively.

5) Sensor Integration and IoT Monitoring in Soilless Systems
Modern soilless cultivation systems extensively employ IoT sensors for real-time monitoring and control, creating data-rich environments that enable precision agriculture at unprecedented scales [140]. The integration of these sensors has become crucial for maintaining optimal growing conditions, maximising resource efficiency, and enabling predictive maintenance of cultivation infrastructure [141]. Advanced sensor networks typically incorporate multiple measurement modalities to create comprehensive digital twins of the cultivation environment [99].

TABLE 10: Advanced Systems Performance Metrics

System Type	Tech Level	Water Eff.	Auto. Potential	Scalability
Fogponics	Experimental	92-97%	High	Low
Bioponics	Development	75-85%	Medium	Medium
Hybrid Systems	Commercial	80-90%	High	High
Smart Hydro	Mature	85-90%	Very High	Very High
Modular Aero	Commercial	90-95%	High	Medium
Container Farms	Commercial	85-95%	High	High

TABLE 11: Advanced Systems Application Focus

System Type	Crop Diversity	Research Focus
Fogponics	Limited	Nutrient uptake
Bioponics	Broad	Microbial ecology
Hybrid Systems	Broad	System integration
Smart Hydro	Broad	AI optimisation
Modular Aero	Medium	Reliability
Container Farms	Medium	Mobility

pH and Electrical Conductivity (EC) sensors form the foundation of nutrient management in soilless systems, providing continuous monitoring of solution chemistry and nutrient concentration [142]. Modern implementations typically achieve accuracy within ± 0.1 pH units and ± 0.01 mS/cm for EC measurements, enabling precise control of nutrient formulations and timely adjustments based on plant requirements [143]. These sensors interface with automated dosing systems to maintain optimal nutrient levels without manual intervention, significantly reducing labor requirements and improving consistency [49].

Environmental monitoring sensors track critical parameters including temperature, humidity, carbon dioxide levels, and

photosynthetic photon flux density (PPFD) [121]. Integrated environmental sensors provide simultaneous temperature measurements with $\pm 0.1^\circ\text{C}$ accuracy and relative humidity with $\pm 1.5\%$ RH precision, enabling precise VPD management [144]. CO₂ sensors utilising non-dispersive infrared (NDIR) technology monitor atmospheric carbon dioxide levels with accuracy up to ± 30 ppm, supporting optimised enrichment strategies for enhanced photosynthesis [145].

6) Resource Efficiency and Sustainability Metrics

Soilless cultivation technologies demonstrate significant advantages in resource efficiency compared to traditional soil-based agriculture, though performance varies substantially between system types and implementations [146]. Comprehensive life cycle assessment studies reveal that well-designed soilless systems can reduce water consumption by 70-95%, land use by 60-80%, and synthetic fertiliser application by 40-60% while simultaneously increasing productivity per unit area by 20-50% [156]. These metrics have been derived from PRISMA based literature review.

The environmental footprint of soilless systems is primarily determined by energy consumption for climate control, lighting, and water circulation [29], [157]. Although these systems typically have higher operational energy requirements than field agriculture, their concentrated production and reduced transportation distances can offset these impacts in many scenarios [158]. The integration of renewable energy sources, energy-efficient technologies, and waste heat recovery systems has become increasingly common in commercial implementations seeking to minimise environmental impacts [159].

Economic sustainability considerations extend beyond simple resource efficiency to include capital investment requirements, operational costs, labor efficiency, and market positioning [160]. Soilless cultivation systems typically require significant initial investment but can achieve favorable returns through higher productivity, premium product quality, and reduced resource costs [170]. The economic viability of specific system types depends heavily on local conditions, including energy costs, water availability, labor markets, and market demand for premium products [171] as shown in Table 12.

The continuous evolution of soilless cultivation technologies, particularly through integration with IoT monitoring systems, AI-driven optimisation algorithms, and renewable energy systems, promises further improvements in resource efficiency, crop quality, and economic viability [172]. Future developments will likely focus on reducing energy inputs through more efficient system designs, enhancing system resilience through redundant components and predictive maintenance, and expanding the range of economically viable crops suitable for soilless production methods [173].

TABLE 12: Resource Efficiency Comparison of Soilless Cultivation Methods

Tech	Water (L/kg)	Energy (kWh/kg)	Land (m ² /kg)	Nutrient Eff.	Labor (hrs/kg)	Carbon	Water Footprint
Soil	200-300	2-4	1.5-2.5	45-55%	0.8-1.2	High	Very High
NFT	20-30	3-5	0.3-0.5	75-85%	0.3-0.5	Medium	Low
DWC	25-35	2-4	0.4-0.6	70-80%	0.4-0.6	Medium	Low
Aeroponics	15-25	5-7	0.2-0.4	80-90%	0.2-0.4	Low	Very Low
Aquaponics	30-40	3-5	0.5-0.7	85-95%	0.5-0.7	Very Low	Low
Substrate	40-50	2-3	0.6-0.8	65-75%	0.6-0.8	Medium	Medium
Fogponics	10-20	6-8	0.2-0.3	85-95%	0.3-0.5	Low	Very Low

C. VISUAL ANALYSIS OF SOILLESS CULTIVATION TECHNOLOGIES

The comprehensive analysis of soilless cultivation technologies is elucidated through systematic visual representations that highlight performance characteristics, resource efficiency metrics, and adoption trends across different system types. These diagrams provide valuable insights for technology selection, operational planning, and investment decisions in modern agricultural enterprises.

The performance radar chart (Figure 8, top-left) reveals the multidimensional strengths and limitations of each soilless technology [47]. Aeroponics demonstrates exceptional performance in water efficiency (93%) and yield increase (95%) but shows limitations in energy use (45%) and cost efficiency (50%). Deep Water Culture exhibits balanced performance with superior scores in energy use (80%) and maintenance ease (90%), while Nutrient Film Technique (NFT) maintains competitive performance across all categories with particular strength in scalability (75%) derived from prisma based literature study [28], [52]. Resource efficiency metrics (Figure 8, top-right) quantify the substantial advantages of soilless systems over traditional agriculture. Hydroponic systems reduce water consumption from 200-300 L/kg to 20-35 L/kg, while aeroponics achieves even greater efficiency at 15-25 L/kg. Land use efficiency shows similar improvements, with soilless systems requiring 0.2-0.8 m²/kg compared to 1.5-2.5 m²/kg for traditional methods. Labor efficiency improvements are equally significant, reducing from 0.8-1.2 hrs/kg to 0.2-0.6 hrs/kg across various soilless technologies.

Growth rate analysis (Figure 8, bottom-left) demonstrates the accelerated development achievable through soilless cultivation [108]. Aeroponic systems achieve 100% growth maturity within 45 days, compared to 60 days for hydroponic systems and 90+ days for traditional soil cultivation. This accelerated growth trajectory directly impacts production cycles and economic returns, enabling more harvests per year and improved resource utilisation efficiency. The adoption timeline (Figure 8, bottom-right) shows the progressive market penetration of these technologies, with NFT and DWC reaching 80%+ adoption rates by 2024, while aeroponics and aquaponics maintain steady growth in specialised market segments.

Technical specifications as shown in (Figure 9) extracted from [152] provide critical operational parameters for system design and management. The comparison reveals that aeroponics operates with higher oxygen levels (8-12 mg/L) and energy requirements (30-45 kWh/m²), while substrate systems offer lower technical complexity and energy consumption. The research work in [152] shows the integration of water reservoirs, nutrient mixing, pumping systems, growing chambers, drainage, filtration, and monitoring sensors, highlighting the principles of circular economy inherent in modern soilless agriculture to maintain optimal growing conditions and resource conservation.

Crop-specific performance analysis demonstrates the universal yield improvements achievable through soilless cultivation methods. The Figure 10 compares traditional soil, hydroponic, and aeroponic yields for six major crop types, demonstrating consistent yield improvements in soilless systems across all categories, with particularly significant enhancements in high-value crops like microgreens and medicinal herbs as discussed in [52]. Tomato yields increase from 18 kg/m² in traditional systems to 25 kg/m² in hydroponics and 30 kg/m² in aeroponics, representing a 66% yield enhancement. Similar improvements are observed across all crop types, with microgreens showing the most dramatic yield increases from 2 kg/m² to 6 kg/m² in aeroponic systems. These performance improvements, combined with resource efficiency gains, position soilless cultivation as a transformative approach to sustainable agricultural intensification [52].

The visual analysis collectively demonstrates that while

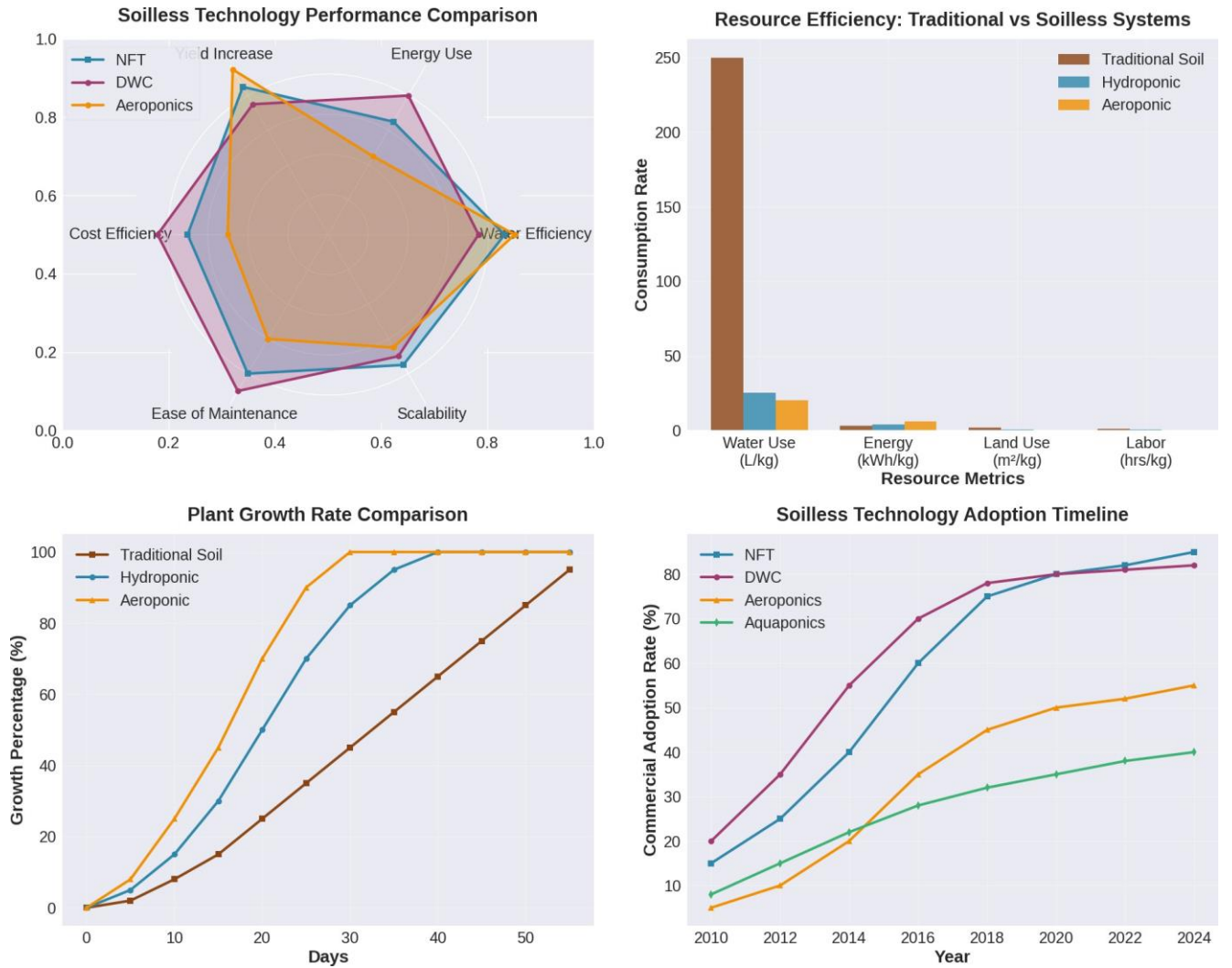


FIGURE 8: Comprehensive analysis of soilless cultivation technologies including (top-left) performance radar chart comparing NFT, DWC, and aeroponics across six key metrics; (top-right) resource efficiency comparison between traditional and soilless systems; (bottom-left) plant growth rate progression across different cultivation methods; (bottom-right) commercial adoption timeline of major soilless technologies from 2010 to 2024.

each soilless technology offers distinct advantages, the selection of appropriate systems must consider specific crop requirements, local resource constraints, economic factors, and operational capabilities. The integration of these technologies with IoT monitoring and automated control systems further enhances their performance and reliability, enabling precise environmental management and optimised resource utilisation in modern agricultural operations.

III. IOT AND SMART FARMING ENABLING VERTICAL FARMS

A. THE IOT-ENABLED SMART FARMING ARCHITECTURE

The IoT serves as the technological backbone of modern vertical farming systems, enabling real-time monitoring, precise control, and data-driven optimisation. The architec-

ture as shown in Figure 11 follows a multi-layer paradigm that facilitates seamless data flow from physical sensors to intelligent decision-making systems.

1) Perception Layer

The perception layer constitutes the physical interface with the farming environment, comprising various sensors and actuators that monitor and manipulate growing conditions. This layer forms the foundation of data acquisition and physical control in vertical farming systems, continuously collecting critical parameters including temperature, humidity, light intensity, nutrient concentration, and plant health indicators [121].

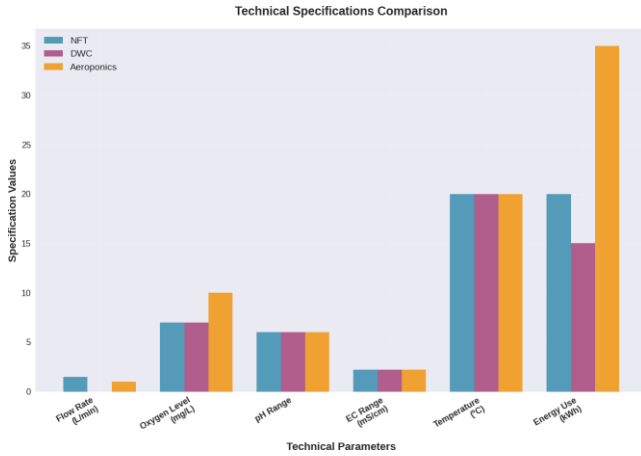


FIGURE 9: Technical specifications comparison of major soilless cultivation systems

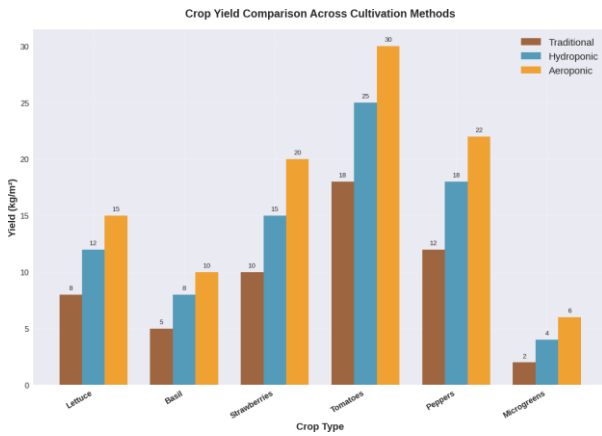


FIGURE 10: Crop-specific yield performance across different cultivation methods.

2) Network/Communication Layer

This layer facilitates reliable data transmission between perception layer devices and processing units. It encompasses various communication protocols and networking technologies optimised for agricultural environments with specific considerations for signal penetration, power consumption, and data rates. The communication layer ensures seamless connectivity across multiple vertical farming levels and enables remote monitoring capabilities [122].

3) Data Processing/Service Layer

The processing layer transforms raw sensor data into actionable insights through edge computing, cloud analytics, and machine learning algorithms. This layer handles data aggregation, normalisation, storage, and advanced computational tasks. It serves as the intelligence core where historical data analysis, predictive modeling, and optimisation algorithms generate control recommendations and operational insights [123].

4) Application Layer

The application layer provides user interfaces, control systems, and decision support tools that enable farmers and automated systems to monitor, control, and optimise vertical farming operations based on processed data and analytical insights. This layer includes mobile applications, web dashboards, automated control systems, and alert mechanisms that translate data intelligence into practical farming actions [124].

B. PERCEPTION LAYER: SENSING AND ACTUATION

The perception layer in vertical farming integrates diverse sensor technologies to monitor critical environmental and plant physiological parameters, and the actuation systems enable precise environmental control. This comprehensive sensing network forms the sensory nervous system of the smart vertical farm.

1) Environmental Monitoring Sensors

The environmental monitoring sensors measure and track conditions in the environment. They collect data that helps monitor plants' growth, quality, and changes over time. Table 13 consolidated and discusses the common sensors used in vertical farming papers as discussed below:

pH and EC Probes: Continuous monitoring of the concentrates in the nutrient solution is essential for plant health. Modern pH sensors employ glass electrodes with automatic temperature compensation, providing accuracy within ± 0.1 pH units [27]. Electrical Conductivity (EC) sensors measure nutrient concentration with precision up to ± 0.01 mS/cm, enabling precise nutrient management [147]. These sensors typically operate with sampling frequencies of 1-5 minutes and require periodic calibration to maintain accuracy in hydroponic environments.

PAR/PPFD Light Sensors: Photosynthetically Active Radiation (PAR) sensors measure light intensity in the 400-700 nm wavelength range, while Photosynthetic Photon Flux Density (PPFD) sensors quantify photons within this spectrum. Advanced quantum sensors provide accuracy within $\pm 5\%$ across the PAR spectrum [148], crucial for optimising LED lighting regimes and calculating Daily Light Integral (DLI) for different crop types.

CO₂ Sensors: Non-dispersive infrared (NDIR) CO₂ sensors monitor atmospheric carbon dioxide levels with accuracy up to ± 30 ppm [33], [149]. These sensors enable precise CO₂ enrichment control, typically maintaining concentrations between 800-1200 ppm for enhanced photosynthesis. Modern CO₂ sensors incorporate automatic baseline calibration and temperature compensation to ensure long-term measurement stability [34].

Temperature and Humidity Sensors: Integrated environmental sensors provide simultaneous temperature ($\pm 0.1^\circ\text{C}$) and relative humidity ($\pm 1.5\%$ RH) measurements [121]. These are critical for maintaining optimal VPD between 0.8-1.2 kPa for most crops. Advanced sensors incorporate dew point calculation and provide real-time VPD values to guide environmental control decisions.

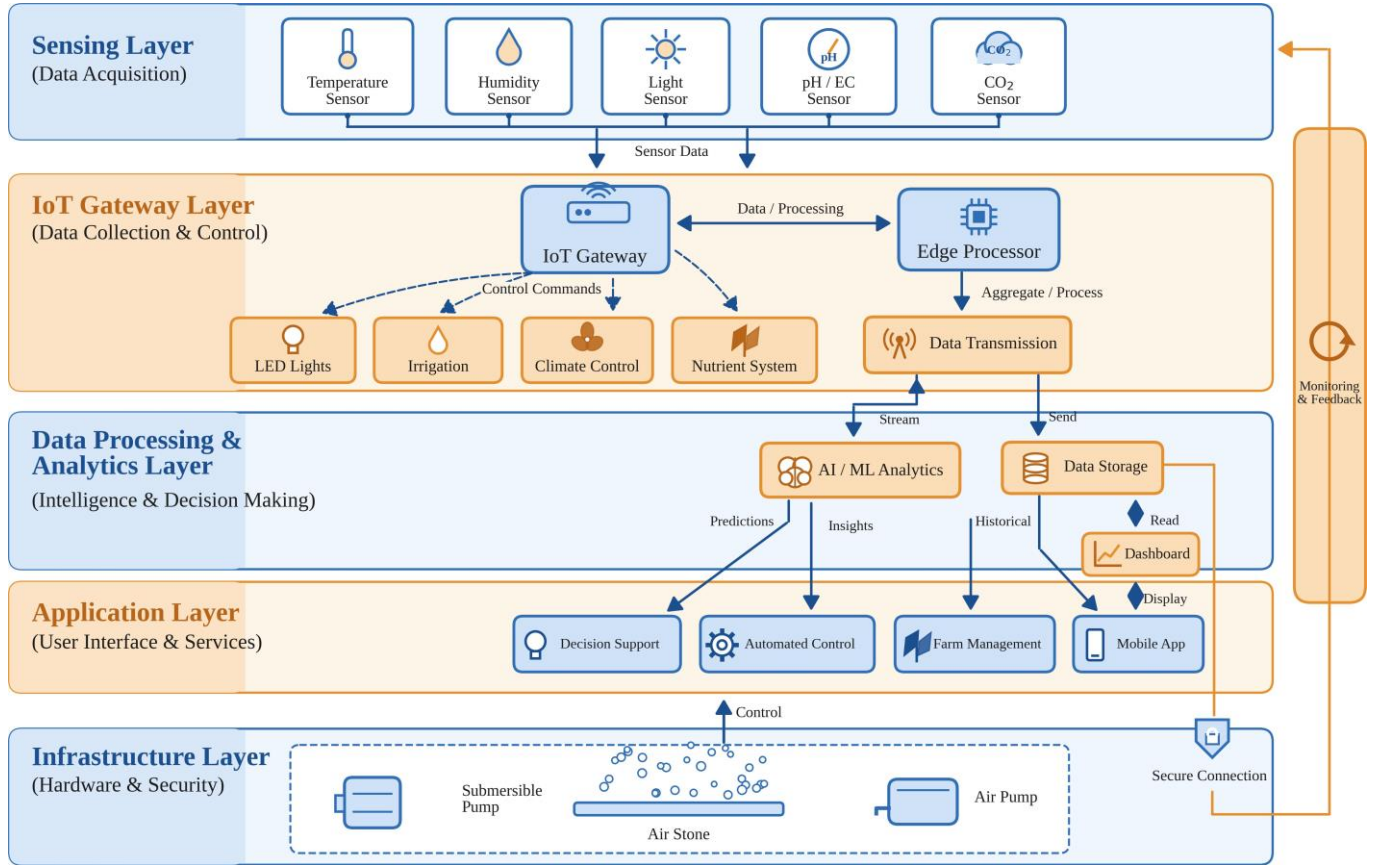


FIGURE 11: Multi-layer IoT architecture for smart vertical farming systems showing data flow from sensors to cloud platforms and control systems

2) Advanced Sensing Technologies

Computer Vision Systems: RGB [31] and multispectral cameras enable non-invasive plant monitoring through machine learning-based analysis of plant morphology, color, and growth patterns. These systems can detect nutrient deficiencies, pest infestations, and growth abnormalities with over 90% accuracy [150]. High-resolution cameras capture plant images at regular intervals, while edge computing devices process these images to extract growth metrics and health indicators.

Hyperspectral Imaging: Advanced imaging systems capture spectral data across hundreds of wavelengths, enabling detailed analysis of plant biochemical composition and early stress detection before visible symptoms appear. Hyperspectral cameras measure reflectance across the 400-2500 nm range, providing insights into chlorophyll content, water stress, and nutrient status that are invisible to conventional cameras [151].

Root Zone Sensors: Specialised sensors monitor root environment parameters including dissolved oxygen, root temperature, and microbial activity, providing insights into root health and nutrient uptake efficiency [152]. These sensors employ optical or electrochemical principles to measure

oxygen diffusion rates and root respiration activity, enabling optimisation of aeration and nutrient delivery systems.

TABLE 13: Sensor Applications in Vertical Farming

Sensor Category	Application Details
pH/EC Sensors	Nutrient solution monitoring
PAR/PPFD Sensors	LED lighting optimisation
CO ₂ Sensors	CO ₂ enrichment control
Temperature/Humidity	Environmental control
Vision Systems	Disease detection, growth monitoring
Dissolved Oxygen	Root zone oxygenation monitoring

3) Actuation Systems

Actuators translate digital commands into physical actions, enabling automated environmental control. These systems form the executive component of the IoT architecture, implementing decisions generated by control algorithms and machine learning models. An overview of actuators used in vertical farming is listed below:

Solenoid Valves: Control nutrient and water flow with response times under 100ms, enabling precise irrigation control and nutrient dosing [153]. Modern valves feature pro-

portional control capabilities and flow monitoring, allowing fine-grained adjustment of solution delivery based on real-time plant requirements.

LED Drivers: Precisely adjust light intensity (0-100%) and spectrum composition through pulse-width modulation (PWM) and constant current drivers [154]. Advanced systems support dynamic lighting recipes that vary intensity and spectrum throughout the growth cycle and diurnal periods, optimising photosynthesis and plant morphology.

Pump Controllers: Manage nutrient circulation, dosing, and aeration systems with variable speed control. These controllers maintain consistent flow rates while adapting to changing system demands [27], ensuring uniform nutrient distribution and adequate oxygenation throughout the vertical farming system.

HVAC Actuators: Regulate temperature, humidity [32], and air circulation through motorised dampers, variable frequency drives, and compressor controls. Integrated climate control systems maintain optimal growing conditions while minimising energy consumption through predictive control strategies [45], [155].

Motorised Systems: Control movable growing racks and robotic harvesters, enabling space optimisation and automated crop handling [26]. These systems incorporate precision positioning of plants, collision avoidance, and coordinated movement to maximise production density and operational efficiency.

C. COMMUNICATION LAYER AND NETWORK PROTOCOLS

The communication layer in vertical farming must address unique challenges, including signal attenuation through dense vegetation, electromagnetic interference from high-power equipment, and the need for reliable operation in enclosed, metallic environments. The selection of appropriate communication protocols depends on factors such as farm scale, data requirements, power constraints, and infrastructure. The suitability of protocols for vertical farming are listed in Table 14 and the technical specification of the communication protocols are detailed in Table 15 ([198]- [203]).

TABLE 14: Suitability of Protocols for Vertical Farming

Protocol	Vertical Farming Application
Wi-Fi	Limited to small farms; supports high-bandwidth video monitoring but consumes relatively high power
Zigbee	Well suitable for localised sensor networks; alternatively mesh networking provides redundancy
LoRaWAN	Suitable for large facilities; long range, low power, supports thousands of devices
NB-IoT	Excellent for urban vertical farms; reliable cellular connectivity, good penetration
Bluetooth LE	Good for short-range monitoring; low energy, suitable for handheld devices
6LoWPAN	Good for IP-based sensor networks; integrates well with existing internet infrastructure

TABLE 15: Technical Specifications of Communication Protocols

Protocol	Range	Data Rate	Power	Cost
Wi-Fi [198]	50-100m	10-600 Mbps	High	Low
Zigbee [199]	10-100m	20-250 kbps	Low	Medium
LoRaWAN [200]	2-15km	0.3-50 kbps	Very Low	High
NB-IoT [201]	1-10km	20-250 kbps	Low	High
Bluetooth LE [202]	10-100m	1-2 Mbps	Low	Low
6LoWPAN [203]	10-100m	20-250 kbps	Low	Medium

1) Protocol Suitability Analysis

Zigbee: Effective for localised sensor networks within individual growing levels or racks. Its mesh networking capability provides redundancy, though coordination complexity increases with network size. Zigbee’s self-healing mesh topology ensures reliable communication even if individual nodes fail, making it robust for environmental monitoring clusters. The protocol supports deterministic latency for time-sensitive applications, though network size limitations may require segmentation in large facilities.

LoRaWAN: Particularly suitable for large vertical farms due to its long-range capability (up to 15km in open areas, 2-5km indoors) and extremely low power consumption. LoRaWAN’s adaptive data rate feature optimises communication based on signal conditions, making it ideal for multi-level farming facilities. The protocol supports thousands of devices per gateway, enabling comprehensive sensor coverage across extensive vertical farming operations while maintaining years of battery life for remote sensors.

NB-IoT: Offers excellent penetration through building structures and dense vegetation, with reliable connectivity in basement and warehouse environments. Its cellular infrastructure provides inherent scalability but requires subscription fees. NB-IoT supports mobility and handover between cells, making it suitable for mobile robotic systems and equipment tracking within large vertical farming facilities. The quality of service guarantees and built-in security features make it appropriate for critical control applications.

Hybrid Approaches: Many commercial implementations employ hybrid architectures combining LoRaWAN for long-range sensor data transmission with Zigbee or Bluetooth LE for localised control clusters. This approach leverages the strengths of each protocol while mitigating its limitations. Gateway devices often serve as protocol translators, aggregating data from multiple communication technologies and providing unified interfaces to cloud platforms.

D. DATA PROCESSING AND CLOUD PLATFORMS

1) Edge vs. Cloud Computing

Edge Computing: Local processing nodes handle time-sensitive operations, including real-time environmental control loops with response times below 100ms, immediate actuator commands for safety-critical systems, local data preprocessing and filtering to reduce bandwidth requirements, and offline operation capability during connectivity issues.

Edge devices typically employ microcontrollers or single-board computers with specialised firmware for deterministic operation and low-latency response [239].

Cloud Computing: Centralised platforms manage long-term data analytics and trend analysis, machine learning model training and deployment, multi-farm data aggregation and benchmarking, and historical performance analysis and reporting. Cloud platforms provide virtually unlimited computational resources for complex simulations, optimisation algorithms, and large-scale data processing that would be impractical on edge devices [64].

2) Data Storage Architectures

Time-Series Databases: Specialised databases like InfluxDB, TimescaleDB, and Prometheus efficiently handle high-frequency sensor data with built-in aggregation, down-sampling, and retention policies [65]. These systems optimise storage for temporal data patterns common in environmental monitoring, providing efficient querying for time-range operations and statistical analysis. Compression algorithms reduce storage requirements by 80-90% while maintaining query performance.

Data Lakes: Centralised repositories store raw sensor data, imagery, and operational logs, enabling comprehensive analytics and machine learning applications without data loss through preprocessing. Data lakes support structured and unstructured data, facilitating correlation analysis between environmental conditions, operational parameters, and crop performance metrics. Metadata management and cataloging systems enable efficient discovery and access to relevant datasets [66].

3) Platform Comparison

Selecting an IoT platform is critical for implementing an efficient vertical farm management system. Platforms differ in deployment models, scalability, integration capabilities, and the learning curve required for implementation (Table 16). These characteristics directly influence how quickly and effectively a farming operation can adopt and benefit from IoT technologies.

Beyond deployment considerations, the analytical and machine learning capabilities of these platforms vary significantly, impacting the sophistication of insights that can be derived from farm data (Table 17). Furthermore, each platform has developed strengths in specific application areas relevant to vertical farming, from multi-farm management to predictive maintenance and growth modeling (Table 18). The choice of platform should align with the farm’s specific operational goals, technical expertise, and long-term scalability requirements. Table 16, Table 17 and Table 18 extracts information from [67]- [72] under the suitable categories.

E. SMART AUTOMATION AND ROBOTICS

1) Automated Nutrient Dosing Systems

Intelligent nutrient management systems (Figure 12) represent a cornerstone of precision agriculture in vertical farming,

TABLE 16: IoT Platform Deployment and Scalability

Platform	Deploy	Scale	Integrate	Learning
AWS IoT [67]	Cloud	High	Extensive	Moderate
Azure IoT [68]	Hybrid	High	Extensive	Moderate
Google IoT [69]	Cloud	High	Extensive	Moderate
IBM Watson [70]	Hybrid	Medium	Good	Steep
ThingSpeak [71]	Cloud	Low	Basic	Easy
Node-RED [72]	On-prem	Medium	Flexible	Easy

TABLE 17: IoT Platform Analytics and ML Capabilities

Platform	Analytics	ML	Cost
AWS IoT [67]	Real-time + Historical	Advanced	High
Azure IoT [68]	Time-series focus	Advanced	High
Google IoT [69]	Big data analytics	Advanced	High
IBM Watson [70]	Industry-specific	Advanced	Medium
ThingSpeak [71]	Basic visualisation	Limited	Low
Node-RED [72]	Custom dashboards	Custom	Low

employing sophisticated predictive algorithms to maintain optimal nutrient composition through multi-layered control strategies [47]. These systems integrate real-time monitoring of pH and electrical conductivity (EC) with closed-loop feedback control, achieving stability within ± 0.1 pH units and $\pm 5\%$ EC tolerance [106]. The integration of plant growth stage recognition with environmental condition monitoring enables dynamic adjustment of nutrient recipes, while historical consumption pattern analysis combined with predictive modeling anticipates future nutrient demands [48].

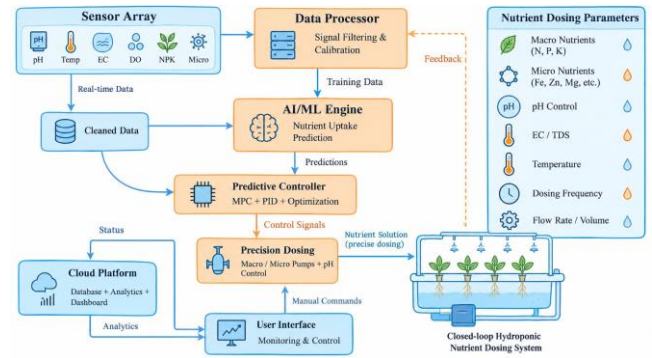


FIGURE 12: System architecture showing micronutrient delivery in closed-loop hydroponic systems

Advanced machine learning architectures, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, optimise nutrient recipes by correlat-

TABLE 18: IoT Platform Vertical Farming Applications

Platform	Vertical Farming Applications
AWS IoT [67]	Multi-farm management, Energy optimisation
Azure IoT [68]	Digital twins, Predictive maintenance
Google IoT [69]	Yield prediction, Growth modeling
IBM Watson [70]	Supply chain, Quality control
ThingSpeak [71]	Prototyping, Research applications
Node-RED [72]	Custom automation, Integration workflows

ing ionic composition with plant physiological responses [49]. These systems have demonstrated 15-25% reduction in fertiliser usage while maintaining or improving crop quality metrics, including biomass accumulation, chlorophyll content, and nutritional density [233]. Ensemble methods combining random forests with gradient boosting machines have shown particular efficacy in predicting nutrient uptake patterns across different plant varieties and growth stages [187].

Modern nutrient delivery systems employ precision peristaltic pumps with resolution of ± 1 mL/min and electromagnetic flow meters achieving $\pm 0.5\%$ accuracy, ensuring precise delivery of macronutrients (N, P, K, Ca, Mg, S) and micronutrients (Fe, Mn, Zn, Cu, B, Mo) according to dynamically optimised recipes [50]. Multi-parameter proportional-integral-derivative (PID) control algorithms maintain ionic balance while preventing nutrient lockout and precipitation through real-time adjustment of chelation agents and pH modifiers [51]. Integration with multi-probe water quality monitoring systems enables automatic compensation for source water variations in hardness, alkalinity, and dissolved solids, maintaining consistent nutrient availability despite fluctuating input conditions [56].

2) Robotic Planting and Harvesting

Seedling Transplantation: Computer vision-guided robotic transplantation systems employ stereo vision and deep learning algorithms to precisely place seedlings in growing media with placement accuracy within ± 1 mm [57]. These systems typically incorporate convolutional neural networks (CNNs) trained on thousands of seedling images to assess viability, orientation, and root development before transplantation [58]. Current commercial systems can process 2000-5000 seedlings per hour, representing 80-90% reduction in labor requirements while ensuring consistent planting density and orientation [231]. Advanced systems integrate hyperspectral imaging for early disease detection and nutrient deficiency identification during transplantation, automatically rejecting substandard seedlings and maintaining comprehensive digital records of planting operations for traceability and quality assurance [59].

Selective Harvesting: AI-powered robotic harvesting systems utilise multi-modal sensing combining RGB, near-infrared (NIR), and depth imaging to identify harvest-ready produce based on size, color, morphological features, and biochemical maturity indicators [60]. The Figure 13 shows a sample visualisation of robotic harvest of apples. Current generation systems achieve harvest success rates of 85-95% for structured crops like lettuce, herbs, and microgreens, with cycle times of 3-5 seconds per harvest operation [61]. Robotic manipulators equipped with compliant, sensor-rich end-effectors perform non-destructive harvesting through adaptive grasping force control and stem localisation algorithms, minimising damage to delicate produce and adjacent plants [62]. Deep reinforcement learning algorithms continuously improve the precision in harvesting through human-in-the-

loop corrections and self-supervised learning from successful harvest operations [73].



FIGURE 13: Integrated robotic harvesting system architecture using computer vision

Quality Inspection and Grading: Automated vision systems perform continuous quality assessment throughout the production cycle, detecting defects, diseases, and nutrient deficiencies with classification accuracy exceeding 95% compared to human expert assessment [192]. Multi-spectral imaging systems combining visible, fluorescence, and near-infrared spectroscopy with deep learning algorithms identify subtle quality indicators, including chlorophyll fluorescence kinetics, water stress indices, and secondary metabolite accumulation patterns invisible to human visual inspection [59]. These systems generate comprehensive quality metrics for each harvest batch, including size distribution, color uniformity, morphological characteristics, and defect classification, supporting blockchain-integrated traceability systems and enabling premium pricing strategies based on quality assessment [74].

3) Environmental Control Feedback Loops

Intelligent environmental control systems implement sophisticated multi-input multi-output (MIMO) feedback mechanisms that continuously optimise growing conditions while balancing competing operational objectives through hierarchical control architectures [75]. These systems represent the pinnacle of cyber-physical system integration in vertical farming, transforming conventional environmental control into adaptive, self-optimising systems capable of learning and improvement over time [76].

Reinforcement Learning for Environmental Optimisation: Deep reinforcement learning (DRL) systems continuously optimise environmental parameters including photosynthetic photon flux density (PPFD), spectral composition, temperature, humidity, CO₂ concentration, and air velocity based on multi-modal plant response metrics [88]. These systems employ actor-critic architectures that explore high-dimensional parameter spaces while respecting operational constraints, discovering non-intuitive growing recipes that often outperform traditional guidelines by 15-30% in resource efficiency metrics [178]. Recent advances in inverse reinforcement learning enable systems to infer optimisation objectives

from expert demonstrations, accelerating the development of effective control policies for novel crop varieties [81].

Predictive Control and Forecasting: Model predictive control (MPC) architectures anticipate environmental disturbances and preemptively adjust control parameters using weather forecast integration, energy price prediction models, and crop transpiration algorithms [93]. These systems solve constrained optimisation problems like balancing high energy costs (lighting, climate control) with operational efficiency, maximising yield, ensuring crop quality, and achieving profitability at regular intervals (typically 5-15 minutes), computing optimal control sequences that achieve desired growth trajectories while minimising operational costs [82]. Integration with building energy management systems enables strategic load shifting and demand response participation, reducing energy costs by 20-35% through temporal optimisation of high-power operations [89].

Multi-objective Optimisation and Decision Support: Advanced control systems balance competing objectives including energy efficiency, growth rate, resource consumption, product quality, and operational costs through Pareto optimisation techniques [175]. These systems generate non-dominated solution sets representing optimal trade-offs between conflicting goals, enabling operators to select operating points aligned with dynamic business priorities and market conditions [83]. Interactive visualisation interfaces allow human operators to explore the solution space and understand the implications of different optimisation priorities, facilitating informed decision-making in complex operational environments [84].

Fault Detection, Diagnosis, and Prognostic Health Management: Automated systems continuously monitor equipment performance and environmental consistency using distributed sensor networks and edge computing infrastructure [94]. Early warning systems employing autoencoder neural networks and support vector machines identify developing anomalies with detection rates exceeding 90%, while Bayesian network-based diagnostic engines identify root causes with 80-85% accuracy [102]. Digital twin technology enables virtual testing of control strategies and failure analysis without risking actual crops, reducing operational risks by 30-40% through proactive maintenance and contingency planning [99].

The integration of IoT technologies with vertical farming represents a paradigm shift in agricultural production, enabling unprecedented levels of precision, efficiency, and scalability [26]. As these technologies continue to evolve, they promise to address key challenges in global food security while minimising environmental impact through optimised resource utilisation and reduced waste [172]. The convergence of IoT, AI, robotics, and biotechnology in controlled environment agriculture heralds a new era of data-driven farming that can sustainably meet the nutritional needs of growing urban populations while adapting to the challenges of climate change and resource scarcity [85].

IV. AI AND MACHINE LEARNING IN VERTICAL FARMING

A. ENERGY EFFICIENCY OPTIMISATION USING AI

AI plays a pivotal role in optimising energy consumption in vertical farming systems, where energy costs can constitute up to 60% of operational expenses [85], [86]. Machine learning algorithms analyse historical energy usage patterns, environmental conditions, and crop requirements to develop predictive models for energy optimisation. Figure 14 shows the AI-driven energy optimisation framework suitable for vertical farming system. Deep neural networks process multi-modal data streams, including electricity pricing, weather forecasts, and plant physiological status, to generate optimal control sequences [87].

Deep reinforcement learning algorithms continuously optimise energy distribution across various subsystems, including LED lighting, HVAC systems, and water pumps [88]. These systems learn optimal control strategies through trial and error, balancing energy consumption against crop growth requirements. For instance, Q-learning algorithms can reduce energy consumption by 15-25% while maintaining optimal growth conditions by dynamically adjusting lighting schedules based on real-time electricity pricing and plant photosynthetic responses [89].

Predictive maintenance systems employing Long Short-Term Memory (LSTM) networks forecast equipment failures before they occur, scheduling maintenance during off-peak hours to minimise disruption and energy waste [95]. These systems analyse sensor data from motors, compressors, and electrical systems to detect anomalies and predict maintenance needs with over 90% accuracy. Transformer-based architectures have shown particular promise in processing temporal sequences of sensor readings to identify degradation patterns in critical components [90].

B. INTELLIGENT LIGHTING CONTROL IN CLOSED ENVIRONMENTS

Lighting represents one of the most significant energy consumers in vertical farming, accounting for 40-60% savings from total energy usage [96]. Despite advances in LED lighting for CEA, species-specific and growth-stage-dependent guidelines for optimising blue light intensity, duration, and spectral ratios remain insufficiently established [219] [193]. Recent advances in photobiology-informed machine learning have enabled the development of lighting recipes that maximise photosynthetic efficiency while minimising energy input [91]. Convolutional Neural Networks (CNNs) analyse multispectral plant images to determine optimal lighting conditions for different growth stages [104]. These systems adjust Photosynthetic Photon Flux Density (PPFD), photoperiod duration, and spectral composition in real-time based on plant morphology, chlorophyll content, and stress indicators. Reinforcement learning algorithms explore lighting recipes that maximise photosynthesis efficiency while minimising energy consumption, achieving 20-30% energy savings compared to fixed lighting schedules [174].

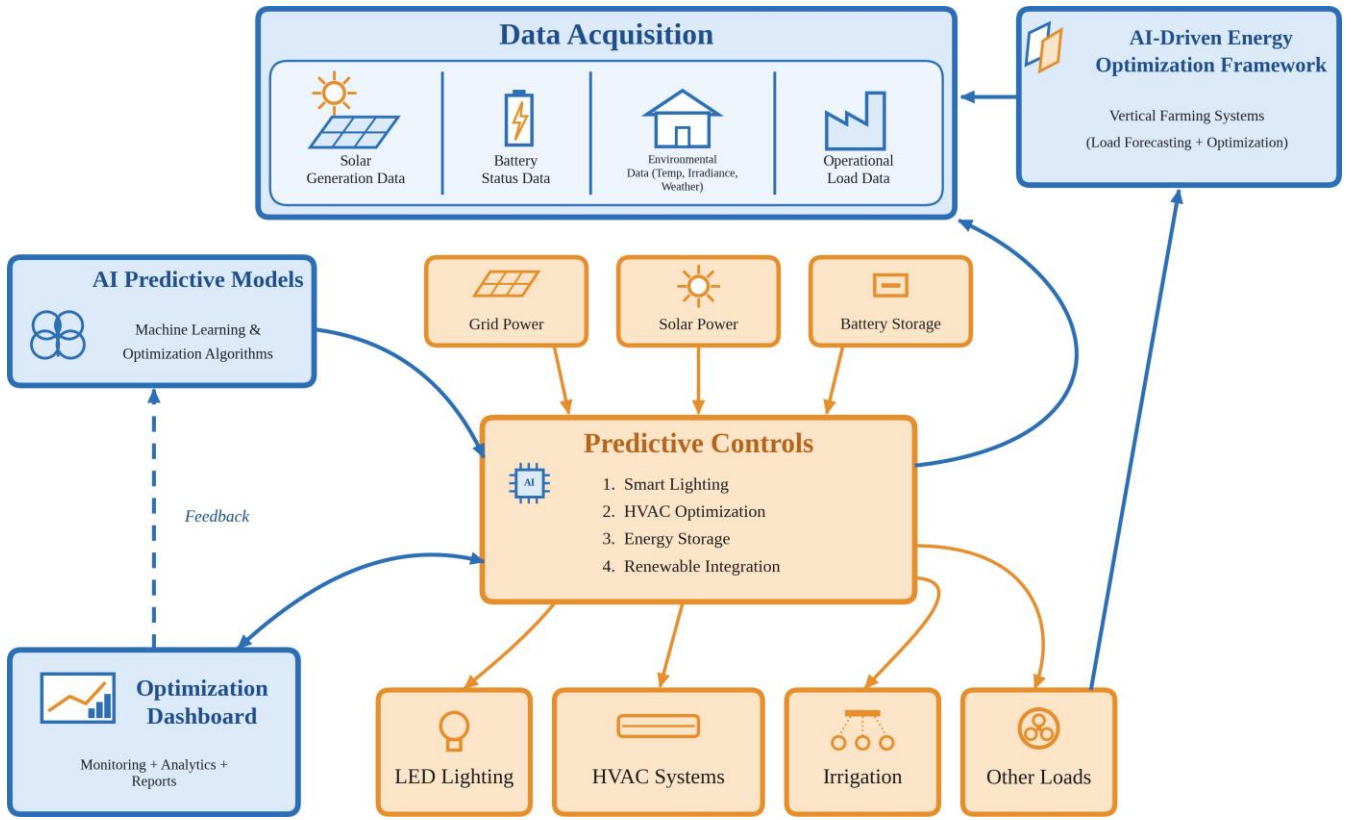


FIGURE 14: AI-driven energy optimisation framework for vertical farming systems showing various predictive controls

Multi-objective optimisation algorithms balance competing objectives, including energy consumption, growth rate, and secondary metabolite production in medicinal plants [175]. These systems employ Pareto optimisation to identify lighting strategies that represent optimal trade-offs between multiple performance metrics, enabling growers to select operating points aligned with specific production goals. Bayesian optimisation frameworks have demonstrated efficient exploration of high-dimensional lighting parameter spaces, rapidly converging to optimal configurations for novel plant varieties [176].

C. REINFORCEMENT LEARNING FOR CLIMATE CONTROL OPTIMISATION

Reinforcement Learning (RL) represents a paradigm shift in environmental control for vertical farming, enabling systems to learn optimal control strategies through continuous interaction with the farming environment [242]. Model-free RL approaches have shown remarkable capability in discovering non-intuitive control policies that outperform traditional rule-based systems.

Deep Q-Networks (DQN) and Policy Gradient methods learn to control multiple environmental parameters simultaneously, including temperature, humidity, CO₂ concentration, and air circulation [178]. These algorithms receive rewards based on crop growth metrics, resource efficiency, and

operational costs, gradually discovering control strategies that outperform human-designed protocols. Model-based reinforcement learning approaches incorporate predictive models of plant physiology to anticipate crop responses to environmental changes, enabling proactive control adjustments [179].

Multi-agent reinforcement learning systems coordinate control across multiple growing zones, optimising resource allocation while respecting global constraints such as total energy consumption and water usage [180]. These systems learn cooperative strategies that maximise overall farm productivity while minimising operational costs. Recent advances in centralised training with decentralised execution have enabled scalable coordination across large-scale vertical farming facilities [181].

D. DIGITAL TWINS AND VIRTUAL FARMING ENVIRONMENTS

Digital twin technology creates virtual replicas of vertical farming systems, enabling simulation, optimisation, and predictive analysis without risking actual crops [182]. The integration of IoT sensors with computational models enables real-time synchronisation between physical and virtual systems, creating living digital representations that evolve with their physical counterparts. Digital twin usecases for manufacturing products in industries are discussed in [63] and a similar twin architecture for implementing vertical farming

is shown in Figure 15.



FIGURE 15: Digital twin architecture for vertical farming integrating real-time sensor data with predictive models for simulation and optimisation.

Physics-informed neural networks combine mechanistic crop growth models with data-driven approaches to create accurate digital representations of plant development [183]. These digital twins simulate crop responses to environmental changes, nutrient variations, and pest pressures, enabling growers to test control strategies virtually before implementation. The integration of computational fluid dynamics models with machine learning predicts microclimate variations within growing areas, identifying hotspots and optimising air circulation patterns [184].

Digital twins facilitate scenario analysis for capacity planning and operational optimisation [99]. Growers can simulate the impact of scaling operations, changing crop varieties, or modifying environmental protocols, reducing financial risks associated with operational changes. Real-time synchronisation between physical systems and their digital counterparts enables continuous model refinement and predictive maintenance. Digital twin technology has demonstrated 30-40% reduction in operational risks and 25-35% improvement in resource allocation efficiency in commercial vertical farming operations [185].

E. MACHINE LEARNING FOR YIELD PREDICTION AND QUALITY ASSESSMENT

Machine learning algorithms transform historical and real-time data into accurate predictions of crop yield and quality, enabling better planning and resource allocation [43], [186]. The integration of computer vision with traditional sensor data has significantly improved prediction accuracy, particularly for complex quality metrics.

Ensemble methods combining Random Forests, Gradient Boosting, and Neural Networks analyse multi-modal data streams to predict harvest yields with 85-95% accuracy [187]. These models incorporate environmental parameters, nutrient levels, plant imagery, and historical performance data to generate probabilistic yield forecasts. Time-series

forecasting using LSTM networks predicts growth trajectories and harvest timing, enabling optimised labor scheduling and market planning [188].

Computer vision systems employing Deep CNNs assess product quality through non-destructive analysis of size, color, shape, and defect patterns [189]. These systems achieve human-level accuracy in quality grading while providing consistent, objective assessments on a 24/7 basis. Transfer learning approaches adapt pre-trained vision models to specific crop varieties, reducing data requirements and accelerating deployment [190]. Recent advances in few-shot learning have enabled quality assessment systems to adapt to new crop varieties with minimal labeled data, significantly reducing implementation barriers for special crop producers [191].

F. AI-DRIVEN DISEASE DETECTION AND PLANT HEALTH MONITORING

AI enables early detection of plant diseases and nutrient deficiencies, significantly reducing crop losses and chemical usage [192]. The integration of hyperspectral imaging with deep learning has enabled the detection of plant stress before visible symptoms appear, creating opportunities for proactive intervention. Figure 16 illustrates an AI system optimised for crop yield monitoring, scheduling, and environmental sensing, resembling a proof-of-concept model of a fully integrated smart agriculture deployment typically pairs all the included management tasks for automated disease detection [42]. Specialised disease detection models utilise high-resolution computer vision to scan foliage for early pathological indicators flagging anomalies with localised bounding boxes and performance metrics.

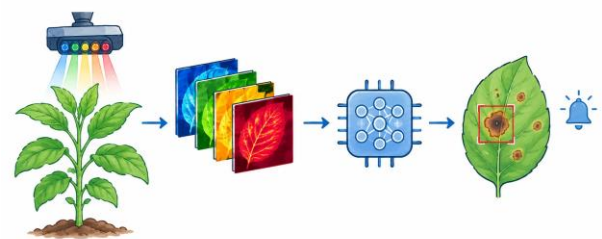


FIGURE 16: AI-based disease detection system using computer vision and multispectral imaging for early identification of plant health issues.

Deep learning architectures including, ResNet, Inception, and EfficientNet, analyse high-resolution plant images to identify disease symptoms at early stages, often before visible to human inspectors [194], [195]. These systems achieve 92-98% accuracy in detecting common diseases, including powdery mildew, botrytis, and nutrient deficiencies. Multispectral and hyperspectral imaging combined with convolutional neural networks detect stress indicators invisible to the

human eye, enabling intervention before significant damage occurs [196].

Anomaly detection algorithms identify unusual patterns in sensor data that may indicate developing health issues [102]. These systems employ autoencoders and one-class SVMs to learn normal operating conditions and flag deviations that warrant investigation. Integration with environmental control systems enables automated responses to detected issues, such as adjusting humidity to suppress fungal growth or modifying nutrient formulas to address deficiencies. Recent research in explainable AI has improved trust in automated detection systems by providing interpretable explanations for disease classifications, helping growers understand the reasoning behind AI recommendations [197].

G. IOT AND AI INTEGRATION FOR REAL-TIME DECISION MAKING

The convergence of IoT and AI creates intelligent vertical farming systems capable of autonomous , data-driven decision making at scale [140]. Edge computing architectures enable real-time processing of sensor data while cloud platforms provide strategic optimisation across multiple facilities.

Edge AI systems process sensor data locally using lightweight neural networks, enabling real-time control decisions with minimal latency [204]. These systems handle time-critical operations, including environmental control loops and immediate actuator commands. Cloud-based AI platforms perform complex analytics, model training, and multi-farm optimisation, leveraging extensive computational resources for strategic decision support [205].

Federated learning approaches enable collaborative model training across multiple farms without sharing sensitive operational data [206]. This distributed learning paradigm improves model robustness while preserving data privacy and commercial confidentiality. Blockchain-integrated AI systems provide transparent, auditable decision trails for quality assurance and regulatory compliance [217]. Recent advances in homomorphic encryption have enabled secure aggregation of model updates in federated learning systems, further enhancing privacy protection in multi-stakeholder agricultural networks [225].

The integration of AI with vertical farming represents a fundamental transformation in agricultural production [35], enabling unprecedented levels of precision, efficiency, and sustainability [26]. As these technologies continue to evolve, they promise to address global food security challenges while minimising environmental impact through optimised resource utilisation and reduced waste. Future research directions include the development of cross-crop transfer learning frameworks, integration of genomic data with environmental optimisation, and the creation of AI systems capable of adapting to climate change impacts on indoor agricultural production [172].

V. COMPARATIVE ANALYSIS OF VERTICAL FARMING ADOPTION: UK VS INDIA

A. GEOGRAPHICAL AND ENVIRONMENTAL CONTEXT

The adoption patterns and implementation challenges of vertical farming systems exhibit significant divergence between the UK and India, primarily driven by their distinct geographical, economic, and environmental contexts. The UK, characterised by its temperate maritime climate and limited arable land availability, faces challenges related to seasonal production limitations and high land costs in urban centers. Conversely, India’s tropical and subtropical climate, combined with rapid urbanisation and water scarcity issues, creates unique opportunities and challenges for controlled environment agriculture implementation. Figure 17 depicts the comparative geographical and climate analysis between UK and India and data extracted from [219], [220].

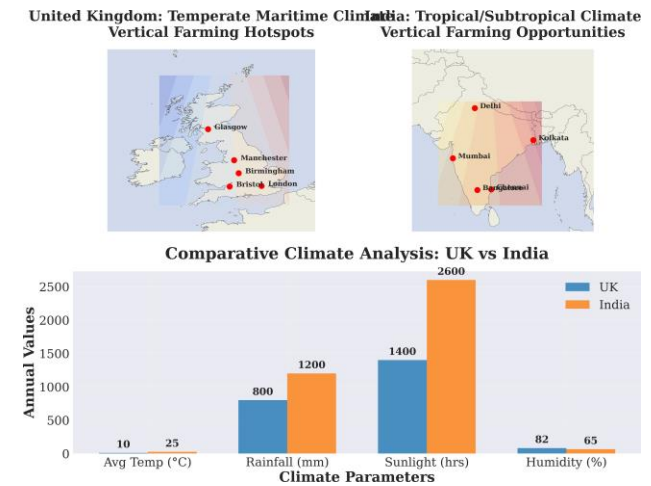


FIGURE 17: Comparative geographical and climate analysis between UK and India

The UK’s vertical farming initiatives are predominantly concentrated in urban corridors, including London, Birmingham, and Manchester, where high population density and premium real estate costs justify capital-intensive agricultural technologies. These systems primarily focus on high-value leafy greens, herbs, and microgreens, targeting premium restaurant markets and health-conscious consumers. The temperate climate, while reducing extreme temperature control requirements, necessitates substantial energy inputs for artificial lighting during winter months and humidity management throughout the year.

India’s vertical farming landscape presents a more complex picture, with implementations ranging from sophisticated commercial facilities in metropolitan areas like Mumbai, Delhi, and Bangalore to smaller-scale community initiatives in rapidly urbanising secondary cities. The tropical climate offers advantages in the availability of natural light, but introduces significant challenges in cooling load management and humidity control. The diverse agricultural landscape spans from high-tech export-oriented facilities to subsistence-level implementations addressing food security concerns in peri-urban areas.

B. TECHNO-ECONOMIC COMPARATIVE ANALYSIS

1) Capital Investment and Operational Costs

The economic viability of vertical farming systems demonstrates substantial variation between the two nations, influenced by local cost structures, market dynamics, and policy environments. In the UK, typical capital investment for commercial-scale vertical farms ranges from £800-£1,200 per square meter, with operational costs dominated by energy expenditures (45-60%), labor (20-30%), and inputs (15-25%). The high energy costs, particularly electricity tariffs averaging £0.18 - £0.25 per kWh, significantly impact operational economics and necessitate sophisticated energy management strategies. Table 19 details the operational cost analysis in Vertical Farming across the UK and India [23] [165], [166].

India's vertical farming cost structure reveals different priorities and constraints, with capital investment ranging from Rs 15,000 to Rs 25,000 per square meter for commercial implementations. Operational costs show energy representing 25-40% of total expenditures, despite significantly lower electricity tariffs (Rs 4 - Rs 8 per kWh for commercial users). Labor costs maintain similar proportional significance despite absolute values being substantially lower, reflecting the different wage structures in agricultural labor markets [37], [38]

2) Market Dynamics and Revenue Streams

The market positioning and revenue models for vertical farming outputs demonstrate notable differences between the two countries. UK implementations typically target premium market segments, with produce selling at 2-3 times conventional market prices. Revenue streams are diversified through direct-to-consumer subscriptions, restaurant partnerships, and retail collaborations, emphasising local provenance and sustainability credentials.

India's vertical farming enterprises navigate more complex market structures, with successful implementations often combining premium urban markets with institutional supply contracts and export opportunities. Price premiums are generally more modest (at most higher than two times the conventional price), with success often dependent on import substitution strategies for high-value herbs and specialty vegetables previously sourced from international markets [112]. Figure 18 comparatively illustrates the distribution channels, value chain and price premiums, consumer motivation analysis across vertical farming sectors of UK [17], [112] and India [111].

C. ENERGY INFRASTRUCTURE AND SUSTAINABILITY CHALLENGES

1) Grid Reliability and Energy Management

The energy infrastructure context presents distinct challenges in both nations. The UK benefits from highly reliable grid infrastructure but faces high energy costs and carbon intensity concerns. Vertical farming operations typically implement sophisticated energy management systems, including time-of-use optimisation, behind-the-meter renewable generation,

and thermal energy storage to mitigate cost and environmental impacts [41].

India's energy landscape is characterised by lower costs but significant reliability challenges, particularly in peri-urban and rural areas where many vertical farming initiatives are located. Implementation success often depends on hybrid power systems combining grid supply with solar PV and battery storage, with diesel generators frequently employed as backup despite their environmental implications [37], [111].

2) LED Technology and Environmental Trade-offs

The widespread adoption of LED lighting in vertical farming introduces complex environmental trade-offs that manifest differently in each national context. While LED technology offers substantial energy efficiency improvements compared to conventional lighting, concerns regarding electronic waste, rare earth element usage, and end-of-life management are increasingly prominent [77], [78].

In the UK, WEEE (Waste Electrical and Electronic Equipment) regulations govern LED disposal, but implementation challenges remain regarding the recovery of valuable materials and the prevention of hazardous substance release. India's rapidly growing electronic waste stream, combined with less developed recycling infrastructure, presents significant environmental risks that require proactive management in vertical farming scale-up scenarios and the environmental impact analysis of LED Technology in Vertical Farming across the UK and India are tabulated in Table 20 [78].

D. CLOSED-LOOP SYSTEMS AND RESOURCE EFFICIENCY

1) Water and Nutrient Management

Closed-loop systems represent a critical sustainability advantage for vertical farming, with implementation approaches varying based on local resource constraints and technological capabilities. UK's implementations typically achieve 85-95% water use reduction compared to conventional agriculture through sophisticated recirculating systems, though these require careful management to prevent pathogen buildup and maintain nutrient balance.

Indian vertical farming systems often prioritise water efficiency due to more acute water scarcity concerns, with many implementations achieving even higher efficiency rates through evaporation control and advanced irrigation techniques. However, challenges related to water quality, particularly in urban areas with contaminated groundwater sources, necessitate additional treatment steps that increase system complexity and cost.

2) Integrated Aquaponics and Bioeconomic Approaches

The integration of aquaponics and other bioeconomic approaches demonstrates different implementation patterns between the two countries. UK's aquaponic systems typically focus on high-value fish species like trout and perch, combined with premium herb and leafy green production, leveraging

TABLE 19: Operational Cost Analysis in Vertical Farming: UK vs India

Cost Component	Absolute Costs		Cost Distribution		Notes
	UK (£/m²/yr)	India (INR/m²/yr)	UK (% of total)	India (% of total)	
Energy	180-250	4,000-7,000	45-60	25-40	UK: High tariff; India: Grid reliability issues
Labor	80-120	3,000-5,000	20-30	20-30	Similar proportion despite wage differences
Nutrients	30-50	1,500-2,500	8-12	10-15	Imported vs. local sourcing differences
Maintenance	25-40	1,000-2,000	6-10	8-12	Higher in UK due to automation complexity
Capital Depreciation	60-90	4,000-6,000	15-20	20-30	Based on 5-7 year equipment lifespan
Total OPEX Range	375-550	13,500-21,500	100	100	Exchange rate: £1 ≈ INR 125

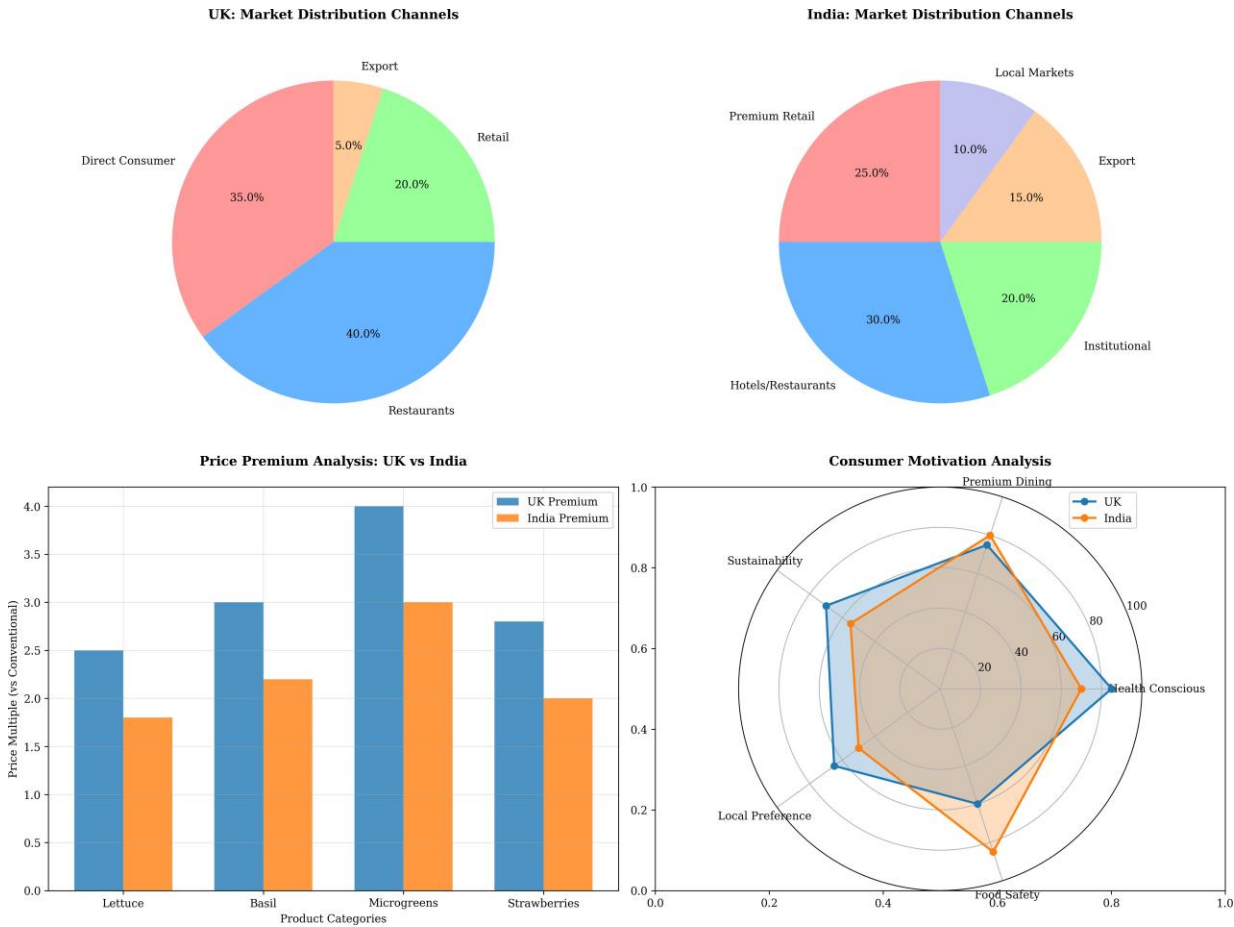


FIGURE 18: Market structure and value chain analysis comparing UK and India vertical farming sectors, showing distribution channels, price premiums, and consumer segmentation

sophisticated environmental control and market positioning strategies [18].

Indian implementations often employ more diverse species combinations, including tilapia and carp, integrated with local vegetable varieties. These systems frequently incorporate elements of traditional knowledge and adaptive management approaches, though they face challenges in maintaining system stability and meeting consistent quality standards required by premium markets.

E. POLICY FRAMEWORKS AND REGULATORY ENVIRONMENTS

1) UK Policy Landscape

The UK’s policy environment for vertical farming is characterised by evolving agricultural subsidies post-Brexit, urban planning considerations, and energy policy interactions. The Environmental Land Management scheme provides potential support mechanisms, while planning regulations regarding urban agricultural activities and building codes present both opportunities and constraints for vertical farming develop-

TABLE 20: Environmental Impact Analysis of LED Technology in Vertical Farming: UK vs India Comparison

Environmental Factor	UK Context	India Context	Mitigation Strategies	Circular Economy Potential (%)
Electronic Waste	High regulatory compliance (WEEE)	Growing concern, limited infrastructure	Extended Producer Responsibility (EPR), modular design for repair	65–75
Rare Earth Elements	Import dependency (China ~90%)	Limited recycling capability	Material recovery programs, alternative phosphor technologies	40–50
Energy Consumption	Carbon-intensive grid (~250 gCO ₂ /kWh)	Grid reliability challenges	Renewable energy integration, smart grid participation	80–90
Thermal Management	Waste heat utilisation	High cooling load (tropical climate)	Phase change materials, heat recovery systems	60–70
End-of-Life Disposal	Advanced recycling facilities	Informal recycling sector dominates	Design for disassembly, take-back programs	55–65
Light Pollution	Strict urban regulations	Emerging concern in metropolitan regions	Directional lighting, spectral tuning, shielding	70–80

ment.

Energy policy represents a significant factor, with the UK’s commitment to net-zero carbon emissions by 2050 creating both pressure for renewable energy integration and potential support mechanisms through various green technology funds and carbon pricing mechanisms. The classification of vertical farming within industrial versus agricultural categories creates regulatory ambiguities that impact permitting, taxation, and support eligibility.

2) Indian Policy Context

India’s policy landscape reflects the tension between traditional agricultural priorities and emerging technology opportunities. Various state-level initiatives, particularly in water-scarce regions, provide support for water-efficient agricultural technologies, while national programs like the National Mission on Sustainable Agriculture offer potential funding avenues.

The complex regulatory environment regarding land use conversion, particularly in peri-urban areas, presents significant challenges for vertical farming scale-up. Energy policy considerations include both subsidy structures for agricultural electricity use and emerging initiatives promoting solar energy adoption, though implementation consistency varies substantially across states. The policy landscape for vertical farming in the UK and India is shown in Figure 19, drawing on [177], [227].

F. SUSTAINABLE DEVELOPMENT GOALS ALIGNMENT

1) Direct SDG Contributions

Vertical farming demonstrates significant potential to contribute to multiple Sustainable Development Goals, though the specific contributions and implementation priorities vary between the UK and Indian contexts. Both countries benefit from SDG 2 (Zero Hunger) through enhanced food security and SDG 6 (Clean Water and Sanitation) via dramatic water use reductions.

The UK’s vertical farming contributions to SDG 11 (Sustainable Cities and Communities) emphasise urban re-

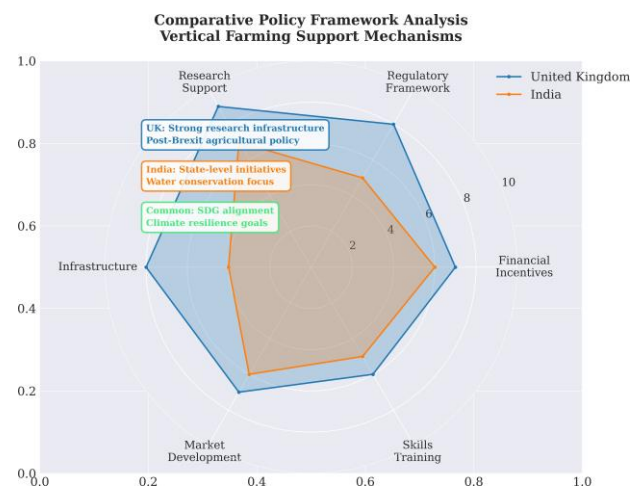


FIGURE 19: Comparative policy framework analysis showing regulatory environments, support mechanisms, and barriers to vertical farming adoption in UK and India contexts.

generation and local food system development, while Indian implementations often focus more strongly on SDG 1 (No Poverty) through livelihood creation and SDG 8 (Decent Work and Economic Growth) via agricultural technology employment opportunities. Table 21 maps the SDG’s to the contributions of vertical farming in the UK and India that is been analysed so far by the authors. However, it is a niche area where projects and mappings are explored by many researchers and the table is subjected to expand or extended by other researchers in the future [215].

2) Climate Resilience and Adaptation

Both nations face climate change impacts on conventional agriculture, though the specific vulnerabilities differ substantially. UK’s vertical farming addresses climate resilience through reduced weather dependency and enhanced supply chain stability, particularly relevant given increasing climate volatility affecting European agricultural production.

India’s vertical farming initiatives contribute to climate

TABLE 21: Sustainable Development Goals Alignment: Vertical Farming Contributions

SDG	Primary Contribution	UK Context Emphasis	India Context Emphasis
SDG 2: Zero Hunger	Year-round production	Urban food security	Nutritional diversity
SDG 6: Clean Water	70-95% reduction	Water quality protection	Water scarcity mitigation
SDG 7: Affordable Energy	Renewable integration	Carbon reduction	Energy access
SDG 11: Sustainable Cities	Urban agriculture	Green infrastructure	Peri-urban development
SDG 12: Responsible Consumption	Resource efficiency	Circular economy	Waste reduction
SDG 13: Climate Action	Emissions reduction	Adaptation resilience	Climate resilience

adaptation by providing production stability despite monsoon variability, extreme heat events, and water scarcity intensification. The technology’s reduced land footprint also supports climate mitigation by reducing pressure for agricultural land conversion and associated carbon emissions.

G. FUTURE TRAJECTORIES AND SCALING CHALLENGES

1) Technology Adoption and Innovation Pathways

The future development of vertical farming in both countries will be shaped by ongoing technological innovation, though adoption patterns and priority areas demonstrate significant divergence [36]. The UK’s innovation focuses on energy efficiency improvements, automation advancements, and integration with urban energy systems, leveraging the country’s strong research infrastructure in robotics, AI, and renewable energy.

Indian technological development emphasises adaptation to local conditions, including the development of lower-cost systems, tropical crop varieties, and solutions addressing specific challenges like frequent power outages and high ambient temperatures. Innovation often occurs through frugal engineering approaches and adaptation of global technologies to local economic and environmental constraints.

2) Scaling Challenges and Opportunities

Scaling vertical farming to meaningful production levels presents distinct challenges in each national context. The UK faces barriers related to high capital costs, energy price volatility, and competition for urban space, though these are partially offset by strong consumer markets for premium products and sophisticated supply chain integration.

India’s scaling challenges include infrastructure limitations, technical skill gaps, and market development requirements, balanced against significant potential for import substitution, rural-urban transition employment, and climate resilience benefits. Successful scaling will likely require hybrid models combining high-tech commercial operations with appropriate technology community implementations.

The comparative analysis reveals that while vertical farming presents significant opportunities in both the UK and India, successful implementation requires careful adaptation to local contexts, resource constraints, and market conditions. The technology’s potential to contribute to sustainable development objectives is substantial, though realising this potential will require targeted policy support, continued technological innovation, and business models that address specific national and regional challenges. Figure 20 depicts the future development trajectories and scaling pathways for vertical farming across the UK and India.

VI. TECHNOLOGICAL INTEGRATION FRAMEWORK FOR NEXT-GENERATION VERTICAL FARMS

Table 22 presents the complete technological integration framework encompassing three critical architectural paradigms: the Cyber-Physical System (CPS) Architecture, the Edge-to-Cloud Continuum, and essential Interoperability Standards [210]. This integrated approach enables real-time synchronisation between physical growing environments and computational intelligence systems. The column 1 of Table 22 is proposed by us, however, the information represented under the columns 2, 3 and 4 for each of the layers are the excerpts from the across all the papers referenced and may suitably vary.

The performance values presented in Table 23 are derived through the four-stage synthesis process (extraction of data from literature, cross-validation, metric standardisation, weighted-average calculation) applied to the peer-reviewed literature as specified in Section I.E and the corresponding references are included in the table.

The CPS architecture’s five-layer hierarchy establishes the foundational data flow from hardware to intelligent applications, while the three-tier computational model optimally distributes processing tasks based on latency and complexity requirements. The interoperability framework ensures seamless integration of components from diverse vendors, reducing implementation timelines significantly.

VII. POLICY RECOMMENDATIONS AND ROADMAP FOR GLOBAL SCALABILITY

A. POLICY LEVELS FOR ADOPTION

Government intervention can accelerate vertical farming adoption [15], [16] through:

- 1) Financial Incentives
 - **Capital Subsidies:** 30-50% of initial investment for urban agriculture projects

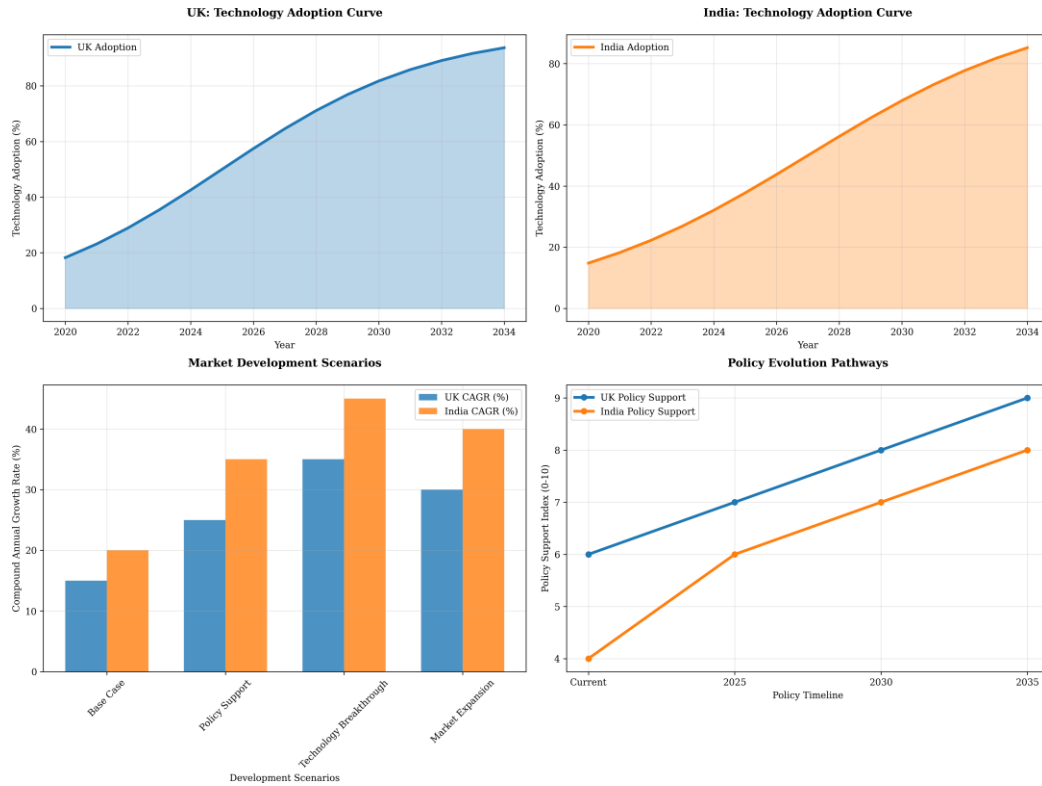


FIGURE 20: Future development trajectories and scaling pathways for vertical farming in UK and India, showing technology adoption curves, market development scenarios, and policy evolution pathways [221], [223], [222], [224]

- **Tax Benefits:** Accelerated depreciation, R&D tax credits, property tax reductions
 - **Grant Programs:** Innovation grants for energy-efficient technologies
- 2) Regulatory Support
- **Zoning Amendments:** Allow agricultural use in industrial/commercial zones
 - **Building Code Adaptations:** Specific provisions for indoor farming facilities
 - **Water Rights:** Priority access for recirculating agricultural systems
- 3) Market Development
- **Procurement Policies:** Government institutions sourcing from vertical farms
 - **Labeling Standards:** "Vertically Grown" certification for premium positioning
 - **Export Support:** Assistance for international market entry

VIII. CONCLUSION

This review paper provides a comprehensive analysis of building sustainable vertical farming technologies: detailing the different types of vertical farming technologies, with

emphasis on the integration of IoT and AI, as well as the role of policy frameworks and climate impacts in enabling or constraining vertical farming implementation across different geographical contexts, specifically the UK and India. By synthesising environmental, technological, and regulatory perspectives, the paper offers a three-dimensional understanding of sustainable vertical farming and presents a technical blueprint informed by comparative insights from both regions.

The first dimension focuses on the infrastructure and system-level requirements for choosing and building the vertical farming structure. a) It critically examines the challenges associated with conventional agricultural practices, explores different soilless cultivation technologies, and various typologies and nomenclatures of vertical farming architectures. It highlights the complexity of controlling key environmental variables such as humidity, temperature, vapor pressure deficit, nutrient delivery, and atmospheric composition. It analyses the quantitative comparisons of water usage and energy requirements, providing insights into the sustainability and scalability of each of the vertical farming architectures. b) The paper details the critical technical parameters governing vertical farming operations, such as nutrient flow rates, CO₂ concentration, pH, electrical conductivity, temperature control, energy consumption, and maintenance requirements; This discussion serves as an environmental guide for stake-

holders seeking to design vertical farming systems tailored to specific environmental and climatic conditions.

The second dimension of this review focuses on the integration of IoT and AI within vertical farming systems a) A detailed overview of various types of sensors and actuators used to monitor and regulate environmental and operational parameters are discussed. b) The communication and networking protocols such as Wi-Fi, Zigbee, LoRaWAN, NB-IoT, BLE, and 6LoWPAN used to interconnect sensors, actuators, and control platforms within vertical farming infrastructures are discussed in terms of their suitability for different deployment scales, latency requirements, power consumption constraints, and data transmission needs suitable for each of the vertical farming systems. The ways of integrating these through IP-based architectures to cloud platforms and the deployment of AI models on these data are elaborated. It details critical challenges in deployment strategies to build an end-to-end scalable system for real-time decision-making, representing a transformative shift in agricultural production.

The third dimension systematically examines deploying the above two, with a focused comparative analysis between the UK and India. Our investigation reveals that while the technological foundations of controlled environment agriculture share common elements globally, their successful implementation is profoundly shaped by regional economic, environmental, and policy contexts. The UK demonstrates a mature ecosystem for vertical farming characterised by advanced automation, strong policy frameworks, and premium market positioning, albeit challenged by high energy costs and capital requirements. Conversely, India presents a more complex landscape where vertical farming must navigate infrastructure limitations, diverse market segments, and acute resource constraints, while offering significant potential for import substitution and climate resilience. Our proposed cyber-physical system architecture and edge-cloud continuum framework provide quantifiable performance improvements and through PRISMA-based review of the literature identified that CPS-based vertical farming systems have been reported to energy efficiency savings by 40-60% and reduce control latency by 80-90% compared with conventional systems. The comparative analysis underscores that while technology transfer is feasible, adaptation to local conditions remains essential for economic viability.

Future advancements in quantum sensing, synthetic biology, and swarm robotics promise to further enhance vertical farming capabilities. However, realising these benefits requires coordinated action across research, industry, and policy domains. We recommend prioritised research in energy optimisation algorithms, development of region-specific business models, and creation of supportive policy frameworks that balance innovation with sustainability objectives.

Vertical farming embodies a paradigm shift toward data-driven, resource-efficient food production. As urbanisation accelerates and climate pressures intensify, the convergence of IoT, AI, and controlled environment agriculture offers a

pathway to more resilient, sustainable, and equitable food systems.

IX. DATA AVAILABILITY

The data is available on Zenodo data at <https://zenodo.org/records/22095348>

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TABLE 22: Proposed Technological integration framework for next-generation vertical farms. The table is synthesised from the literature reviewed in the preceding sections and reflects the authors’ perspective on how the technological layers are integrated.

Cyber-Physical System (CPS) Architecture			
Layer	Components & Specifications	Key Functions	Technical Details
Physical Layer	- Hydroponic/aeroponic cultivation systems [229] - LED arrays (400-800 $\mu\text{mol}/\text{m}^2/\text{s}$ PPFD) [230] - HVAC with variable frequency drives - Robotic manipulators (± 1 mm precision) [231]	- Hardware foundation for cultivation - Environmental control - Automated operations	- Modular rack designs optimise vertical space [232] - Uniform airflow distribution maintained
Sensing Layer	Nutrient: [229] - pH (± 0.1) - EC (± 0.01 mS/cm) - DO (± 0.1 mg/L) Environmental: [233] - Temp/Humidity ($\pm 0.1^\circ\text{C}$, $\pm 1.5\%$ RH) - CO₂ (± 30 ppm) Optical: [234] - RGB cameras - Multispectral (400–1000 nm) - Hyperspectral (400–2500 nm)	- Real-time environmental monitoring - Plant health and stress detection [235] - Biochemical analysis	- Distributed IoT sensors [39] 1–5 second sampling intervals - Sensory nervous system of the farm
Network Layer	- LoRaWAN (2–15 km range, 10–20 mW) [236] 5G-NR (1–10 Gbps bandwidth) [237] - Time-Sensitive Networking (TSN) [238]	- Long-range, low-power sensor communication - High-bandwidth video/robotic data - Deterministic safety-critical operations	- Hybrid protocol optimisation - Sub-millisecond latency for TSN - Application-specific transmission
Computation Layer	- Edge computing nodes [239] - Cloud analytics platforms [240]	- Local time-critical operations (< 100 ms latency) [239] - Complex ML training and optimisation [235]	- Edge-cloud continuum architecture [239] - Distributed processing approach - Predictive synchronisation enabled
Application Layer	- Digital Twin interfaces [241] - Autonomous control systems - Predictive analytics dashboards	- Simulation-based optimisation [241] - Reinforcement learning control [242] - Real-time performance visualisation	- Anticipates system states 5–10 min ahead - Multi-objective reward functions [242] - Reduces control lag by 65–80%
Edge-to-Cloud Continuum Architecture [239], [240]			
Tier	Hardware/Platform Examples	Primary Responsibilities	Performance Characteristics
Tier 1: Edge Devices	- ARM Cortex-M microcontrollers - Raspberry Pi - NVIDIA Jetson	- Real-time sensor preprocessing - Immediate actuator control - Local anomaly detection (ML < 10 MB)	- Lowest latency (local only) [239] - Offline operation capability - Handles network disruption
Tier 2: Fog/Edge Servers	On-premise regional servers	Multi-camera video analysis	Intermediate processing [239]
Tier 3: Cloud Platforms	- AWS - Azure - Google Cloud	- Short-term prediction (1–24 hour horizon) - Local data aggregation - Long-term data storage and analysis - Complex ML model training - Multi-farm benchmarking	- Protocol translation - Reduces cloud bandwidth needs - Highest computational power [240] - Global supply chain integration [39] - Centralised analytics
Interoperability Standards & Protocols			
Standard	Key Features	Implementation Benefits	Technical Specifications
OpenFARM Protocol	- Based on OPC-UA (IEC 62541) [243], [244] - Standardised agricultural data structures - Role-based access control	- Specifically designed for agriculture - Secure communication framework	- Publish-subscribe and client-server patterns [244] - Encryption and authentication - Emerging industry standard
Agri-Connect Middleware	- Protocol translation (ModbusMQTTxREST) [245] - Semantic mapping to ontologies - QoS management	- Enables multi-vendor integration - Plug-and-play component addition	- Blockchain-based authentication [246] - Time-critical data prioritisation - Reduces integration from weeks to days

TABLE 23: Indicative Performance Benchmarks for Traditional and CPS-Based Vertical Farming Systems

Performance Metric	Traditional	CPS-Based	Reported Change	Unit	Sources	Basis of Comparison
Control system latency	500–1,000	50–100	80–90	ms	[64], [100], [239]	Indicative cloud-centric and edge-executed control-loop latency ranges. The reduction is calculated using the range midpoints.
Data volume	10–100	1,000–10,000	~100×	MB/day	[66], [103]	Illustrative data-volume comparison between conventional logging and multi-sensor time-series architectures
Energy efficiency	Baseline	40–60% savings	40–60	% savings	[82], [89], [93], [96], [174]	Indicative aggregate savings attributed to lighting, HVAC, and pumping control strategies. Subsystem savings cannot be directly added without a consistent energy baseline and subsystem weighting.
System uptime	95–98	99.5–99.9	+1.5 to +4.9	Percentage points	[94], [99], [102], [185]	Illustrative availability ranges. The difference between the range limits gives a 1.5–4.9 percentage-point increase; the cited methods do not by themselves establish these uptime values.
Nutrient utilisation efficiency	75–85	90–95	+10 to +20	Percentage points	[49], [98], [108], [233]	Illustrative nutrient-utilisation ranges for conventional and sensor-controlled systems. The precise values would require a common definition of nutrient utilisation against crop types, variety and conditions.
Water consumption	20–30	8–12	~60–70	% reduction	[97], [98], [101], [108]	Illustrative consumption ranges for conventional soilless or aeroponic systems. The reduction is calculated from range midpoints.
Anomaly detection time	15–30	2–5	~80–85	% reduction	[94], [99], [102]	Illustrative manual or threshold-based versus automated monitoring times. Sampling interval alone may not establish end-to-end detection latency.
Yield prediction accuracy	75–85	90–95	+10 to +20	Percentage points	[186]–[188]	Illustrative prediction-performance ranges. The reported values are variable to datasets, and evaluation protocols.

Note: Each entry in Table 23 are indicative benchmarks synthesised from the reviewed literature, not results of experiments in this work. For each metric, baseline and CPS-based ranges were extracted from the cited studies, converted to common units, and cross-checked where more than one source was available. Derived changes are computed from range midpoints (relative reduction for latency, water use and anomaly detection time; percentage-point difference for uptime, nutrient utilisation and yield prediction accuracy)