VERTICAL FARMING AND AI IN AGRICULTURE

INNOVATIONS FOR A CHANGING CLIMATE

EDITOR
Mannir Kabir

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VERTICAL FARMING AND AI IN AGRICULTURE: INNOVATIONS FOR A CHANGING CLIMATE

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PREFACE

The book brings together four interdisciplinary studies that explore how emerging technologies are reshaping modern agriculture. As climate change intensifies pressure on global food systems, the chapters in this volume provide timely insights into how artificial intelligence, data-driven methods, and innovative farming models can support more resilient and sustainable agricultural practices.

Chapter 1 examines the integration of artificial intelligence with irrigation and soil data, demonstrating how advanced analytics can enhance climate-smart agriculture. By improving water management and soil monitoring, the chapter highlights how AI-driven solutions can significantly boost efficiency, productivity, and environmental sustainability.

Chapter 2 turns to the rapidly evolving field of vertical farming, offering a detailed look at its sustainability potential and the often-overlooked logistics of transportation. The analysis underscores the importance of optimizing supply chains to fully realize the environmental advantages of vertical farming systems.

Chapter 3 explores the role of AI-powered robotics and drones in precision farming. This chapter illustrates how automation and real-time data collection are transforming crop management, enabling farmers to make faster, more accurate decisions while reducing labor demands and resource use.

Chapter 4 focuses on climate resilience innovations in pig farming, discussing novel technologies and adaptive strategies that can help livestock systems withstand environmental stress. It emphasizes the growing importance of integrating climate-resilient practices into animal agriculture.

Together, these chapters offer a comprehensive overview of the technological shifts redefining agriculture in the era of climate change. As the editor, I hope this collection will contribute to ongoing research and inspire further innovation in building sustainable and future-ready food systems.

Editorial Team
November 21, 2025
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CHAPTER 1
INTEGRATING ARTIFICIAL INTELLIGENCE WITH IRRIGATION AND SOIL DATA FOR CLIMATE-SMART AGRICULTURE

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INTRODUCTION

Agriculture is undergoing a rapid transformation as climate variability, resource scarcity, and the growing demand for food challenge traditional farming systems. Among the most critical aspects of agricultural sustainability are efficient irrigation management and maintaining soil health. Artificial Intelligence (AI) has emerged as a transformative tool to address these challenges by enabling data-driven, adaptive, and predictive solutions. This chapter explores the integration of AI with irrigation systems and soil data to advance climate-smart agriculture. It reviews state-of-the-art machine learning, deep learning, and decision-support models that optimize water allocation, predict soil nutrient dynamics, and support sustainable crop management. Case studies from diverse agro-ecological regions highlight the role of AI-powered tools in improving irrigation efficiency, reducing water losses, enhancing soil fertility monitoring, and supporting precision agriculture. The chapter discusses challenges such as data availability, interoperability, cost barriers, and ethical considerations, along with future opportunities to scale AI adoption in resource-constrained farming communities. By bridging AI innovations with soil and water management, this chapter contributes to the development of resilient, resource-efficient, and climate-smart agricultural systems.

1. AGRICULTURE IN THE ERA OF CLIMATE UNCERTAINTY

Agriculture is at the core of global sustainability, not only as a provider of food and raw materials but also as a major employer and a key determinant of rural livelihoods. The sector currently faces a paradox: while demand for agricultural production is expected to grow substantially, climate change and resource degradation are steadily eroding the foundations of food security. The Intergovernmental Panel on Climate Change (IPCC, 2022) highlights that climate-induced disruptions—ranging from rising temperatures to erratic rainfall patterns—are reducing yields of staple crops such as wheat, maize, and rice in many vulnerable regions. In addition, shifting pest and disease dynamics further threaten agricultural productivity and food availability.

Among the most pressing challenges are water scarcity and soil degradation. Globally, irrigated agriculture consumes more than 70% of freshwater withdrawals, and in some regions this figure exceeds 90% (FAO, 2023).

At the same time, over 33% of soils are moderately to highly degraded due to erosion, nutrient depletion, salinization, acidification, and compaction (UNCCD, 2022). These stressors are interlinked: poor irrigation practices often exacerbate soil degradation, while degraded soils require more irrigation to sustain crop productivity. The cycle threatens both ecological balance and farmer livelihoods.

1.1 The Shift Toward Climate-Smart Agriculture

To meet these challenges, the concept of climate-smart agriculture (CSA) was introduced by the FAO in 2010. CSA promotes three complementary objectives:

- Sustainably increasing productivity to meet future food demands.
- Enhancing adaptation and resilience of farming systems to climate risks.
- Reducing or removing greenhouse gas emissions from agricultural activities.

Soil health and irrigation management sit at the heart of these goals. Healthy soils with balanced nutrient cycles and high organic matter can improve water-holding capacity, reduce greenhouse gas emissions, and support stable yields. Similarly, precision irrigation can save up to 30–50% of water compared to traditional flood irrigation methods (Fereres & Soriano, 2007). Yet, realizing these efficiencies requires real-time, site-specific decision-making—a task difficult to achieve with conventional approaches.

1.2 The Rise of Artificial Intelligence in Agriculture

Over the past decade, Artificial Intelligence (AI) has become one of the most promising enablers of precision and climate-smart agriculture. AI refers to computational systems capable of learning patterns, making predictions, and improving decisions with minimal human intervention. Within agriculture, AI applications span:

- Machine learning (ML) models for yield prediction and irrigation scheduling.
- Computer vision for soil surface characterization, root analysis, and early detection of salinity.
- Deep learning algorithms for processing multispectral satellite imagery and drone data.
- Decision-support systems that integrate weather, soil, and crop models to guide farmer practices.

For irrigation, AI can analyze soil moisture sensor data, weather forecasts, and crop growth models to provide dynamic recommendations on when and how much to irrigate. For soil health, AI can synthesize vast datasets—including geospatial maps, sensor readings, and laboratory analyses—to assess fertility, detect nutrient deficiencies, and predict risks such as salinization.

Notably, AI does not act in isolation but as part of an integrated digital agriculture ecosystem, alongside Internet of Things (IoT) devices, geographic information systems (GIS), remote sensing, and big data analytics. This convergence allows farmers to transition from generalized management practices to hyper-localized interventions, thereby improving input efficiency, reducing waste, and safeguarding ecosystems.

1.3 Why Integrate Irrigation and Soil Health Through AI?

While irrigation and soil management are often treated as separate domains, they are deeply interconnected. Excess irrigation can leach nutrients, degrade soil structure, and cause salinization. Conversely, poor soil health—such as low organic matter or compacted layers—reduces water infiltration and retention, increasing irrigation demand. Thus, optimizing one without considering the other may lead to unintended trade-offs.

AI offers an unprecedented opportunity to integrate soil and water management by modeling the dynamic interactions among soil, water, crops, and climate. For example, AI-driven irrigation systems can account for soil type, structure, and moisture retention capacity, while soil health models can incorporate irrigation histories to predict nutrient dynamics.

Such integration is essential for building climate-smart farming systems that are resilient, efficient, and sustainable.

1.4 Global Relevance and Case Examples

Countries across the globe are already experimenting with AI-driven solutions:

- In India, machine learning models have been used to optimize irrigation scheduling for rice and wheat, reducing water use by 20–30% while maintaining yields (Patel et al., 2021).
- In Israel, AI-powered drip irrigation systems integrate soil sensor data and weather forecasts to provide real-time recommendations, achieving some of the highest water-use efficiencies in the world.
- In Sub-Saharan Africa, pilot projects have combined remote sensing with AI-based soil fertility mapping to guide smallholder farmers in managing both irrigation and fertilizer application simultaneously (Mugo et al., 2022).

These cases underscore the potential of AI not just for large, industrial farms but also for resource-constrained farmers in developing regions.

1.5 Chapter Objectives and Structure

This chapter aims to provide a comprehensive analysis of how AI can be harnessed to integrate irrigation and soil data for advancing climate-smart agriculture. Specifically, it will:

- Review key AI approaches applied to irrigation and soil health.
- Highlight real-world applications and case studies.
- Examine barriers such as data scarcity, infrastructure costs, and policy gaps.
- Discuss opportunities for scaling AI adoption in diverse agricultural contexts.

The chapter is organized into six major sections:

- Introduction (this section).
- AI in Irrigation Management.
- AI for Soil Health Monitoring.

- Integration of AI with Irrigation and Soil Data.
- Challenges and Limitations.
- Future Prospects and Opportunities.
- Conclusion

By situating AI within the broader framework of climate-smart agriculture, the discussion emphasizes not only technological innovation but also ecological and social sustainability.

2. AI IN IRRIGATION MANAGEMENT

Water is a limiting factor in agriculture, and irrigation is essential to ensure reliable yields, particularly in semi-arid and arid regions. Globally, irrigated land represents only about 20% of cultivated land but contributes more than 40% of total food production (FAO, 2023). This disproportionate contribution underscores irrigation's importance, but it also highlights the vulnerability of global food systems to water scarcity.

Traditional irrigation scheduling often relies on farmers' experience or fixed calendars, which rarely align with actual crop water requirements. Climate variability exacerbates the problem, as rainfall is becoming less predictable, while extreme heat events increase evapotranspiration rates. AI-based irrigation management offers a way forward by dynamically adjusting decisions to real-time conditions and predictive analytics.

2.1 Machine Learning Models for Irrigation Scheduling

Crop water demand is primarily governed by evapotranspiration (ET). Traditional models like the Penman-Monteith equation require multiple meteorological parameters, which may not be readily available in all regions. Machine learning (ML) models can estimate ET with fewer inputs by learning from historical datasets.

- Artificial Neural Networks (ANNs): ANNs have been successfully used to estimate daily ET from limited weather data, outperforming empirical models in diverse climatic zones (Truong et al., 2019).
- Support Vector Regression (SVR): SVR has been applied to predict daily and seasonal irrigation needs, particularly where non-linear relationships exist between climatic inputs and crop responses.

- Hybrid Models: Combining ANN with optimization algorithms (e.g., genetic algorithms, particle swarm optimization) has been shown to improve prediction accuracy for irrigation scheduling (Kisi et al., 2020).

Time-Series Forecasting

LSTM (Long Short-Term Memory) networks and other recurrent architectures are especially valuable because irrigation decisions depend not only on current soil moisture but also on past and future conditions. These models can predict soil moisture trends days or weeks ahead, allowing farmers to plan irrigation events around rainfall forecasts.

Decision Support Systems (DSS)

ML models are increasingly embedded in DSS platforms that provide farmers with actionable recommendations. For example, the iCrop platform integrates weather, soil, and crop models with ML to guide irrigation decisions across diverse farm types.

2.2 IoT and Sensor-Based AI Systems

The Internet of Things (IoT) has expanded the possibilities of irrigation monitoring. Networks of sensors now continuously measure soil moisture, soil temperature, nutrient levels, and even sap flow within plants. These high-frequency data streams are processed using AI to generate adaptive irrigation schedules.

Closed-Loop Irrigation Systems

AI enables closed-loop systems, where real-time sensor data directly informs irrigation actions. For instance, when soil moisture falls below a threshold, the system can autonomously activate drip irrigation and shut it off once optimal moisture is reached. Such systems minimize human error and reduce water wastage. Additionally, these AI-driven solutions can adapt to changing weather conditions by integrating climate forecasts into their decision-making processes. They can also learn from historical data to optimize irrigation schedules over time.

Integration with Smart Infrastructure

- Smart Valves and Pumps: AI algorithms optimize pump operation, reducing energy consumption.
- Fertigation Systems: AI integrates irrigation with nutrient application, adjusting fertilizer delivery according to soil and crop needs.
- Wireless Communication: LoRaWAN and 5G technologies are increasingly being paired with AI-driven IoT devices to ensure data flow even in remote rural areas.

2.3 Remote Sensing and AI for Irrigation Planning

Remote sensing provides regional-scale insights that complement ground-based sensors. AI models enhance the interpretation of satellite and drone imagery.

Crop Water Stress Detection

Thermal and hyperspectral imagery can detect canopy temperature and leaf water content. AI models classify stress levels and recommend irrigation to mitigate yield losses.

Soil Moisture Mapping

Synthetic Aperture Radar (SAR) data, combined with convolutional neural networks (CNNs), generates high-resolution soil moisture maps. These are valuable for large farms or regional water authorities managing irrigation systems.

Early Warning Systems

AI-enhanced remote sensing can provide early warnings of drought stress, allowing proactive irrigation planning. This is particularly useful in climate-vulnerable regions where rainfall is uncertain. By analyzing satellite imagery and ground-based sensor data, AI can identify subtle changes in vegetation health before visible symptoms appear. This enables farmers to take timely corrective measures and prevent yield losses.

2.4 Case Studies in AI-Driven Irrigation

- California Almond Orchards (USA): By integrating ML with IoT soil moisture probes, researchers reduced irrigation water use by 25%, with no significant yield loss (Burt et al., 2019).
- Vineyards in Spain: AI-based DSS improved grape quality by scheduling irrigation at key growth stages, reducing water consumption by 20% (Martínez et al., 2020).
- Rice Fields in India: AI combined with IoT sensors optimized irrigation frequency, reducing groundwater extraction by 30% and supporting long-term sustainability (Patel et al., 2021).
- Cotton Farms in Australia: Satellite imagery processed with AI algorithms enabled large-scale irrigation planning, saving millions of cubic meters of water annually (Smith & Jones, 2020).
- Israel: AI-powered drip irrigation systems like NetBeat integrate real-time soil and weather data to fine-tune irrigation and fertigation, achieving world-leading water productivity.

2.5 Benefits of AI in Irrigation Management

AI ensures that water is applied only where and when needed, reducing both consumption and energy used for pumping. This precision irrigation approach helps maintain optimal soil health and prevents issues like waterlogging or nutrient leaching. In the long term, it contributes to sustainable farming practices and lowers operational costs for farmers.

Enhanced Yields

By maintaining optimal soil moisture, crops experience less stress, leading to improved growth and productivity.

Environmental Sustainability

AI reduces nutrient leaching and minimizes salinization, thus protecting soil and groundwater quality.

Economic Returns

Although initial investments in AI-driven systems may be high, long-term savings in water, energy, and fertilizer costs can lead to substantial economic benefits for farmers.

2.6 Limitations and Challenges

- Scarcity of Ground Data: Many developing regions lack the dense sensor networks or weather stations required for accurate AI training.
- Data Quality Issues: Inconsistent or faulty sensor readings can lead to erroneous irrigation recommendations.

Infrastructure and Cost Barriers

The cost of IoT devices, drones, and connectivity can be prohibitive for smallholders. Without subsidies or cooperative models, large-scale adoption may remain limited to commercial farms.

Digital Divide

Farmers' digital literacy remains a challenge. AI platforms need to be accessible via mobile phones and in local languages to ensure usability.

Connectivity Issues

Stable internet connectivity is often lacking in rural areas, hampering real-time data transfer. Offline-first or SMS-based solutions may be necessary alternatives.

2.7 Policy and Institutional Considerations

Governments and institutions play a critical role in enabling AI adoption for irrigation:

- Subsidies and Incentives: Financial support can help farmers adopt AI-powered irrigation technologies.
- Capacity Building: Training programs are essential to build farmers' confidence in AI tools.

- Data Infrastructure: Public investment in weather stations, remote sensing platforms, and open-access datasets can improve AI model performance.
- Collaborative Platforms: Partnerships between governments, research institutions, and the private sector can foster innovation.

3. AI FOR SOIL HEALTH MONITORING

Soil health is the foundation of sustainable agriculture. It refers to the capacity of soil to function as a living ecosystem that sustains plants, animals, and humans (FAO, 2020). Healthy soils provide essential ecosystem services: nutrient cycling, water retention, carbon sequestration, and biodiversity support. However, soil degradation threatens over 33% of the world's arable land (UNCCD, 2022). Erosion, nutrient depletion, salinization, and compaction reduce agricultural productivity, requiring farmers to apply higher inputs to maintain yields—often leading to a vicious cycle of declining fertility and increasing environmental impacts.

Traditional soil health assessment relies on laboratory analyses of physical, chemical, and biological parameters (e.g., pH, organic matter, nutrient content, microbial activity). While accurate, these methods are time-consuming, expensive, and spatially limited. With farms often spanning hundreds or thousands of hectares, it is impractical to measure soil properties everywhere at once. This is where Artificial Intelligence (AI), integrated with digital technologies, provides game-changing opportunities for real-time, large-scale soil monitoring.

3.1 Machine Learning in Soil Fertility and Nutrient Assessment

Machine learning (ML) models can estimate soil properties—such as organic matter, nitrogen, phosphorus, and potassium—based on limited samples and auxiliary data (remote sensing, climate, land use). For example:

- Random Forest (RF) Models: RF has been widely applied to predict soil organic carbon by integrating satellite imagery, terrain attributes, and limited soil samples (Brevik et al., 2019).

- Support Vector Machines (SVM): SVM models can classify soils into fertility categories using datasets of spectral reflectance.
- Deep Learning (DL): Convolutional Neural Networks (CNNs) have shown success in interpreting hyperspectral data for nutrient estimation at high spatial resolution (Li et al., 2021).

3.1.1 Soil Nutrient Mapping

AI-driven soil nutrient maps provide farmers with actionable insights for site-specific fertilizer application. In India, ML models trained on soil health card data and satellite imagery have enabled digital soil fertility maps covering millions of farms (Chaudhary et al., 2020). These maps reduce over-application of fertilizers, cutting costs and minimizing environmental risks like eutrophication.

3.2 AI in Soil Moisture and Structure Analysis

Soil structure and moisture-holding capacity are critical for crop productivity and irrigation efficiency.

- Soil Moisture Estimation: AI models trained on satellite data (e.g., Sentinel-1 SAR) can estimate surface soil moisture at field scales. By combining this with in-situ sensor data, AI can model subsurface moisture dynamics, which are otherwise difficult to measure.
- Compaction Detection: ML algorithms analyzing ground-penetrating radar and remote sensing data can detect compacted layers, which restrict root growth and reduce water infiltration.
- Soil Texture Classification: CNNs applied to soil images can classify textures (sand, silt, clay) more rapidly than manual methods.

3.3 Soil Carbon and Climate Mitigation Potential

Healthy soils act as major carbon sinks, storing more carbon than the atmosphere and vegetation combined. AI is increasingly used to monitor soil organic carbon (SOC) stocks and predict sequestration potential.

- Global Soil Carbon Mapping: The SoilGrids project, for example, uses machine learning to predict global SOC stocks at 250 m resolution.

- Carbon Sequestration Potential: AI models can predict the impacts of different management practices (e.g., cover cropping, reduced tillage) on SOC, helping design climate-smart policies.
- MRV Systems (Measurement, Reporting, Verification): AI supports carbon credit markets by providing low-cost, scalable methods to quantify soil carbon changes over time.

3.4 Soil Contamination and Degradation Detection

AI models process multispectral and hyperspectral data to detect soil salinity, a growing problem in irrigated regions. ML classification techniques can distinguish between saline, sodic, and normal soils at field and regional scales.

Heavy Metal Contamination

AI-enhanced spectral analysis detects heavy metal contamination (e.g., lead, cadmium, arsenic) in soils near industrial areas. CNNs trained on spectral libraries can rapidly identify contaminants, reducing dependence on expensive lab tests.

Erosion Risk Assessment

AI integrates topography, rainfall, vegetation, and land management data to predict erosion-prone areas. These predictions help farmers and policymakers implement preventive measures like contour farming, mulching, or terracing.

3.5 Integration of Soil Data with Remote Sensing

Remote sensing provides spatially continuous soil data, while AI improves interpretation.

- Spectral Libraries: Large datasets of soil reflectance spectra (e.g., LUCAS soil database in Europe) are used to train ML models for predicting soil parameters.
- Drone-Based Monitoring: Drones equipped with multispectral cameras provide high-resolution soil imagery. AI processes these data to detect spatial variability in soil properties within fields.

- Global Soil Observatories: Combining satellite data with AI enables near-real-time global monitoring of soil health indicators, supporting international initiatives like the UN Sustainable Development Goals (SDGs).

3.6 Case Studies in AI for Soil Health Monitoring

- Kenya: AI-based soil fertility maps developed using satellite data and limited samples provided farmers with recommendations on balanced fertilizer use, improving maize yields by 15% (Mugo et al., 2022).
- China: Deep learning applied to hyperspectral imagery successfully mapped soil salinity across the Yellow River Delta, enabling targeted reclamation strategies (Zhang et al., 2021).
- Brazil: ML-based models predicted soil organic carbon stocks in the Cerrado region, guiding land management practices for carbon sequestration (Silva et al., 2020).
- Europe: The LUCAS soil database combined with AI models has been used to monitor soil fertility trends across EU member states, supporting the Common Agricultural Policy (CAP).

3.7 Benefits of AI in Soil Health Monitoring

- Scalability: AI enables large-scale soil monitoring at farm, regional, and global levels.
- Cost Efficiency: Reduces reliance on expensive laboratory tests.
- Precision Agriculture: Supports site-specific soil management practices, reducing input costs.
- Sustainability: Promotes practices that improve soil quality and mitigate environmental impacts.
- Policy Support: Provides data for evidence-based policymaking in land management.

3.8 Limitations and Challenges

- Data Quality and Availability: Soil datasets are often sparse, inconsistent, or biased toward certain regions.

- Model Transferability: AI models trained in one agro-ecological zone may not perform well in others without retraining.
- High Initial Costs: Sensors, drones, and hyperspectral imaging systems remain costly.
- Farmer Adoption: Farmers may be reluctant to adopt AI-based recommendations without clear evidence of economic benefits.
- Ethical Concerns: Data ownership and privacy issues arise when soil data are collected by private companies.

4. INTEGRATION OF AI WITH IRRIGATION AND SOIL DATA

Irrigation and soil health are inseparable components of sustainable agriculture. Over-irrigation accelerates soil degradation through nutrient leaching, compaction, and salinization, while degraded soils require more water to sustain crop productivity. Traditionally, these domains have been addressed separately: irrigation engineers focus on water delivery, while soil scientists emphasize fertility and structure. However, climate-smart agriculture requires a systems perspective, where soil and water are managed together.

Artificial Intelligence (AI) provides the computational capacity to handle the complexity of soil–water–crop interactions. By integrating irrigation data (soil moisture, evapotranspiration, irrigation events) with soil data (fertility, texture, organic matter), AI models can generate holistic recommendations that optimize both water use and soil health.

4.1 Big Data and Predictive Analytics for Soil–Water Interactions

The proliferation of sensors, satellites, drones, and farm management platforms has created vast datasets describing soil, water, crop, and climate conditions. AI can extract actionable insights from these datasets.

- Soil–Water–Crop Models: Machine learning algorithms simulate crop responses to different irrigation and soil conditions. For example, LSTM models can forecast how irrigation events affect soil nutrient leaching over time.

- Predictive Fertigation Systems: AI integrates soil nutrient maps with irrigation data to optimize the timing and quantity of fertilizer dissolved in irrigation water.
- Holistic Decision Support Systems (DSS): Platforms like AquaCrop-AI integrate soil, water, and crop data to provide recommendations that minimize water use while maintaining soil fertility.

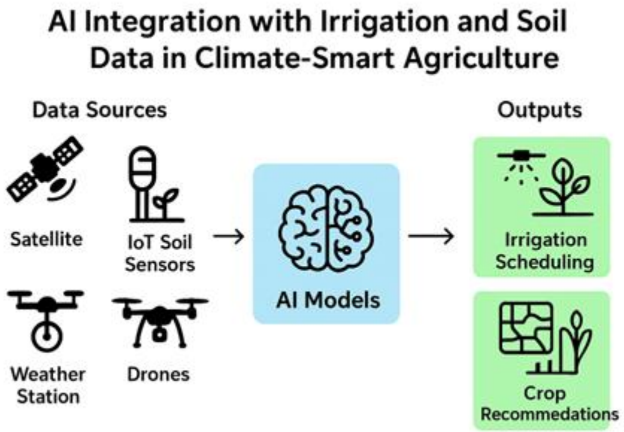

Figure 1. Conceptual framework for AI integration in climate-smart agriculture, where multiple data streams are analyzed to optimize irrigation and crop management

4.2 AI-Based Crop–Soil–Water Interaction Models

- Mechanistic Models (e.g., DSSAT, APSIM) simulate soil–crop–climate interactions using predefined equations. While robust, they require extensive calibration.
- Data-Driven Models (AI/ML) learn directly from observed data, identifying hidden relationships. Increasingly, hybrid models combine mechanistic and AI approaches for greater accuracy.

Multi-Modal AI Models

Advanced models now integrate multiple data streams:

- Soil: moisture, fertility, carbon, salinity.
- Water: irrigation history, groundwater levels, rainfall.
- Crop: growth stage, stress indicators from remote sensing.

- Climate: temperature, humidity, wind, solar radiation.

By fusing these datasets, AI generates site-specific recommendations for irrigation timing and soil management, ensuring long-term resilience.

4.3 Climate-Smart Decision Frameworks

AI integration supports the three pillars of climate-smart agriculture:

- Productivity: Optimizing irrigation and soil fertility boosts yields while reducing input costs.
- Adaptation: Predictive models help farmers adapt to climate variability by anticipating droughts or nutrient deficiencies.
- Mitigation: Healthy soils store carbon, while efficient irrigation reduces energy use and methane emissions from waterlogged fields.

For instance, AI-driven deficit irrigation strategies can reduce water use without significantly affecting yields, while also preventing soil salinization. Similarly, integrating soil organic matter data into irrigation decisions ensures that soils retain more moisture, enhancing resilience to drought.

4.4 Case Studies of Integrated Systems

These case studies demonstrate the practical applications of AI-integrated irrigation systems across diverse agricultural contexts. They highlight how combining soil, weather, and crop data enables smarter resource management and improved sustainability. Overall, AI-driven solutions contribute to higher productivity, reduced environmental impact, and more resilient farming systems.

- Israel – NetBeat Platform: Combines soil moisture sensors, nutrient data, and weather forecasts. AI algorithms optimize both irrigation and fertigation, leading to up to 40% water savings and improved soil fertility.
- India – AI4Water Project: Uses ML models to integrate soil health card data with irrigation scheduling for smallholder farmers, reducing input costs and improving yields of wheat and rice.
- USA – Almond Irrigation DSS: Incorporates soil nutrient data with irrigation models, ensuring that fertigation aligns with crop demand and reducing nitrate leaching into groundwater (Burt et al., 2019).

- China – Yellow River Basin: Integrated AI models predict soil salinity buildup under different irrigation regimes, guiding farmers to adopt practices that maintain soil productivity while conserving scarce water.

4.5 Challenges of Integration

Despite its potential, integrating AI for soil–water management faces several barriers:

- Data Interoperability: Soil and irrigation datasets are often stored in incompatible formats. Lack of standardization limits integration.
- Data Scarcity: Soil fertility and structure data are less available than weather or irrigation data, creating unbalanced models.
- Model Complexity: Integrating heterogeneous datasets (e.g., spectral, time-series, tabular) requires advanced AI architectures that are difficult to deploy at scale.
- Smallholder Constraints: Farmers in low-income regions often lack access to sensors or digital tools necessary for integration.
- Institutional Gaps: Agricultural policies and extension services often treat irrigation and soil management separately.

4.6 Opportunities and Future Directions

- Digital Twins of Agro-Ecosystems: AI can create real-time virtual models of farms, simulating the impacts of irrigation and soil management decisions before implementation.
- Edge AI for Farmers: AI models embedded in mobile phones or low-cost devices can provide offline recommendations for irrigation–soil management integration.
- Blockchain and Data Sharing: Secure, transparent platforms can improve data exchange between farmers, researchers, and policymakers.
- Integration with Robotics: Autonomous robots could one day apply water and nutrients precisely based on AI-driven soil–water models.
- Policy Alignment: Governments can encourage integrated approaches through subsidies for AI-based fertigation systems or incentives for soil carbon monitoring.

5. CHALLENGES AND LIMITATIONS

While the integration of Artificial Intelligence (AI) with irrigation and soil data is revolutionary, multiple challenges hinder its widespread application. These challenges are multidimensional, spanning technical, economic, institutional, environmental, and ethical considerations. A deeper examination of these barriers is necessary to design realistic pathways for implementation.

5.1 Technical Challenges

Data Scarcity and Quality;

- Soil Data Limitations: Unlike weather data, which are continuously collected by meteorological stations, soil data are sparse, episodic, and costly to obtain. For example, in sub-Saharan Africa, comprehensive soil fertility maps cover less than 20% of arable land (FAO, 2022).
- Heterogeneity of Soil Data: Soil properties vary dramatically over short distances. Without dense sampling, AI models often fail to capture local variability, leading to misleading recommendations.
- Label Noise: Laboratory analyses, while considered reliable, can introduce errors due to differences in sample handling, chemical reagents, and human interpretation. AI models trained on noisy data risk propagating these errors.

Sensor Reliability and Calibration

Field sensors are prone to drift—gradual deviations from accuracy over time. Soil moisture sensors, for instance, often require recalibration due to salinity or temperature effects. In India's early digital irrigation projects, nearly 35% of deployed sensors failed within the first year due to dust, monsoon flooding, or rodent damage (ICRISAT, 2021).

Integration of Heterogeneous Data

AI must integrate data streams of varying formats and resolutions:

- Soil: static, irregularly sampled lab tests.
- Irrigation: time-series data from sensors.
- Remote sensing: raster imagery from satellites or drones.

- Climate: continuous meteorological records.

Fusion of such heterogeneous data requires sophisticated architectures (e.g., multi-modal deep learning), which are complex to design and deploy.

Model Transferability and Bias

AI models trained in one region may perform poorly in another. For instance, an irrigation scheduling model trained on California almond farms may not generalize to Ethiopian maize fields due to differences in soils, crop varieties, and farmer practices. Bias in training datasets leads to "AI colonialism", where models developed in the Global North are exported to the Global South without adaptation, often producing poor results.

Computational Infrastructure

Advanced models such as deep neural networks demand GPUs, cloud storage, and stable internet connections. In many rural regions, electricity and connectivity are unreliable, limiting access to high-performance computing.

5.2 Economic Challenges

- IoT devices (USD 200–800 per soil sensor set).
- Drone imagery (USD 5–15 per hectare for routine flights).
- Cloud subscriptions for AI platforms (USD 100–500 per month).

For smallholder farmers earning less than USD 2/day, such costs are prohibitive without subsidies or cooperative models.

Uncertain ROI (Return on Investment)

AI systems often promise long-term gains—such as improved soil fertility or reduced groundwater depletion—but farmers typically prioritize short-term returns. If benefits are not visible within one or two cropping seasons, adoption stalls. This gap between long-term sustainability goals and short-term economic needs remains a major challenge for widespread adoption. Providing financial incentives, training, and demonstration projects can help bridge this divide.

Unequal Access to Finance

Large-scale commercial farms often secure credit to invest in digital tools, while smallholders face limited access to loans or microfinance. This exacerbates inequality, creating a digital divide in agricultural productivity.

5.3 Institutional and Policy Challenges

In many countries, water management falls under ministries of irrigation, while soil management is handled by agriculture departments. The lack of cross-ministerial coordination results in fragmented programs and funding streams, limiting the development of integrated AI solutions.

Weak Extension Systems

AI-driven recommendations are only useful if farmers understand and trust them. However, extension-to-farmer ratios are often inadequate: in sub-Saharan Africa, one extension worker may serve over 3,000 farmers (World Bank, 2021). Without human intermediaries, even the most advanced AI platforms risk underutilization.

Lack of Standards and Regulation

No global standards currently exist for digital soil or irrigation data. As a result, different companies use proprietary formats, making it difficult to merge datasets or migrate between platforms. This lack of standardization limits interoperability and slows the adoption of AI-based agricultural solutions. Establishing common data protocols and open-access frameworks would enable seamless data sharing across systems.

5.4 Social and Ethical Challenges

- Access Gap: Rural farmers may lack smartphones or internet access. In South Asia, less than 40% of rural women own a mobile phone (GSMA, 2020).
- Skills Gap: Even when devices are available, digital literacy is often low, reducing the effective use of AI systems.

Trust Deficit

Farmers often view AI systems as "black boxes". For instance, a farmer may receive a recommendation to reduce irrigation by 20%, but without clear reasoning, they may perceive this as risky and ignore it. Developing explainable AI (XAI)—which clarifies the reasoning behind decisions—can improve adoption.

Equity Concerns

If AI data platforms are controlled by private corporations, farmers risk losing sovereignty over their own data. For example, agritech companies may aggregate soil and irrigation data for commercial gain, without ensuring that farmers benefit from data monetization.

5.5 Environmental Challenges

Sensors buried in saline soils corrode quickly, and those in flood-prone regions may be destroyed by standing water. This creates recurring replacement costs, undermining economic feasibility.

Over-Reliance on AI Models

There is a risk of technological determinism, where traditional ecological knowledge (e.g., indigenous soil fertility indicators, water-sharing practices) is devalued. Over-reliance on AI may result in less resilient farming systems if technology fails.

Resource Intensity of AI

AI itself consumes significant computational energy. Training a single deep learning model can emit as much CO_2 as five cars in their lifetime (Strubell et al., 2019). If not powered by renewable energy, AI-based agriculture may unintentionally increase carbon footprints.

5.6 Strategies to Overcome Challenges

- Open Data Platforms: Initiatives like FAO's International Soil Information System should be scaled globally, ensuring standardized, interoperable soil–water datasets.

- Low-Cost IoT Devices: Development of rugged, solar-powered, and low-cost soil/irrigation sensors is critical for smallholder adoption.
- Farmer Cooperatives and Shared Services: Community-based drone imaging and shared AI platforms can reduce individual costs.
- Capacity Building: Governments and NGOs should integrate digital literacy into agricultural training.
- Explainable AI (XAI): AI systems must offer interpretable outputs, e.g., "Reduce irrigation by 20% because soil moisture is above crop demand thresholds."
- Ethical Data Frameworks: Policies must ensure farmers retain ownership of their data and share in profits generated from it.
- Integration of Traditional Knowledge: AI models should complement, not replace, indigenous knowledge systems.
- Green AI: Prioritize energy-efficient models and cloud services powered by renewables.

5.7 Case Studies of Failures and Lessons Learned

Despite the growing enthusiasm for AI in agriculture, several initiatives have faced setbacks. These cases reveal the practical, social, and institutional barriers that must be addressed to make AI-based irrigation and soil health management more effective.

India – Early Digital Irrigation Platforms

In the mid-2010s, pilot projects introduced AI-based irrigation scheduling apps in states like Maharashtra and Karnataka. While the models performed well in controlled trials, adoption by farmers was minimal.

Failure Factors:

- Apps were in English, inaccessible to farmers with low literacy.
- Irrigation recommendations ignored local water availability (e.g., canal schedules).
- Sensors deployed in fields failed frequently due to monsoon flooding.
- Lesson Learned: Localization of AI systems, integration with local water governance, and robust low-cost sensors are essential for adoption.

Sub-Saharan Africa – Soil Health Card Programs

AI tools were used to analyze soil samples and generate digital “soil health cards” for farmers. However, the initiative faltered after two years.

Failure Factors:

- Soil testing labs were far from rural areas, delaying updates to the database.
- Farmers distrusted recommendations that contradicted traditional practices.
- Lack of extension agents meant results were never properly explained to farmers.
- Lesson Learned: AI systems must be embedded in strong extension frameworks and designed to complement, not replace, traditional knowledge.

China – Remote Sensing for Salinity Detection

An AI project aimed to map soil salinity using satellite data in the Yellow River Delta. While technically accurate, the initiative did not improve farming practices.

Failure Factors:

- Farmers lacked resources to reclaim saline soils even when identified.
- Results were not linked to actionable management recommendations.
- Lesson Learned: AI outputs must be actionable and affordable for farmers; otherwise, information alone has limited value.

USA – Precision Irrigation in California Vineyards

AI-based irrigation scheduling systems were introduced to vineyards in California to optimize water and fertilizer use. Some growers discontinued use after two seasons. The main reasons included high implementation costs, technical complexity, and the need for continuous data management. However, others reported significant improvements in water efficiency and grape quality. The case highlights both the potential and the challenges of adopting advanced technologies in traditional agricultural systems.

Failure Factors:

- Farmers perceived recommendations as too conservative, fearing yield losses.
- Integration with existing irrigation hardware was expensive.
- Cloud-based platforms raised data privacy concerns.
- Lesson Learned: Farmer trust and transparency are critical. Explainable AI (XAI) and participatory model design can improve long-term adoption.

Kenya – Drone-Based Soil Fertility Mapping

Drones equipped with multispectral sensors were piloted to generate soil fertility maps for smallholder maize farms. The project struggled to scale.

Failure Factors:

- High costs of drone flights limited repeat monitoring.
- Farmers lacked smartphones to access map-based outputs.
- No integration with local credit or fertilizer supply chains.
- Lesson Learned: Successful AI initiatives must build ecosystems of support, linking data insights to credit, input supply, and extension services.

5.8 Synthesis of Lessons Learned

From these failures, several common themes emerge:

- Localization Matters: AI systems must adapt to local languages, cultures, and water/soil management practices.
- Infrastructure is Critical: Without reliable sensors, connectivity, and hardware, even the best AI models fail.
- Trust and Transparency: Farmers need clear, interpretable recommendations. Black-box systems breed mistrust.
- Affordability and Actionability: Insights must translate into affordable actions farmers can realistically take.
- Integration into Ecosystems: AI should not function in isolation but as part of a broader support system involving extension services, financial institutions, and supply chains.

Table 1. Challenges, Case Study Examples, and Lessons Learned in AI for Irrigation and Soil Health

Challenge Area	Case Study Example	Observed Failure	Lesson Learned
Technical – Sensor Reliability	India – Digital Irrigation Projects	Frequent sensor breakdowns due to flooding and dust; poor calibration	Develop robust, low-cost, climate-resilient sensors for field conditions
Data Scarcity & Quality	Sub-Saharan Africa – Soil Health Cards	Sparse soil sampling; delayed updates; low farmer trust	Strengthen soil labs, ensure continuous updates, integrate farmer knowledge
Interoperability & Actionability	China – Salinity Detection (Yellow River Delta)	Salinity identified but no actionable management plan	AI outputs must be linked to practical, affordable interventions
Trust & Transparency	USA – Precision Irrigation in Vineyards	Farmers perceived AI recommendations as too risky; privacy concerns	Use explainable AI (XAI) and co-design systems with farmers
Economic Barriers	Kenya – Drone-Based Soil Fertility Mapping	High costs of drone flights; farmers lacked smartphones	Lower costs via cooperatives; adapt outputs to farmers' devices and contexts
Institutional Weakness	Sub-Saharan Africa – Soil Health Programs	Lack of extension agents to interpret results	Strengthen extension services and train them in digital literacy
Equity & Access	Across regions (general)	Smallholders excluded due to cost and literacy gaps	Ensure inclusive design, subsidies, and community-based models
Over-Reliance on Technology	Multiple contexts	Ignored traditional practices; poor adoption	Blend AI with indigenous knowledge for trust and sustainability

6. FUTURE PROSPECTSD RESEARCH DIRECTIONS

The integration of AI with irrigation and soil data is still in its early stages. While numerous pilots and research initiatives demonstrate its promise, the future will be shaped by advances in technology, data systems, farmer-centered innovation, and policy frameworks. This section outlines emerging trends and priority areas for research that can enhance adoption, scalability, and sustainability.

6.1 Technological Innovations

A digital twin is a virtual replica of a farm ecosystem that integrates soil, water, crop, and climate data in real time. By simulating different management scenarios, digital twins allow farmers to test irrigation and soil management strategies before implementing them in the field. This could minimize risks while optimizing resource use.

Edge AI and Offline Tools

Most current AI solutions rely on cloud computing, which demands internet connectivity and costly infrastructure. Edge AI enables AI models to run directly on mobile devices or low-cost farm sensors, providing offline recommendations in rural areas with limited connectivity.

Next-Generation Sensing Technologies

- Hyperspectral imaging mounted on satellites and drones can capture soil and water properties with unprecedented resolution.
- Nano-sensors may soon measure soil nutrients and contaminants in real time at microscopic scales.
- Wireless sensor networks can provide continuous, spatially distributed soil and water data.

6.2 Advances in AI and Data Science

Traditional AI requires centralized data collection, raising privacy and ownership concerns. Federated learning allows models to be trained across multiple devices or farms without sharing raw data. This approach could protect farmer privacy while enabling large-scale AI development.

Explainable AI (XAI)

Future models must not only predict outcomes but also explain reasoning in farmer-friendly language. Research in XAI will make AI systems more trustworthy and actionable, e.g., "Irrigation reduced because soil organic matter increases water retention."

Hybrid AI–Mechanistic Models

The next generation of crop and soil–water models will merge mechanistic models (e.g., DSSAT, APSIM) with AI-driven data analytics. These hybrid systems can leverage the strengths of both approaches: mechanistic rigor and data-driven adaptability.

6.3 Integration with Climate-Smart Policies

AI could become central to Measurement, Reporting, and Verification (MRV) in soil carbon markets. Low-cost AI-enabled monitoring will allow farmers to earn carbon credits for soil health improvements like cover cropping or reduced tillage.

Water Governance and AI Tools

Governments can integrate AI-based irrigation scheduling into policy frameworks, ensuring sustainable groundwater use. For example, basin-level digital water governance platforms could regulate extraction based on AI predictions of soil moisture and recharge.

Incentives for Digital Adoption

Subsidies, credits, or cooperative financing models may be necessary to encourage smallholder adoption. AI systems should be integrated into national agricultural development plans and extension services.

6.4 Farmer-Centered Innovation

Involving farmers in the design, testing, and adaptation of AI systems will ensure cultural relevance, trust, and practical utility. Future research must adopt participatory methods rather than top-down technology transfer.

Gender and Inclusion

Globally, women represent ~43% of the agricultural labor force but often have less access to digital tools. Research must focus on making AI tools gender-sensitive and inclusive, considering literacy, language, and affordability barriers.

Localized Knowledge Integration

AI systems should not replace but rather augment indigenous knowledge systems. For instance, combining AI irrigation models with traditional water-sharing practices can enhance both trust and resilience.

6.5 Global Research Priorities

- Standardization of Soil–Water Data: Develop global protocols for soil fertility, moisture, and irrigation datasets.
- Affordable AI Platforms for Smallholders: Research low-cost, smartphone-based AI solutions that run offline.
- Climate Adaptation Modeling: AI-driven predictions of soil and water stress under different climate scenarios.
- Ethical Data Frameworks: Governance models for farmer-owned data and equitable benefit-sharing.
- Scaling from Pilot to Practice: Transitioning from experimental plots to large-scale adoption through cooperative and policy support.

CONCLUSION

The dual challenges of feeding a growing population and conserving finite natural resources demand a radical transformation in agricultural practices. Water scarcity, soil degradation, and climate variability are pressing threats that cannot be solved with conventional methods alone. This chapter has examined how Artificial Intelligence (AI) can transform irrigation and soil health management to advance the goals of climate-smart agriculture.

We have seen that AI systems—powered by sensors, remote sensing, machine learning, and decision-support platforms—can optimize irrigation schedules, predict soil nutrient dynamics, and enable precision interventions.

Integrating irrigation and soil data through AI not only enhances water-use efficiency but also supports long-term soil fertility and resilience. Real-world case studies demonstrate both successes and failures, revealing that while AI technologies hold immense promise, their effectiveness depends on localization, farmer trust, affordability, and supportive institutions.

The future of AI in agriculture lies in inclusive and adaptive innovation. Emerging tools such as digital twins, federated learning, and explainable AI will make predictions more accurate, transparent, and scalable. Yet technology alone is insufficient. Effective adoption requires a systems approach—linking AI with extension services, input supply chains, credit systems, and policy frameworks. Importantly, AI must complement rather than replace traditional and indigenous knowledge systems, ensuring cultural relevance and farmer ownership of data.

In summary, AI-enabled irrigation and soil health management represent a powerful pathway toward achieving climate-smart, resilient, and sustainable agriculture. However, realizing this potential requires coordinated efforts across research, policy, and practice. As we move forward, the priority must be to design farmer-centered, affordable, and trustworthy AI systems that bridge the gap between technological innovation and practical on-farm realities. Only then can AI contribute meaningfully to securing global food security while safeguarding the natural resource base for future generations.

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CHAPTER 2
SUSTAINABLE VERTICAL FARMING AND THE ASPECTS OF TRANSPORTATION

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INTRODUCTION

Due to more regular extreme weather conditions, overpopulation yet decreasing number of farmers, soil loss, and insecure food supply, the importance of Controlled Environmental Agriculture (the abbreviation CEA will be used hereafter) is tending to play more and more important roles in the future of cities as well. The resource use efficiency, versatility, productivity and quality of the products grown in CEA are way more advanced compared to those grown in open fields and conventional greenhouse systems. However, mainly due to artificial lighting demand that is used in high-tech greenhouses and in closed-type vertical farms it is turned out that they can be very energy demanding with high operations of costs. Especially, after COVID-19 and the Russian-Ukrainian war, lot of vertical farms experienced unfavourable financial conditions or even faced with bankruptcy. Therefore, a new generation of vertical farms, production methodologies and business strategies were developed individually yet commonly across several cases. In this study we would like to emphasise the possible reasons and causes why several industry players went bankrupt and why others survived and progressed further. For instance, many failures were noted when in many cases a lot of farms did not rely on already existing expertise and tried to resolve complex developments by themselves. On the other hand, it seems it has been a winning strategy for instance to apply in-house renewable energy powerplant to reduce operating expenses (opex) and carbon footprint as well. Finally, this study explains the current situation of CEA in Hungary and transportation aspects.

1. LITERATURE REVIEW

By 2050 over 9.5 billion people are supposed to live on planet Earth (Siegel & Siegel, 2015) and all of them will require at least 1,500 calories a day (Howard R. LeWine, 2024). By the time from just around 20 years, around 0.24 ha/person of arable land only 0.20 ha/person supposed to be available (FAO, 2023). Therefore, it is required to increase our production by 60-70%, (FAO Publications Catalogue 2023, 2023), or in another words, if we do not increase our productions systems efficiency, we might need around 70 million hectares. Besides that, approximately 5 billion people are supposed to be scarce on water for at least one month in the year by 2050 (Nitnaware, 2023).

Moreover, according to ‘Groundswell: Preparing for Internal Climate Migration’ World Bank Group report, 140 million people supposed to be climate refugee, but the Institute for Economics & Peace even proclaims the possibility of 1.2 billion climate refugee by 2050 (Bellizzi et al., 2023). To tackle these above-mentioned challenges, new cultivation techniques have to be developed. CEA solutions, vertical farms, could be a partial solution for the previously noted challenges. To humanity, CEA is not a new thing. Even in ancient Mesopotamia initial vertical farms and hydroculture could be observed just like in the Aztec civilization as well (Al-Kodmany, 2018). It was further developed by the Romans. Western Europeans and Americans introduced the ancestors of greenhouses in the 18-19th centuries. Besides many important discoveries regarding plant physiology and especially plant nutrition, like the Hoogland solution in the late 1800s, early 1900s, it was notable progress for industry during the Second World War, when the salad supply for the Pacific Ocean US fleet was supplied by hydroponically grown lettuces (Gordon-Smith; Henry, 2020). In the modern age, Dickson Despommier professor’s vertical farm pilot vision in 1999 resulted in a new wave of attraction toward vertical farming. Besides that, advanced space exploration also pioneered many techniques and methods what are currently used in the industry, such as narrow bandwidth LED lighting, aeroponics, etc. (Kozai et al., 2019a). Up to 2020s, an almost uncontrolled amount of money fueled the construction and development of new vertical farms (Cameron, 2024). At this time many investors and operators did not really calculate and check the positive cash flow of production with proper return on investments (ROI). Many growers and fundraisers are just rather focused on noble promises seeking for extra round of fundraising instead of creating viable businesses. While others, of course, took the fundings responsibly. However, according to (Hayashi & Kubota, 2021) those farms who had to relied on their own money had a better survival rate in Japan comparing to those who gained their economic background from founding for vertical farm construction and operation.

COVID-19 and especially the Russian invasion of Ukraine in 2022 resulted many promising and painful lessons. First, even in the near future local food security have to gain higher importance.

Second, many efforts have to be made in order to be more competitive in terms of sustainability and production cost with current ‘conventional’, open field production, but especially high-tech greenhouses. Some of the competitors did not survive these years, however, it’s a natural process of selection and understandable that a newborn industry still needs more development, standardisation, etc. According to the U.S. BLS, approximately 20% of new businesses fail during the first two years of being open, 45% during the first five years, and 65% during the first 10 years. Only 25% of new businesses make it to 15 years or more (Deane, 2024). Yet the industry is facing a promising compound annual growth rate (CAGR) of 20-28% (Pranav, 2023). Applying CEA generally can be useful, when an area with a high density of people is lacking in water, food, workforce, appropriate climate, food security due to war, embargos or pandemias. It is also necessary due to severe pest outbreak, or when the natural resources are exploited, etc. On the other hand, it demands reasonable financial background and advanced engineering and manufacturing support. Perhaps most importantly, affordable energy from renewable sources is also needed. Previously mentioned features are especially crucial for vertical farms. Lately due to high energy prices the main focus regarding vertical farms is targeting energy reduction and more importantly carbon footprint reduction in the production line (Kozai et al., 2019b). The electricity demand of vertical farms is significant. Depending on location, climate, crop, cultivation technique and technology, the actual consumptions may vary greatly but according to (McDonald, 2022) vertical farms have a significantly higher average energy use at 38.8 kWh per kg of produce compared to traditional greenhouses, which average 5.4 kWh per kg. On top of that the capital expenses (capex) of a vertical farm could reach 1200-2250 GBP per m2 (Cambridge, 2022) which is 5-10, even could be 20 times higher, generally 10 times higher compared to a high-tech greenhouse, which is around 100-400 EUR per m2, but generally around 200-250 EUR per m2 (Orsini, 2023). These numbers also vary due to the above-mentioned factors like location, crop, cultivation technique and technology, etc. The main energy consumer in a vertical farm is lighting, which, depending on the crop, growth technique, and the efficiency of the lamps, usually takes around 42-80% of the energy consumption and running cost, but more generally at least 66%.

The rest is mainly the consumption of the heating, ventilation and air-conditioning (HVAC) system with possible of 10-42%, in average around 33%, especially due to the vapor condensation process. The rest of the processes need only around 1% of the energy (Kozai et al., 2019b;Orsini, 2023). To tackle these challenges, the industry developed different strategies which are mainly in connection with lighting. Initially, increasing energy efficiency of the lamp from around 2.8-4 μmol/J would result in a massive amount of electricity reduction. But we need more, with demand response energy consumption according to several other industry players further 5-30% could be saved (Kozai et al., 2019b). Moreover, with dynamic lighting strategies further drastic energy reduction can be utilized yet various research has to be done on vertical farms. Also, creating smaller distances between canopy and lamps by using wide optic lamps and chips could result in better area usage which may lead to higher productivity and further energy saving. Growers have to create such growing techniques where electricity consumption is minimised and replaced by other environmental inputs such CO2 fertilisation, vertical grow bads with vertical positioned lamps, higher EC, etc. Finetuning heating and air conditioning also could result in massive reduction of energy demand. Harvesting LED lamps driver heat (van der Lans, 2022) or applying geothermal heat (Peters, 2022) or waste heat from another industrial process could also be a solution (Hoffmann, 2023). In this way heating costs could be reduced in a sustainable way. As a location it is considered to use brownfield options, for instance, waste mines, abandoned logistics parks or factory fields, yet the building has to be perfectly suitable for plant production otherwise it's worthwhile reconsidering the building. A good example for this is YASAI vertical farming in Switzerland, which thrives in an abandoned mine due to their superior engineering and team work with leading industry partners. YASAI also managed to solve 100% energy independence by operating its own renewable energy plant. A least good example for building a vertical farm into an existing infrastructure is Growing Underground from UK which built their vertical farm in an abandoned metro tunnel system in London (with the help of University of Cambridge). Eventually, besides the benefits of the stable temperature, and brown field construction with existing infrastructure, tunnels turned to be a limiting factor in terms of utilising proper machinery and production line.

Unfortunately, this company was closed in 2023. Recently, plant factories are being steered to accommodate themselves in industrial parks near to suburban areas as well since they already have reasonable logistic, electric and municipal infrastructure. For the above-mentioned challenges recent studies claim only in that case a product produced in vertical farm is more sustainable compared to a product that is conventionally produced and transported from thousands of kilometers, especially in wintertime, if the source of the energy input for the vertical farm is coming from sustainable sources (Martin et al., 2023). Featuring electricity demand, it is advised to build and use renewable/grey energy sources next to vertical farm/greenhouses, for instance, wind, geothermal, bypass heat and electricity from a powerhouse during wintertime, etc. This feature was quite common for those big vertical farm companies that survived the previous years. An example for this is Ferme d'Hiver (Canada), where the excessive amount of heat from the LED lamps, driver is transferred into a greenhouse (Récolter Les Fruits de l'innovation - Ferme d'Hiver, n.d.). In Hungary the thermal drain water is used in some cases for aquaculture production (Bakó, 2022). On the other hand, Jones Food Company (UK) uses in-house solar power system (Heynes, 2024). Yet using solar panels for energy production to vertical farms is questionable, it also occurs that farmers are not just using the generated electricity for lighting. Growers, due to their in-house powerplant, dimmable lamps and energy storage system, can constantly react to the prices of electricity. According to that, they can choose between selling it or using it for lighting (Simons Niko, 2024). Partly to the above-mentioned reasons new types of vertical farms emerging. Hybrids of greenhouses and closed vertical farms are tested at various points of the Globe. The goal is to receive free natural light but utilize the productivity of a vertical farm (Boekhout, 2024). It has to be noted that in greenhouse-vertical farm hybrids supplemental lights may be needed. Because of their multilayered construction, natural sunlight won't deliver as much light as in the case of a conventional, one-layered greenhouse. Yet closed type vertical farming will be important in the future since there are several cases when closed environments would be more superior compared to high-tech greenhouses.

For instance, in a situation where superior production volume, freshness, homogeneity and timing is needed or due to harsh climatic environments, high urbanisation or security reasons the production is forced into closed type production systems. Additionally, in urban environments, it is also a requirement to create closed environments to avoid light pollution. Closed type vertical farms can be an option in those conditions where all the environmental parameters have to be controlled precisely and homogenously, and the crops are reasonably small, valuable with fast growth cycle. The crop list varies region by region and country by country regarding to the prices and cleanness of energy input, availability and the price of conventionally grown foods or special tax on imported goods, etc. It seems the list of the crops and regions will elevate as the climate change and soil erosion, urbanisation and population will grow. Currently, plantlets, medicinal crops, strawberries, forage, mushrooms, algae, insect and even high-wired crops could be feasible (Kozai et al., 2019b). Lettuce, leafy greens as a standalone product may not be adequate in all circumstances (Oosterwijk, 2022), but if some value-added product is made on vertical farms such as no need to wash, processed or Vitamin D induced etc., it could gain market.

2. TECHNOLOGY

Both in terms of vertical farm and humanity, the most important features and resources are similar in the near future: water, energy and carbon footprint. In this part, some initial introductions will be discussed regarding these aspects from a viewpoint of vertical farm.

2.1 Hydroponics and Aeroponics

The well-known comparison between vertical farms, greenhouse production and open field production (Naus, 2018) shows that vertical farms have the lowest water use per kg of lettuce, the highest crop yield per m2, and the lowest food miles in transportation. Greenhouses have better results, and the open field production has the worst figures. The differences in the numerical values are of at least one order of magnitude.

One of the key reasons for CEA is the water use efficiency. According to (Naus, 2018), the same amount of biomass with 200 times less water quantity comparing it to open field counterparts whose are in harsh environment with least developed technology. It is important to note that this kind of water saving efficiency could be achieved in high tech greenhouses as well (Gordon-Smith; Henry, 2020b). In some cases, this ability of CEA might overwrite other important features such as cost or energy demand. However, to create long lasting sustainable projects not just a few features should be evaluated. The word 'hydroponic' is originated from the Greek hydro (water) and ponos (the spirit of labor) (Lakkireddy et al., 2012). 'Hydroponics is a technology for growing plants in nutrient solutions (water containing fertilizers) with or without the use of an artificial medium (sand, gravel, vermiculture, rockwool, perlite, peat moss, coir, or sawdust) to provide mechanical support. Theoretically waste majority of the crops can be grown in hydroponic systems yet mainly high-wired crops, berries, lettuce, plantlets, microgreens and cut flowers are the main targets.' (Kovács et al., 2005). Elementary hydroponic system existed even in Babylonian and Aztec Empires. Yet many developments had to be made to reach its current stage and provide a viable solution for commercial production. For instance, Hoogland in 1938 created the complex nutrition solution for wholesale hydroponic production, what is even nowadays widely used. Tragic, but important development was made by the US Army during the Second World War, where the first major application of hydroponic crop production occurred in the Pacific Ocean. Nowadays this technology is used and developed mainly in countries that are still relied on imported food or located in arid or very densely populated areas. Besides that, builders must have enough wealth to establish this technology or both. These regions among the world can be such as wealthier Middle East countries, the Netherlands, Japan, Australia, coastal part of the USA, the Nordic countries, and Far East Asia (Kozai et al., 2019b).

The demand for long-distance space travel, the water scarcity, the food security as well as the goal for profitability and efficiency supposed to induce the development of hydroponic systems both in research activities and commercial production.

One of the most significant challenges however in hydroponics is the sufficient application of the nutrient solution and constant sterilisation without the use of harmful herbicides and fungicides. It is crucial to supply the plant with proper amount and quality of fertilizers without accumulation of toxic compounds such as nitrate, algae and bacteria. By resolving this the crops can be consumed without washing with no chemical residues as well. Within Hydroponic system there are several subcategories (Dr Kovács et al., 2005). The main hydroponic system subcategories could be checked at (NoSoilSolutions, n.d.): Nutrient film technique, Deep water culture, Wick hydroponics, Ebb and flow (flood & drain system), Drip hydroponics, Aeroponics, and the Kratky method of hydroponics.

In greenhouses and vertical farms mainly Ebb and flow, Nutrient film technique and Drip hydroponics are applied. In Ebb and flow system there is circular flooding and draining without keeping the root system dry. The number of floods differs from crops, growth strategy, infrastructure and phenophase. Drip irrigation is mainly applied for berries and high-vired crops but can be applied in open fields as well. By applying drip irrigation, in thin pipelines the nutrient solution is directed in small dosages to the rootzone. In the case of nutrient film technique, a thin layer of nutrient solution is constantly flowing under the roots, resulting in a simple solution for irrigation. At Deep water culture crop roots are merged in water continuously, lettuce production is regularly applying this technology. Deep water culture and Ebb and flow are more frequent among microgreen leafy green, plantlet and lettuce production. Finally, perhaps NASA founded aeroponic system could gain extra yield compared to conventional system, but due to high cost, mechanic and automatization requirements it is not really became frequent in commercial production (Kozai et al., 2019b; Kovács et al., 2005).

2.2 Lighting

Just like a lot of major inventions nowadays, the use of LEDs in agriculture originated to space technology. Astronauts at deep space explorations needed a light and efficient lighting source for general purposes and for growing their plants (Massa et al., 2008). Why is supplemental lighting in agriculture needed?

With the increasing geographical latitude, the amount of daily light integral (DLI) is decreasing, but areas with lower geographical latitude also struggle with fluctuating natural light conditions such as shading by mountains, trees, clouds, smog, dust and the natural daily and yearly irradiance variations. These changes have major crop growth limiting factors since plants do have specific photoperiodical, spectral and intensity requirements. In closed type vertical farms or greenhouses that operate in almost the same conditions as a closed CEA production facility, like Nordic greenhouses, artificial lighting is obligatory. With artificial lighting, growers can easily control the timing and quality but most importantly, multiply their biomass production (Olle & Viršilė, 2013). Besides this important feature, with artificial light market participants can rely on year-round quality production from various plants and stable working conditions, which is crucial in the market in many aspects. For instance, in the viewpoint of farmers, consumers and government as well it is important to supply constant food security, workforce demand and income.

Several types of artificial light sources can be chosen as supplemental or full-source indoor lighting systems, such as fluorescent tubes, High-Intensity Discharge lamps (HID) as High-Pressure Sodium (HDS) and metal halide lamps (MH). These tubes have been widely used but more and more outdated for plant cultivation, micropropagation, etc. (Kauck, 2022). They are inefficient, and production in many cases is declining from these products. Therefore, nowadays in plant factories and modern greenhouses switching from conventional lighting source to LED. Yet due to their acknowledgement and reasonable price, at least HPS lamps, supposed to be remain with the industry for a while. The advances of LED lighting technology over the other artificial light sources are summarized in Table 1. The utilization of Light-Emitting Diode (LED) technology could improve the efficiency of indoor plant cultivation (Singh et al., 2015). Combinations of different types of LEDs and drivers can provide high fluence which can reach the level of the sunlight if necessary, and customized wavelengths for plant cultivation. At the same time, LEDs have low energy consumption, long lifetimes and stable spectral distributions (Darko et al., 2015). The properties of different light sources are summarized in Table 1.

Table 1. Properties of different light sources

Type	Lighting efficiency (µmol/J)	Spectral specificity	Lifespan (1000h)	Energy cost	Heat generation	Controlling
Fluorescent lamps	1	Polychrome (white)	8-24	Low	Low	No
High-intensity discharge lamps: - Metal halide - Sodium	1,3 1,85	Blueish Yellowish	10-20 >24	Very high	Medium	Low
LEDs	Indoor ~2,5-3,2 Greenhouse ~3,2-4	Broad spectrum/ narrow spectrum	<25-50	Very low	Very low	Very high

Why LEDs become more superior compared to conventional lighting technologies? They are light weight and compact, easy and cheap, durable to manufacture (Kozai et al., 2019b; Snowden et al., 2016). Besides that, they are energy efficient. They can be easily operated (modify light quality and quantity even during operation, optimize lighting spectra selectively (Olle & Viršilė, 2013). Due to the low heat production and wide optic beams, it can be placed to plants closer (even 10cm in vertical farms) which makes production more efficient because it can send this way light beams into previously shaded areas and requires less space so more plants can be grown vertically.

Several types of LEDs have been produced and many of them are also specified for plant cultivation, like 440nm, 660nm or "Hortiwhite chips". Applying the proper lighting sources is important because 60-80% of total electricity cost and 30-40% of total cost can rely on artificial illumination (Qichang et al., 2013). LEDs can reduce operating costs if we consider keeping the same light level by almost 2/3 against conventional lamps in the long term. It is not enough for the future yet, within LED technology. We have to find another 50% or more efficiency increase, so dynamic lighting strategies are needed.

With proper dynamic lighting strategies where the light intensity, spectrum and daylength is varies daily or longer regimes according to the phenophase or the production goal can achieve even 50% less energy demand on lighting with resulting the same yield.(Bíró, 2024; Kaiser et al., 2024)

2.3 Factors Affecting the Growth and Development of Plants

Why is the light so crucial for plants? Light is essential for plant growth. Both plant morphology and physiology are strongly influenced by the light fluence, photoperiod and quality, which refers to the color or wavelength of light reaching the plant surface (Han et al., 2017).

Through photosynthesis, light, mainly blue and red wavelengths provide energy required for plant growth and development, but through photoreceptors, light regulates several morphogenetic processes including plant elongation, leaf expansion, stomatal opening, circadian clock and flowering. At the biochemical level, the light spectra influence both primary and secondary metabolism, affecting nutritional quality, carbohydrate and nitrogen metabolism (Darko et al., 2015; Lőrinc et al., 2019) the production of flavor, color, volatile and aromatic compounds, as well as plant defense mechanisms (Samuolien et al., 2009; Utasi et al., 2023). The effect of light intensity and spectral distribution on the growth and development are summarized in some review papers (Olle & Viršilė, 2013; Sipos et al., 2021).

However, it should be mentioned that the effects of light quality to plant growth and metabolism is complex, and strongly depend on the species and other environmental conditions.

2.4 Features of Spectrums

Different wavelengths of light can have different effects on plants:

Far red: Generative growth, flowering inducer, protein/carbohydrate ratio, sweetness, decreased chlorophyll carotenoid and anthocyanin content, leaf area increase, shade avoidance syndrome/ stem elongation.

- Red: Generative growth, most efficient LED chips, high biomass production, germination.
- Green: Generally lower energy efficiency than blue, deeper canopy penetration, needed for humans, cameras and animals as well.

- Blue: Vegetative growth, inhibition of shoot elongation, coloration, chlorophyll concentration, opening stomata, increase polyphenols, anthocyanin, carotenoid and ascorbic acid content, entraining circadian rhythm, activating cryptochrome, improving biomass with red, low energy efficiency.
- UV: Induce compact morphology, increase essential oils, increase of total antioxidant capacity, least energy efficient chip with shortest working hours.

The importance of the environment-specific lighting recipes to supply given plant with the possibly best environment to achieve its top genetic abilities. If we consider making a recipe, we have to think about it firstly from lighting aspects, such as lighting level indicated by the Daily Light Integral (DLI), which is varied between 5-60, but usually, 8-20 mol/day/m2 could be required for vertical farm grown crops (Philips, 2015). Furthermore, light spectrum, required uniformity, position, and duration should be also considered. Moreover, the sensitivity of different plant species to the different lighting environment has to be determined. However, farmers have to choose between different lighting strategies prioritizing for instance flavor, oil content, mass, or energy efficiency. This decision might require compromission because in many cases if one feature is increased, it may cause on the other hand undesired effects as well. For instance, pleasant taste can come with an undesirable outlook. Furthermore, lighting technology can be utilized in post-harvest treatment too (Lőrinc et al., 2019).

3. VERTICAL FARMS IN HUNGARY

In this part some Hungarian examples are described, mostly based on the experience of the authors.

3.1 Historical Review

In Hungary the CEA infrastructure development was similar in terms of timeline compared to worldwide tendencies. Perhaps in terms of date of appearance and square meter area, Hungary has a disadvantage compared to more advanced and populated countries such as Japan, the Netherlands, or the USA.

However, back in time, before Hungarian rule, the Carpathian basin was ruled by many nations. Among them, the first notable ones were the Romans in terms of advanced horticulture. Romans introduced advanced horticulture into the region. During this time walnuts, grapes, peaches, apples, pear, and plums were cultivated as an orchard. Besides the main arable crops, (wheat, rye, barley, oat) lentil, horse bean and pea were also introduced (Gyulai, 2022). After the collapse of the Roman Empire, many Roman cultivation methods remained, for instance, viticulture. Yet, due to regular conflicts, depopulation and less civilized nations in terms of horticulture, the volume and the quality of horticulture production were degraded. Before the settlement of the Magyars in the Carpathian Basin, a slight number of documents remained about arable crop production since they lived a nomadic lifestyle mainly dealing with animal grazing. Yet due to their animal husbandry, they cultivate some wheat, barley and millet. After the Settlement, the first notable history of Hungarian horticulture began with transferring from a nomadic lifestyle into settled lifestyle communities (Wenzel, 1887).

During this process major effect was made by converting into Christianity which also affected horticulture as well. Professional gardening was reintroduced into the Carpathian Basin, Hungarian Kingdom around 1000 AD, initially by Western European monks, mainly Benedictines, Cistercians and Premonstratensians. The monks were obliged by their own regulations to establish gardens within their monasteries for horticultural production to cover their own needs and provide food, spice, beverages and medicine for the neighboring area to those who were in need. They cultivated for instance lovage, rosemary, sage, celery, mint, lavender, St. John's wort, hyssop and thyme. Besides that, notable ornamental gardens were recorded during the 15th century at the Royal castle of Buda and Visegrád. These were demolished by Ottoman rule and rediscovered around the end of 19th century. Moreover, historians pointed out that during the 15th century large scale open field horticultural production could be observed, especially between the Danube and Tisza rivers (Wenzel, 1887). The main crops were at this time hop, cabbage, carrot, onion, pumpkin, asparagus, bean, pea, rape, poppy, sunflower, flax, hemp, etc. Furthermore, numerous medicinal and ornamental plants were grown as well, mainly around monasteries' strongholds and castles.

Rapidly after the discovery of America, tobacco production emerged in Hungary and Transylvania as well. Other crops like potato, pepper and tomato later gained popularity in the country, around 16-17 century. Just like in many other places, the first closed type CEA facilities were introduced by research facilities, aristocrats and horticulturalists. Around 16-17th centuries, Hungarian aristocrats also brought orangeries into the country to mimic Western European trends, for instance, Festetics castle in Keszthely, which also became a stronghold of Hungarian agricultural education. Until the beginning of the 20th century the main purpose of the orangeries was recreation and privilege of the wealthiest class. A lot of orangeries were built nearby monasteries, castles, and fortresses. Most of them were demolished but few of them are renovated, for instance Eszterházy castle in Fertőd. During the 18th century, after the Ottoman occupation, several people were brought in from different ethnic groups with various industrial knowledge to fill up the population which was lost during the Ottoman wars. For the horticulture sector, the most notable ones were the refugee Bulgarian horticulturalists, who settled down mainly among the Danube River, and started advanced levels of horticultural production. In many cases, these horticulturalist brigades lived a semi-nomadic lifestyle. During cropping time, they were settled in Hungary, but at the end of the season they travelled back to Bulgaria.

The horticulturalists usually rented the best soils among the Danube River and applied heavy fertilisation on them. In the 19th century the first closed type horticultural production facilities could be observed with glass or oily paper covering, yet most of the production was open field, or in semi-submersed buildings in the ground. In 1870 underground champignon mushroom production was noted. In the early 20th century, the first metal-framed greenhouses appeared providing a broader variety of crops for larger population compared to orangeries. For instance, Hungarian-Belgian modern glasshouses were settled in Vác town, in 1910. It was a 7000 m2 facility with a role of fruit and vegetable plantlet and ornamental plant production (Jeszenszky, 1995).

3.2 Recent Events

Between the two World Wars, but especially during the Communist period in Hungary (1949-1990), just like in other parts of the world, the first commercial greenhouses appeared mainly for plantlet and high wired crop production. The biggest ones were in the South-Eastern region of Hungary, between Szentes, Kecskemét, Szeged and Orosháza, one example is Árpád-Agrár Ltd. in the city of Szentes. The region was mainly focused on the modern horticultural sector after thermal water springs were discovered during the search for oil and natural gas during the 1960s. However, the first closed type plant production facilities with lamps were introduced in research institutes at the Hungarian Academy of Sciences, Agricultural Department in Martonvásár, Fertőd and Szeged, during 1940-80s. The main purpose of these facilities was cereal breeding and basic plant physiology-related research. Martonvásár and Szeged recently upgraded their indoor research infrastructure with an autonomous phenotyping system. One of the first notable vertical farm in Hungary was operated between 2016 and 2018, namely 'LivingIsland', which was introduced as a project scale commercial vertical farm in Budapest by Biopolus Institute (with the partnership of Budapest Waterworks) as a pioneer of Hungarian urban vertical farming for demo production scale vertical farms.

No description of Hungary would be complete without a description of an old, world-famous lighting company. A larger scale of 150 sqm production area R&D vertical farm was realized at Tungsram Operations Ltd. HQ in Budapest in 2021, after Tungsram Agritech division was established in 2019. Tungsram decided to start the vertical farm as a new business unit, because approximately 30% of the installation costs of such a farm is the cost of lighting, and the company had more than 100 years of experience in lighting. The focus was research and development of vertical farm hardware production, but most importantly horticultural lighting production, and making farm production experiments. The farm was realized with the significant financial support of the Hungarian government, and with the partnership of Biopolus Institute. The company has also developed a range of different agricultural lamps and Growth Cabinet, a mobile vertical farm (Figure 1).

Figure 1. Growth Cabinet, a mobile vertical farm made by the Hungarian Tungsram. Source: Authors' own photo (2024)

Sadly, Tungsram which was founded in 1896 went into bankruptcy in 2022, due to COVID-19 pandemic (disappearance of customers, collapse of the supply chain), and as side effect of the Russian invasion of Ukraine started in 2022. It was also due to unfavourable governmental support and inappropriate management decisions, and in many cases outdated product portfolio and manufacturing technique. The liquidation process started in 2023 and is still ongoing. The Agritech business unit survived all difficulties.

Its successors are Csillagváros Ltd. and Food Autonomy Ltd. still managed to break into the global elite group in terms of lamp production and research (with Wageningen University & Research – WUR, Living Lab). Csillagváros Ltd. is mainly focusing on vertical farm related research and development programs with focusing on crop growth recipe development (Fig. 2) and Deep Space related research trials on vertical farms with the help of Orion Space Generation Foundation. Orion has sent 100g seeds from 23 species among (lavender, hyssop, thyme) to the space in a polar orbit route for research and educational goals.(Fenyőfalvi & Mátyás, 2024) Food Autonomy Ltd. products are mostly horticultural lamps.

Figure 2. Vertical farm of Csillagváros Ltd. in Budapest, inherited from Tungsram Operations Ltd.

The first photo shows the vertical farm from the window of the enclosed visitor corridor. The second photo shows one of the shelves where special Tungsram Agritech LEDs, fans, water pipes for the hydroponic nutrient supply and a sensor clearly visible.

Moreover, other Hungarian vertical farm related companies are notable as well. Debrecen based Green Drops Farm Ltd. with their innovative ‘Rotower’ products is promoting home-scale vertical farm crop production. With their innovative smart irrigation system Gremon Systems Ltd. (in Szeged) is also an important player of the Hungarian CEA industry. Their crop and drain water mass measuring system (Trutina) achieved several business and crop growth successes all around the world by saving water and predicting, modelling crop growth. Besides hardware production and research there are several food production companies as well. Bedrock.farm Ltd. in downtown Budapest focuses on microgreen production with mini vertical farms supplying greens for fine-dine restaurants and retails. Arundo Biotechnology Ltd. deals with asexual plant propagation of Arundo donax on vertical farms, providing quality rootstock material for bioenergy production. BSF Systems Kft. (Grinsect) and Agroloop Hungary Ltd. are both a black solider fly farming company focusing currently only on pet food production due to strict regulations against insect based human foodstuff. Finally, Smartkas a global key player of vertical farming, especially strawberry producing has strong Hungarian origin as well since its CEO and Founder Dávid Mészáros is from the city of Szombathely. Additional smaller players are for example PlayGrowned Ltd. from Budaörs (operates a gardening webshop), Mikrozöldség Ltd. from Budapest and Mikrozöldség Farm from Váchartyán (small vertical farm plant growing companies with webshops).

As far as CEA scientific research is concerned, several researches are being carried out at many Hungarian universities and research institutes. These initiatives focus on improving controlled environment agriculture techniques and optimizing resource use. Collaboration between industry and academia is helping to accelerate innovation in vertical farming. Moreover, pilot projects are being implemented to test AI-driven irrigation and nutrient management systems in real-world settings.

4. FINDINGS

4.1 Sustainability

Thinking about sustainability in the aspects of vertical farming is a complex phenomenon. We have to define our goals in a symbiotic way with civil engineering, agriculture, biotechnology, urban architecture, transportation, circular economy and energetic aspects as well. For instance, in the future, employing recycled materials in addition to renewable and residual energy sources may mitigate the environmental impacts of the consumables and other inputs. Sustainable solutions for more integrated food, water, energy, and transportation will become increasingly important (Martin & Orsini, 2023). Nevertheless, vertical farming can significantly reduce the use of land and water resources and food scarcity, compared to traditional farming methods (Petrovics & Giezen, 2022).The use of advanced LED lighting and hydroponic systems in vertical farms may improve productivity and reduce the environmental footprint of food production paired with a reasonable amount of renewable energy sources (Martin & Molin, 2019; Nájera et al., 2023; Van Gerrewey et al., 2022). Notably, these renewable energy sources seek a given area where it is placed. Yet this can be applied in space-saving ways such as on rooftops, agrivoltaics (Hickey, 2023) or on water. But, with current technology not all types of crop's energy demands can be covered fully in all geographical positions.

However, it depends on the efficiency and type of renewable energy source as well. For instance, as pairing tomato with photovoltaics in Sweeden is not satisfactory (Kobayashi et al., 2022). Seasonality is also an important factor whether a given product with a given technology is sustainable or not. Since in wintertime, it is more obvious to compare our production models with import products from thousands of kilometers compared to a summertime production in an occasional neighboring high-tech greenhouse. According to recent research regarding vertical farming's sustainability and life cycle, a vertical farm energy usage is double compared with greenhouses, in terms of kWh/kg of lettuce. Furthermore, it could be 100 times more, compared with open field production. Therefore, open-field farming and transport usually cause less emissions than local vertical farms.

Moreover, water savings and elimination of chemical use are also achievable in greenhouses as well, therefore the benchmark for evaluating vertical farms viability should be high-tech greenhouses, not open fields (Stanghellini & Katzin, 2024). In top of that the carbon footprint of a vertical farm was 5.6-16.7 times higher than conventional farming methods in the baseline scenario, and 2.3 to 3.3 times in the alternative scenario (Blom et al., 2022). Finally, the eco-friendliest way of vegetables production is the high-tech greenhouse, because of its high resource-use-efficiency but reasonably low energy demand (Kobayashi et al., 2022).

4.2 Economic Feasibility

Regarding to economic feasbility, there has to be assign many aspects too. For instance, policy making, technological development, funding, crop management, marketing, sales, and macroeconomics, etc. As it was previously indicated the function of when the vertical farm operation is economically positive is complex. It depends mainly on automation, facility size, crop variety, crop growth strategy, wage, input material price, and of course selling price. Nowadays the most trending topic is energy price, energy consumption and ecofriendliness of energy. Therefore, the economic feasibility and optimization of vertical farm systems are still under evaluation, with considerations needed mainly for energy consumption, carbon footprint and bill of materials (BOM) costs. Moreover, the industry still lacks proper policy and social implications, such as the integration of vertical farm into urban planning and the acceptance by stakeholders. It would be crucial for the successful implementation and scaling of vertical farm systems (Petrovics & Giezen, 2022). Because of these aspects, vertical farms are generally outliers of horticulture focused governmental funds both in country and EU levels. It is also a challenge to get into a market with products from vertical farms, since the legislation and regulations are still not prepared for vertical farms in terms of quality control. Moreover, the farmers' association could be better in terms of numbers and activity, which could also affect funding and policy making. Perhaps without governmental funding the industry still was in a reasonably good position due to capital ventures.

The success of vertical farming is heavily reliant on advancements in agricultural technologies. Techniques such as hydroponics, aeroponics, and aquaponics have revolutionized soilless farming, enabling plants to grow efficiently with minimal water and nutrient inputs. These technological advancements are dimmable LED lamps, automatic conveyor belt systems, in-house renewable energy supply. The integration of Internet of Things (IoT) and automation technologies plays a crucial role in optimizing vertical farm operations. IoT devices can monitor environmental parameters such as temperature, humidity, and light intensity in real-time, allowing for precise adjustments to create optimal growing conditions. Automation reduces labor costs and improves consistency in crop production. These technological advancements make vertical farms more feasible on a scale, enhancing its potential for widespread adoption (Al-Chalabi, 2015). These technologies allow for precise control over growing conditions, can lead to higher yields and better-quality produce compared to traditional farming methods (Martin & Orsini, 2023; Van Gerrewey et al., 2022). As previously indicated, the initial investment costs for setting up vertical farms are high, these systems can be economically profitable in the long term. In this question there are several consultancies and calculators available on the internet, such as iFarm Leafy Greens Vertical Farm Startup Cost Calculator, provided by the iFarm company (iFarm, 2024), or the Agritecture Designer by Agritecture advisory services and technology firm (Agritecture, 2024).

The reduced need for large plots of land and the ability to utilize underused urban spaces can offset the high startup costs. Moreover, the potential for multiple harvests per year and higher crop yields can improve the economic feasibility of vertical farms. Regarding feasibility, sizing is a crucial factor in many aspects. According to CambridgeHOK, the minimum vertical farm size is at least 5000 sqm (Haworth, 2022). Perhaps there can be profitable business under that scale as well, especially in the case of research or advertising purposes, however in this case the rational profitability might be marketing heavy and fluctuating. Vertical farms can compete with traditional farming methods in terms of production costs, but it is highly reliant on energy prices seasonality, wages, automation crop growth techniques and taxes as well.

The market potential for vertical farming is substantial and increasing. This growth is fueled by increasing urbanization rates, rising awareness of sustainable agricultural practices, and government initiatives supporting innovative farming techniques. As cities continue to expand, the demand for vertical farming solutions is expected to grow, making it a key area for investment and development.

4.3 Transportation Aspects of A Vertical Farm

It is worth investigating how much additional load the operation of a vertical farm places on the transport network, as a significant load requires a rethink of the transport system and may also raise issues of environmental pollution. As vertical farms are typically located in cities and even within buildings, the road transport sub-sector is primarily affected.

A vertical farm is a factory that needs raw materials. The need for electricity and heat can be met in the traditional way (wires, pipelines, use of solar energy, etc.). Raw materials (chemicals, seeds, additional consumables e.g. trays, root holders, and protective equipments are usually transported by road. Only part of the staff can work from home office, the others have to work on site, which is increased by customers, occasional visitors and the appearance of specialists.

Plants grown on the farm have to be delivered in the same way (on the road again) and, of course, some hazardous and non-hazardous waste (e.g. green waste) is produced, all of which can typically be transported by road (Martin, 2023). It can therefore be concluded that a vertical farm puts a strain on the road network, the extent of which depends largely on the size of the farm.

However, there are also some favourable characteristics:

- Because of the fine-tunable light receipt, the exact time of ripening and therefore harvesting can be delayed by a few days, thus optimising the time of delivery.
- A vertical farm operates 0-24 hours a day, requiring only a few days of downtime throughout the year, the dates of which are known in advance. By planning downtime in advance, transport activities can be optimised and, if necessary, organised for off-peak periods.

- Budapest based BedRock Farm Ltd. transports the plants grown on the farm by special cargo bikes (it is done by human power), this method of transport puts a completely different burden on the public road network.
- Farm products are delivered over relatively short distances (especially when there are many smaller farms in a settlement) compared to traditional crop cultivation and transport methods.

In summary, a vertical farm does put a strain on the road network, but with proper planning and optimisation, it is less than traditional crop production methods. Let's also not forget that exotic plants and herbs can be grown on a vertical farm if needed, so there is no need to transport them from distant countries.

A vertical farm can be an important factor in the smart city concept, as lots of ICT devices are also used on the farm, a self-sustaining local community can be one step closer, and finally, a vertical farm can be an integral part of a local ecosystem, including wastewater treatment, cultivation of animal feed, new special food production (flour made from insects).

CONCLUSION

Controlled Environmental Agriculture concept goes back at least 100 years, but developments have only really taken off in the last 15 years or so, thanks to the latest lighting, software and other technical developments, as well as the latest biological knowledge that can be applied. So, from a technological point of view, the conditions are there. On the promotional side, global warming (and its impacts), sustainable development and providing healthy food for an ever-growing world population are perhaps the most important buzzwords. One of the solutions to these challenges could be the 21st century type greenhouse (supported by horticultural lighting) and the vertical farm, which fits perfectly into the smart city concept, as it can be linked to several factors in an ecosystem-like way. However, the initial momentum seems to have slowed down and although there are companies involved in vertical farms, the crops produced are not yet competitive (more expensive) compared to traditional open field cultivation. So, it seems that we are now in a period of moderate interest and development.

A vertical farm obviously puts a strain on the road network, but this strain is less than the transport needs associated with traditional crop cultivation.

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CHAPTER 3
AI-POWERED ROBOTICS AND DRONES IN PRECISION FARMING

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INTRODUCTION

The global agricultural sector faces the dual challenge of increasing food production to meet the demands of a growing population while simultaneously reducing environmental impacts (Foley et al., 2011). Precision agriculture, broadly defined as the application of advanced technologies to optimize agricultural inputs and outputs, has emerged as a transformative solution to these challenges (Gebbers & Adamchuk, 2010). Within this paradigm, artificial intelligence (AI), robotics, and unmanned aerial vehicles (UAVs, commonly referred to as drones) have gained prominence as enabling technologies that enhance decision-making, resource management, and labor efficiency in farming systems. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

AI-powered robotics and drones are increasingly deployed in modern agricultural systems to perform tasks that traditionally relied on human labor and conventional machinery. These include site-specific weeding, targeted pesticide application, crop monitoring, yield prediction, and autonomous harvesting (Shamshiri et al., 2018). For example, John Deere's autonomous tractor, unveiled at the Consumer Electronics Show (CES) in 2022, integrates computer vision and machine learning to conduct fully automated plowing, planting, and soil preparation with minimal human intervention (John Deere, 2022). Similarly, companies such as Blue River Technology have developed AI-driven "See & Spray" systems that differentiate between crops and weeds in real time, applying herbicides only where necessary, thereby reducing chemical usage by up to 90% (Slaughter et al., 2008; Blue River Technology, 2021). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Drones equipped with AI-driven imaging systems have also demonstrated considerable value in precision farming. By capturing multispectral and thermal imagery, drones can detect early signs of crop stress, pest infestation, and nutrient deficiencies that are invisible to the human eye (Maes & Steppe, 2019).

In India, the Indian Council of Agricultural Research (ICAR) demonstrated the potential of drones for efficient pesticide spraying in Varanasi in 2024, highlighting both reduced labor requirements and improved spray uniformity (ICAR-IIVR, 2024). These innovations illustrate how AI-powered robotics and drones are reshaping the agricultural landscape, offering scalable solutions that align with sustainability and food security objectives. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

This chapter critically examines the role of AI-powered robotics and drones in precision farming. It begins with a historical overview of the evolution of precision agriculture, followed by an exploration of the technological foundations, applications, and socio-economic implications of robotics and UAVs in farming. The chapter further discusses emerging trends, challenges, and policy considerations relevant to integrating AI-driven automation into global agriculture. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

1. EVOLUTION OF PRECISION AGRICULTURE

The origins of precision agriculture can be traced to the mechanization revolution of the early 20th century, when the introduction of tractors and mechanical implements replaced animal-powered farming systems (Basso & Antle, 2020). The adoption of mechanized equipment significantly increased farm productivity but did not address the variability inherent in soil, crop, and climate conditions across fields. The limitations of uniform, large-scale application of inputs such as fertilizers and pesticides led to inefficiencies, environmental degradation, and rising production costs. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

The emergence of global positioning system (GPS) technologies in the 1990s marked a turning point in precision farming. Farmers were able to use GPS-guided tractors and variable rate application (VRA) technologies to apply inputs more accurately, thereby reducing waste and improving crop performance (Mulla, 2013).

For instance, yield mapping combined with GPS-enabled equipment allowed producers to analyze field heterogeneity and optimize seeding and nutrient applications (Zhang & Kovacs, 2012). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

The 2000s witnessed the integration of remote sensing, geographic information systems (GIS), and Internet of Things (IoT) devices into agricultural practice. These tools enhanced data-driven decision-making by providing real-time insights into crop growth, soil health, and weather dynamics (Wolfert et al., 2017). The development of cloud computing and big data analytics further accelerated the ability of farmers and researchers to analyze large datasets, improving predictions of yield outcomes and resource needs. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Today, precision agriculture has entered what may be termed the "AI-automation era." In this phase, machine learning algorithms, robotics, and drones converge to deliver autonomous, adaptive, and highly responsive farming systems (Shamshiri et al., 2018). Unlike earlier phases, which relied primarily on human interpretation of data, AI systems now process real-time sensor inputs, learn patterns, and execute autonomous actions with minimal supervision. For example, robotic systems such as the LaserWeeder G2 employ AI-powered computer vision to identify and eliminate weeds without damaging crops, significantly reducing herbicide dependency (Carbon Robotics, 2023). Similarly, swarm robotics and UAV fleets are being developed to coordinate tasks such as seeding, irrigation, and crop protection, signaling a future where farms operate as interconnected, intelligent ecosystems. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Thus, the trajectory of precision agriculture reflects a steady progression from mechanization to digitization and now to automation. The integration of AI-powered robotics and drones represents not merely a technological advancement but also a paradigm shift toward sustainable intensification of agriculture.

This transformation aligns productivity with environmental stewardship and global food security imperatives. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

2. AI IN AGRICULTURAL ROBOTICS

The integration of artificial intelligence (AI) into agricultural robotics has enabled the development of autonomous systems capable of performing complex tasks traditionally carried out by human laborers. These robotic platforms employ machine learning, computer vision, and sensor fusion technologies to perceive their environments, make decisions, and execute precise actions in real time (Bechar & Vigneault, 2016). AI-powered robotics are applied across diverse domains of agricultural production, including ground-based field operations, harvesting, and soil and crop monitoring. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

2.1 Autonomous Ground Robots

Autonomous ground robots have gained prominence as multifunctional platforms for precision agriculture. A key application is weed management, where robots use AI-driven vision systems to differentiate between crops and weeds. For example, the LaserWeeder G2 developed by Carbon Robotics employs deep learning algorithms and high-resolution cameras to detect weeds and eradicate them with laser bursts, reducing herbicide use and minimizing environmental impact (Carbon Robotics, 2023). Similarly, John Deere's See & Spray system integrates AI and computer vision to selectively target weeds during chemical application, achieving significant reductions in herbicide usage compared to blanket spraying approaches (Blue River Technology, 2021). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results. Such technologies could enhance productivity, reduce labor intensity, and promote more sustainable farming practices.

In addition to weeding, AI-powered robots are increasingly utilized in harvesting operations. Robotic fruit pickers, equipped with vision-based ripeness detection systems, can identify mature produce and harvest it without damaging either the crop or the plant (Lehnert et al., 2017). For instance, Agrobot's robotic strawberry harvester leverages AI algorithms to detect fruit color, size, and maturity level, enabling continuous harvesting under greenhouse and field conditions (Agrobot, 2022). Such technologies address labor shortages in horticultural production systems, particularly in regions where seasonal labor availability is declining. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Ground robots are also used for soil monitoring and data collection. Platforms such as the TerraSentia rover integrate AI-enabled sensors to map soil health indicators, crop growth parameters, and microclimatic conditions across fields (Young et al., 2019). These data support predictive modeling and variable-rate management strategies, enhancing resource use efficiency and yield outcomes. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

2.2 Tractors and Intelligent Machinery

Autonomous tractors represent another important application of AI in agricultural robotics. Unlike traditional GPS-guided tractors, AI-enabled machines combine computer vision, LiDAR, and machine learning for full autonomy in field operations. Deere & Company's autonomous tractor, introduced in 2022, can plow, plant, and cultivate without operator input, relying on real-time environmental perception and decision-making algorithms (John Deere, 2022). This technology enhances operational efficiency, particularly for large-scale farms, while also reducing reliance on skilled operators.

Furthermore, intelligent planters and seeders employ AI and sensor systems to adapt seeding depth and spacing according to localized soil conditions.

Such adaptive machinery ensures optimal germination, reduces input wastage, and supports site-specific crop management strategies (Shamshiri et al., 2018). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

2.3 Case Studies in Agricultural Robotics

Several case studies highlight the transformative impact of AI-driven agricultural robots:

- In California, robotic strawberry harvesters have been deployed commercially to address chronic labor shortages in fruit-picking operations, significantly reducing labor costs and post-harvest losses (Agrobot, 2022).
- Blue River Technology's See & Spray system demonstrated reductions of up to 90% in herbicide usage in field trials, underscoring the economic and environmental benefits of AI-guided weed control (Slaughter et al., 2008).
- The TerraSentia rover has been adopted in agricultural research to facilitate high-throughput phenotyping, enabling breeders and agronomists to evaluate crop traits more efficiently and accurately than manual observation (Young et al., 2019). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Collectively, these innovations illustrate how AI-powered robotics are reshaping field management, harvesting, and data-driven decision-making in agriculture. They not only enhance productivity and sustainability but also redefine the labor dynamics of modern farming systems. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

3. AI IN AGRICULTURAL DRONES

Unmanned aerial vehicles (UAVs), commonly known as drones, have become integral components of precision farming due to their ability to collect high-resolution data and execute site-specific interventions.

When integrated with artificial intelligence (AI), drones transcend their role as remote sensing platforms to become decision-support and action-oriented tools in agriculture (Tsouros et al., 2019). AI-powered drones are equipped with computer vision, machine learning algorithms, and multispectral imaging capabilities that enable farmers to monitor crop health, apply inputs, and manage resources with unparalleled accuracy. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

3.1 Applications of Drones in Precision Agriculture

Crop Monitoring and Imaging

AI-enabled drones facilitate real-time crop monitoring through multispectral and hyperspectral imaging, allowing the detection of crop stress, nutrient deficiencies, and pest or disease outbreaks before they manifest visually (Maes & Steppe, 2019). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) are derived from aerial imagery to assess canopy vigor and predict yield potential (Zhang & Kovacs, 2012). For instance, vineyards in Spain have successfully adopted UAV-based NDVI imaging to optimize irrigation schedules and improve grape quality (Matese et al., 2015). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Aerial Spraying and Input Application

Beyond monitoring, drones are increasingly utilized for site-specific spraying of pesticides, fertilizers, and micronutrients. AI-powered flight planning algorithms optimize spraying routes, ensuring uniform coverage and minimizing chemical drift (Lan et al., 2017). In India, the Indian Council of Agricultural Research (ICAR-IIVR) demonstrated drone-assisted spraying in 2024, reducing labor requirements and improving spray efficiency in vegetable production (ICAR-IIVR, 2024). Similarly, Chinese agricultural drone manufacturer XAG reported reductions of up to 30% in pesticide usage through AI-driven spraying drones (XAG, 2023).

Pollination and Planting

Emerging drone applications include artificial pollination and seed dispersal. Companies such as Dropcopter in the United States employ AI-equipped pollination drones to supplement declining bee populations, improving fruit set in orchards (Dropcopter, 2021). Seed-planting drones, particularly in reforestation and cover cropping efforts, are also being developed to accelerate large-scale planting operations (Chang et al., 2020). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Livestock Monitoring

AI-integrated UAVs are also applied in livestock systems, where drones equipped with thermal cameras and movement-detection algorithms monitor animal health, detect heat stress, and track herd distribution across grazing lands (Anderson et al., 2013).

3.2 AI Integration in Drone Operations

The integration of AI transforms drones from passive observation tools into active decision-making platforms. AI-based image recognition systems process aerial imagery to automatically detect crop diseases such as wheat rust and maize blight (Kamilaris & Prenafeta-Boldú, 2018). Machine learning models predict yield variability across field zones, guiding variable-rate application of inputs. Furthermore, reinforcement learning algorithms enable drones to autonomously adjust their flight paths in response to changing field conditions, ensuring efficient energy use and accurate data collection (Kim et al., 2019).

3.3 Case Studies in AI-Powered Drone Deployment

- In Karnataka, India, a pilot project employing AI-driven spraying drones reduced water usage in ragi (finger millet) production by 90%, while improving yields of pulses such as tur dal (Times of India, 2025).
- In Australia, UAVs equipped with AI-based imaging systems were deployed in wheat fields to detect nitrogen stress, resulting in significant improvements in nitrogen use efficiency (Hunt et al., 2018).

- The company DJI Agriculture has launched AI-powered drones such as the Agras T40, capable of both spraying and spreading fertilizers with adaptive load balancing, enhancing operational efficiency in rice and maize systems (DJI Agriculture, 2023).

3.4 Advantages and Limitations

The advantages of AI-integrated drones include rapid data acquisition, reduced input costs, improved timeliness of interventions, and enhanced sustainability outcomes. However, their adoption faces barriers such as high acquisition costs, limited battery life, regulatory restrictions on aerial spraying, and the need for technical training among farmers (Tsouros et al., 2019). In addition, reliable connectivity and data management infrastructure remain critical challenges in rural and developing regions.

4. BENEFITS OF AI-POWERED ROBOTICS AND DRONES IN PRECISION AGRICULTURE

The integration of artificial intelligence (AI) with robotics and drones in precision agriculture presents transformative benefits that directly impact productivity, efficiency, profitability, and sustainability. These technologies not only enhance farm management practices but also address global challenges such as food insecurity, resource scarcity, and environmental degradation (Wolfert et al., 2017). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

4.1 Enhanced Operational Efficiency

AI-powered robotics and drones streamline agricultural processes by automating time-consuming tasks such as weeding, spraying, and harvesting. This automation reduces labor dependency and mitigates the challenges posed by rural-to-urban migration and the aging farm workforce (Shamshiri et al., 2018). For example, robotic harvesters like the Rubion strawberry-picking robot can pick fruits at a faster rate while minimizing post-harvest losses (van Henten et al., 2019).

Similarly, spraying drones have demonstrated efficiency by covering hectares of farmland in significantly less time than manual spraying, reducing fatigue and labor costs (Lan et al., 2017).

4.2 Improved Yield and Productivity

By enabling real-time monitoring of soil and crop conditions, AI-driven systems provide farmers with actionable insights for targeted interventions. Drones equipped with multispectral cameras detect nutrient deficiencies, while machine learning algorithms predict optimal fertilizer application schedules, leading to higher yields (Hunt et al., 2018). Case studies in rice-growing regions of China show that AI-powered drones increased yields by up to 15% due to precision spraying and better pest control (XAG, 2023). Robotic seeders also enhance uniform planting density, which is strongly correlated with improved crop performance (Shamshiri et al., 2018). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

4.3 Cost Reduction

Precision farming enabled by AI significantly reduces input costs through optimized use of fertilizers, pesticides, and water. Variable-rate application techniques ensure that resources are applied only where necessary, thereby minimizing waste. Studies have reported reductions of up to 30% in pesticide use with AI-enabled drones (Lan et al., 2017), while robotic irrigation systems have reduced water consumption in vineyards by as much as 25% (Matese et al., 2015). These savings translate into lower production costs and increased profitability for farmers. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

4.4 Sustainability and Environmental Protection

AI-powered robotics and drones contribute to sustainable agriculture by promoting efficient resource utilization and reducing environmental footprints. Precision spraying reduces chemical runoff, protecting soil and water quality (Kamilaris & Prenafeta-Boldú, 2018).

Automated weed control robots further minimize the need for herbicides, thereby supporting ecological balance. For instance, the ecoRobotix weeding robot targets weeds with pinpoint herbicide applications, reducing herbicide use by up to 90% (ecoRobotix, 2022). Additionally, drones monitoring crop health aid in early detection of disease outbreaks, preventing large-scale crop failures and enhancing food system resilience (Tsouros et al., 2019). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

4.5 Climate Adaptation and Resilience

AI-integrated drones and robotics help farmers adapt to climate variability by offering predictive insights. Machine learning models forecast weather-related risks, enabling farmers to adjust irrigation, planting dates, and crop management strategies accordingly (Liakos et al., 2018). For example, drones monitoring water stress in maize fields can guide adaptive irrigation strategies, reducing vulnerability to drought (Maes & Steppe, 2019). Such resilience-oriented interventions are crucial for ensuring stable food production under changing climate conditions.

5. CHALLENGES AND LIMITATIONS OF AI-POWERED ROBOTICS AND DRONES IN AGRICULTURE

Despite their transformative potential, AI-powered robotics and drones in precision agriculture face several challenges that hinder widespread adoption, especially in developing regions. These limitations can be categorized into economic, technical, environmental, and regulatory barriers that must be addressed to fully harness their benefits (Shamshiri et al., 2018). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results. However, inadequate infrastructure and limited digital literacy remain significant obstacles to implementation.

High Initial Investment and Economic Barriers

The cost of procuring AI-driven drones and agricultural robots remains prohibitive for smallholder farmers who dominate global food production. A typical agricultural spraying drone may cost between USD 10,000–25,000, excluding maintenance and software subscription fees (DJI Agriculture, 2023). Similarly, advanced robotic harvesters can exceed USD 100,000, making them accessible primarily to large-scale farms (van Henten et al., 2019). Limited access to credit and financing mechanisms in rural communities exacerbates the affordability challenge (Liakos et al., 2018). This raises an important question: how can we ensure that smallholder farmers in regions like West Africa are not left behind in this technological shift?

Technical Challenges and Infrastructure Gaps

AI-powered systems rely on stable electricity, internet connectivity, and digital literacy. In many rural areas, weak infrastructure limits drone operations and data transmission (Wolfert et al., 2017). Battery capacity also constrains UAVs, restricting flight times to 20–40 minutes, which reduces coverage of large farms (Tsouros et al., 2019). Additionally, AI algorithms often require high-quality training datasets to deliver accurate predictions, but agricultural datasets are fragmented, unstandardized, and region-specific (Kamilaris & Prenafeta-Boldú, 2018).

Data Privacy and Cybersecurity Concerns

AI-based agricultural systems generate massive amounts of geospatial and farm-level data. Questions of data ownership, privacy, and security remain unresolved, especially when data are stored on third-party cloud platforms (Wolfert et al., 2017). Farmers risk losing control over sensitive information such as yield levels, soil fertility status, or water usage, which could be exploited by corporations or competitors. Without proper data governance frameworks, these concerns may discourage adoption. Establishing transparent data governance policies is therefore crucial to building trust among stakeholders.

Environmental and Ecological Concerns

While drones and robots aim to minimize environmental impacts, unintended consequences exist. For instance, the use of aerial spraying drones may increase chemical drift if not properly calibrated, potentially affecting non-target organisms (Lan et al., 2017). Furthermore, increased reliance on robotics may lead to soil compaction from heavy autonomous machinery, undermining soil health (Shamshiri et al., 2018). Drone noise pollution may also disturb wildlife in sensitive ecosystems (Anderson et al., 2013).

Human Capacity and Skill Gaps

The operation of AI-integrated drones and robotics requires technical expertise in programming, machine learning, and remote sensing. However, many farmers particularly smallholders lack the necessary training to effectively utilize these technologies (Liakos et al., 2018). Extension services in developing countries are often under-resourced, limiting knowledge transfer and capacity building. Consequently, there is a risk of technological exclusion, where wealthier and technologically literate farmers benefit disproportionately.

Regulatory and Policy Challenges

Drone operations are subject to aviation regulations that vary across countries. In many regions, laws restrict aerial spraying, limit flight altitudes, or require special permits for UAV use (Tsouros et al., 2019). Such regulatory hurdles often discourage adoption, especially among smallholders who lack resources to navigate bureaucratic processes. Moreover, the absence of standardized guidelines for AI-based agricultural robotics creates uncertainty for developers and users.

CONCLUSION

Artificial intelligence (AI)-powered robotics and drones are reshaping the landscape of precision agriculture by offering unprecedented opportunities for efficiency, sustainability, and profitability. From autonomous weeding robots to AI-driven aerial spraying drones, these technologies have demonstrated their potential to transform traditional farming practices into highly data-driven and resource-efficient systems.

The integration of AI enhances decision-making, reduces input costs, increases yields, and strengthens climate resilience, thereby addressing the dual global challenges of food security and environmental sustainability (Wolfert et al., 2017; Liakos et al., 2018). In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.

Nevertheless, challenges such as high investment costs, data governance issues, infrastructural gaps, and regulatory barriers continue to limit widespread adoption, particularly among smallholder farmers who form the backbone of agricultural production in developing countries. Without inclusive strategies, there is a risk of deepening the digital divide between technologically advanced large-scale farms and resource-constrained farmers (Shamshiri et al., 2018). This raises an important question: how can we ensure that smallholder farmers in regions like West Africa are not left behind in this technological shift?

Looking forward, several future perspectives emerge:

- **Affordability and Accessibility:** Scaling down the cost of AI-driven agricultural technologies through government subsidies, cooperative ownership models, and private sector innovations will be crucial to democratize access (Kamilaris & Prenafeta-Boldú, 2018).
- **Integration with IoT and Big Data:** Combining AI-powered drones and robots with the Internet of Things (IoT) and big data analytics will create robust farm management ecosystems. Such integration will enable predictive analytics for yield forecasting, disease outbreak prevention, and resource optimization (Wolfert et al., 2017).
- **Sustainable and Green Robotics:** Research into solar-powered drones, lightweight robotic systems, and biodegradable spraying mechanisms could mitigate some of the ecological concerns associated with these technologies (Shamshiri et al., 2018).
- **Capacity Building and Digital Literacy:** Investments in farmer training, extension services, and knowledge-sharing platforms will bridge the skill gap, ensuring that farmers not only access but also effectively utilize AI-powered systems (Liakos et al., 2018).

- **Policy and Regulatory Harmonization:** Governments must update regulatory frameworks to support safe drone usage, protect data privacy, and encourage innovation while safeguarding public interest (Tsouros et al., 2019).

In conclusion, the successful future of AI-powered robotics and drones in agriculture depends on collaborative efforts between policymakers, researchers, industry players, and farmers. By addressing current challenges and harnessing future opportunities, these technologies can be scaled to contribute meaningfully to global food security, environmental conservation, and sustainable rural development. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results. As we look ahead, it is vital to consider how these innovations can be tailored to local realities, including soil types, crop varieties, and farmer knowledge systems.

Recommendations

For Researchers

- Prioritize interdisciplinary research that integrates AI with IoT, blockchain, and remote sensing for holistic precision agriculture systems. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.
- Develop algorithms optimized for low-resource settings, including offline AI models suitable for regions with poor internet connectivity.
- Conduct socio-economic studies on adoption to better understand farmer perceptions, cultural barriers, and long-term impacts.

For Policymakers

- Establish supportive regulatory frameworks for drone usage, data governance, and AI applications in agriculture. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.
- Provide subsidies, grants, and credit facilities to support smallholder farmers in accessing robotics and drone technologies.

- Invest in rural digital infrastructure, including broadband access and reliable electricity, to create enabling environments.

For Practitioners and Farmers

- Adopt AI-powered tools gradually, beginning with low-cost solutions such as drone-based crop monitoring before scaling to fully autonomous systems. In Nigeria, crops like cassava, maize, and cocoa are central to rural livelihoods, and integrating AI into their cultivation could yield transformative results.
- Collaborate with extension agents and technology providers for training and continuous technical support.
- Foster cooperative ownership models, where farmer groups pool resources to acquire and share robotic and drone technologies.

For Industry Stakeholders

- Design affordable, rugged, and modular AI-powered robots and drones tailored to the needs of smallholder farmers.
- Partner with governments and NGOs to pilot inclusive business models that expand access in underserved regions.
- Enhance transparency in AI algorithms to build farmer trust and ensure ethical use of agricultural data.

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CHAPTER 4
CLIMATE RESILIENCE INNOVATIONS IN PIG FARMING

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INTRODUCTION

Pig production is a cornerstone of the global agricultural economy, with the European Union alone being the world's second-largest producer and top exporter of pork products (Renaudeau & Dourmad, 2022). However, the sector faces a dual challenge in the era of climate change. It is associated with significant environmental impacts, including global warming and land-use change (Ndue & Pál, 2022), with pig farming contributing about 9% of all livestock-related greenhouse gas emissions (Hörtenhuber et al., 2020). Simultaneously, climate change threatens the industry's stability through direct impacts like heat stress and indirect effects such as disruptions to feed production and the spread of diseases (Hörtenhuber et al., 2020; Renaudeau & Dourmad, 2022)

This complex relationship necessitates a shift towards climate-resilient practices. Building resilience in pig farming involves a multi-faceted approach, from implementing thermally insulated and well-ventilated housing systems to ensuring the availability of feed and water during extreme weather events such as droughts and floods (Hörtenhuber et al., 2020). To navigate this future, the industry is exploring innovative pathways. These range from high-input, high-output systems focused on sustainable intensification and precision farming to reduced-input models centered on developing animal breeds that are more robust and better adapted to climate change and low-quality local feeds (Rauw et al., 2020). This chapter will delve into these pioneering strategies, examining the technological, genetic, and managerial innovations that are shaping a more sustainable and resilient future for pig farming.

1. THE IMPERATIVE FOR RESILIENCE: CLIMATE CHANGE AND PIG PRODUCTION

Pig production is a cornerstone of the global agricultural economy, with the European Union (EU) standing as the world's second-largest producer and leading exporter of pork products (Renaudeau & Dourmad, 2022). However, the sector is at a critical juncture, facing a complex, dual relationship with climate change that threatens its long-term sustainability and profitability.

On one hand, pig farming contributes significantly to environmental challenges such as global warming and land-use change (Ndue & Pál, 2022), accounting for 9% of all livestock-related greenhouse gas (GHG) emissions (Hörtenhuber et al., 2020). On the other hand, the industry is increasingly vulnerable to the direct and indirect consequences of a changing climate, which jeopardize animal welfare, productivity, and global food security (Hörtenhuber et al., 2020). This dynamic makes building climate resilience not merely an option but an urgent necessity.

The Dual Threat: Environmental Impact and Climate Vulnerability: The imperative for resilience stems from the industry's simultaneous role as both a contributor to and a victim of climate change. The environmental footprint of pig production is substantial, with major impacts arising from feed production, manure management, and on-farm energy use (Ndue & Pál, 2022). This contribution to GHG emissions creates a feedback loop where the industry exacerbates the very conditions that threaten its stability.

The Vulnerability of Pig Production to Climate Change Manifests in Several Critical Areas

Pigs are highly susceptible to heat stress, and rising global temperatures, coupled with more frequent heatwaves, pose a direct threat. Most pig housing in the EU relies on mechanical ventilation, which is often insufficient to cool facilities during summer months, leading to indoor temperatures that exceed the animals' thermoneutral zone and negatively affect performance (Renaudeau & Dourmad, 2022). Physiologically, pigs respond to heat by reducing feed intake to lower their metabolic heat production, which directly impairs growth and efficiency (Hörtenhuber et al., 2020). In addition, prolonged heat stress can compromise reproductive performance and increase susceptibility to diseases. Implementing strategies such as improved cooling systems, shading, and dietary adjustments can help mitigate these negative effects. Research into genetic selection for heat-tolerant pig breeds also offers a long-term solution to enhance resilience in the face of climate change.

Indirect Impacts on Feed and Health

Climate change indirectly disrupts the pig production system in ways that can be even more damaging than direct heat stress.

- **Feed Availability and Cost:** Feed represents 60-70% of production costs, and climate change is predicted to reduce yields of key cereal crops while increasing price volatility (Renaudeau & Dourmad, 2022). This poses a significant economic threat to producers.
- **Disease and Pathogens:** A warming climate can alter the geographic distribution and survival of pathogens and disease vectors, increasing the risk of exposure to new and existing diseases (Renaudeau & Dourmad, 2022).
- **Mycotoxin Contamination:** Changes in weather patterns can increase the risk of mycotoxin contamination in cereal crops. Pigs are highly sensitive to these toxins, which can compromise their immune systems and reduce the effectiveness of vaccines (Renaudeau & Dourmad, 2022).

Pathways to a Resilient Future: Addressing these multifaceted challenges requires a strategic shift towards resilient production models. A climate-resilient pig farm is characterized by proactive measures to mitigate both internal and external shocks (Hörtenhuber et al., 2020). Key elements include:

- Thermally insulated and well-ventilated housing systems with a constant power supply (Hörtenhuber et al., 2020).
- Secure access to feed and water, especially during extreme weather events like droughts and floods (Hörtenhuber et al., 2020).
- A focus on high animal performance to minimize resource consumption (Hörtenhuber et al., 2020).

To achieve this, the industry is exploring two primary contrasting pathways. The first is a high-input, high-output model focused on sustainable intensification and precision farming to maximize efficiency. The second is a reduced-input model centered on developing more robust animal breeds that are better adapted to climate change and can thrive on lower-quality, local feeds (Rauw et al., 2020). The optimal path forward will likely involve a combination of these strategies, tailored to local conditions, to ensure the pig production sector can adapt, survive, and thrive in a changing world.

Conclusively, pig production is a cornerstone of the global agricultural economy, with the European Union (EU) alone standing as the world's second-largest producer and leading exporter of pork products (Renaudeau & Dourmad, 2022). However, the sector is at a critical juncture, facing a complex, dual relationship with climate change that threatens its long-term sustainability and profitability. On one hand, pig farming contributes significantly to environmental challenges like global warming and land-use change (Ndue & Pál, 2022), accounting for 9% of all livestock-related greenhouse gas (GHG) emissions (Hörtenhuber et al., 2020). On the other hand, the industry is increasingly vulnerable to the direct and indirect consequences of a changing climate, which jeopardize animal welfare, productivity, and global food security (Hörtenhuber et al., 2020). This dynamic makes building climate resilience not merely an option but an urgent necessity.

1.1 Climate Change Impacts on Pig Farming

Climate change presents a multifaceted threat to pig production, with direct and indirect effects that impact the health, welfare, and productivity of the animals (Renaudeau & Dourmad, 2022). These challenges range from immediate physiological stress to long-term disruptions in feed supply and disease landscapes.

- **Direct Effects:** Heat Stress and Extreme Weather: Rising global temperatures and the increasing frequency of extreme weather events like heatwaves directly harm pigs, which are particularly vulnerable to heat due to their limited ability to sweat (Renaudeau & Dourmad, 2022).
- **Productivity and Performance:** The primary response of pigs to heat stress is a reduction in feed consumption, an adaptive mechanism to lower their metabolic heat production (Renaudeau & Dourmad, 2022). This directly translates to poorer performance. For every 1°C increase above their thermal comfort zone, growing pigs can experience a 2.4% drop in body mass gain, while finishing pigs see a more significant 4.2% reduction (Renaudeau & Dourmad, 2022).
- **Health and Mortality:** Severe heat stress can lead to illness and death (Renaudeau & Dourmad, 2022).

The 2003 European heatwave, for instance, caused thousands of heat-related deaths in pigs (Renaudeau & Dourmad, 2022).The risk is highest for heavy finishing pigs and lactating sows (Renaudeau & Dourmad, 2022). Physiologically, heat stress can reduce blood flow to vital organs, leading to oxidative stress and a "leaky gut" condition, where bacteria enter the bloodstream and trigger a systemic inflammatory response, a key element of heat stroke (Renaudeau & Dourmad, 2022).

- **Indirect Effects:** Disease, Feed, and Nutrition: The consequences of a warming climate extend beyond direct heat exposure, creating secondary challenges that disrupt the stability of pig farming operations.
- **Altered Disease Patterns:** Higher temperatures can create more favorable conditions for the survival and spread of pathogens and disease vectors, increasing the risk of exposure to both existing and emerging diseases (Renaudeau & Dourmad, 2022). Furthermore, heat stress may compromise a pig's immune system, making it more vulnerable to infections (Renaudeau & Dourmad, 2022).
- **Feed Availability and Quality:** Climate change is predicted to reduce global yields of major crops like wheat (by 6.0% per °C increase) and maize (by 7.4% per °C increase) (Renaudeau & Dourmad, 2022). Since feed constitutes 60–70% of production costs, climate-induced yield reductions and price volatility pose a significant economic threat to the pig industry (Renaudeau & Dourmad, 2022).
- **Mycotoxin Contamination:** Changes in climate can increase the risk of contamination in cereal crops by mycotoxigenic fungi. Pigs are highly sensitive to these toxins, which can target the immune system, increasing susceptibility to disease and potentially reducing vaccine effectiveness (Renaudeau & Dourmad, 2022). Contaminated feed can also impair growth, reproduction, and overall productivity in pigs. Regular monitoring of mycotoxin levels and implementing proper storage practices are essential to minimize exposure. Additionally, the use of mycotoxin binders or detoxifying agents in feed can help protect animal health and maintain performance.

1.2 Economic and Food Security Risks: Quantifying the Financial Losses and Threat to the Global Protein Supply Posed by Climate Vulnerability in the Pig Sector

Climate change poses a significant threat to the stability of the global pig production sector, creating cascading economic and food security risks. These challenges jeopardize the profitability of farms and threaten the availability of a crucial source of animal protein for millions worldwide (Pius et al., 2024). The impacts range from direct financial losses due to reduced animal performance to systemic shocks in the global food supply chain.

Quantifying the Financial Losses

The economic viability of pig farming is directly undermined by climate-related stressors, which increase costs while reducing output.

- **Reduced Productivity and Profitability:** Heat stress is a primary driver of financial loss. For every 1°C increase above their thermal comfort zone, growing pigs can experience a 2.4% drop in body mass gain, while finishing pigs see a more significant 4.2% reduction (Hörtenhuber et al., 2020). This retarded growth has direct economic consequences for producers (Renaudeau & Dourmad, 2022). The financial strain is compounded by a worsening feed conversion ratio, meaning more feed is required per kilogram of weight gain, further eroding profit margins (Hörtenhuber et al., 2020).
- **Feed Price Volatility:** Feed constitutes 60-70% of total production costs, making the industry highly sensitive to fluctuations in the grain market (Renaudeau & Dourmad, 2022). Climate change is predicted to reduce global yields of key crops like wheat (by 6.0% per °C increase) and maize (by 7.4% per °C increase) (Renaudeau & Dourmad, 2022). This reduction in supply, coupled with increased competition for land and resources, is expected to drive significant price increases. One simulation suggests that world crop prices could double, and price volatility could increase fivefold, by 2080, creating a major threat to farm profitability (Renaudeau & Dourmad, 2022).

- **Extreme Weather and Labor Impacts:** The increasing frequency of extreme weather events inflicts direct damage on farm infrastructure, leading to substantial economic losses. In 2022 alone, weather-related events in Latin America caused an estimated US$15.6 billion in losses, 93% of which were uninsured (Hartinger et al., 2024). Furthermore, heat stress reduces labor capacity in the agricultural sector, leading to significant potential income losses, which in some Latin American nations amounted to nearly 7% of GDP in 2022 (Hartinger et al., 2024)

Assessing the Threat to Global Protein Supply

As a major contributor to the global diet, the vulnerability of the pig sector represents a direct threat to food security (Adesehinwa et al., 2024; Renaudeau & Dourmad, 2022).

- **Reduced Pork Availability:** The cumulative effects of heat stress, disease, and feed disruptions lead to a tangible reduction in the global pork supply. Lower growth rates, decreased reproductive efficiency, and higher mortality rates mean less pork is available for a growing global population.
- **Increased Food Insecurity:** Reduced supply and higher production costs inevitably lead to higher prices for consumers. This can exacerbate food insecurity, particularly for low-income households. The impact of climate events on food security is already evident; in 2021, heatwaves and droughts were associated with an additional 9.9 million people experiencing moderate to severe food insecurity in Latin America (Hartinger et al., 2024).
- **Compounding Health and Disease Risks:** Climate change alters the landscape for infectious diseases, potentially increasing the spread of pathogens that constrain pig production (Renaudeau & Dourmad, 2022). Additionally, changing weather patterns can increase the risk of mycotoxin contamination in cereal crops, to which pigs are highly sensitive. These toxins can compromise animal health and further reduce the efficiency and output of the pork supply chain (Renaudeau & Dourmad, 2022).

1.3 Climate Resilience in Pig Systems: Establishing the Key Metrics and Goals for a Climate-Resilient Pig Farm

The modern pig farm sits at a challenging crossroads. As a cornerstone of global food production, it supports the livelihoods of billions, yet it is both a contributor to and a victim of climate change. The sector accounts for a significant portion of livestock-related greenhouse gas emissions while simultaneously facing threats from the very changes it helps to accelerate. More frequent heatwaves, unpredictable rainfall, and disruptions to feed supply chains are no longer distant threats but present-day realities that jeopardize animal welfare, productivity, and economic stability.

In this new reality, the conversation must shift from a narrow focus on mitigation—simply reducing emissions—to a more holistic and dynamic concept: resilience. True climate resilience is not merely about building stronger walls or weathering the next storm. It is a farm's capacity to navigate a complex cycle of environmental, economic, and social challenges (Pfeifer et al., 2022). This involves a combination of three core capacities:

- **Robustness:** The ability to withstand shocks and stresses without needing to fundamentally change operations. This is the farm’s first line of defence (Pfeifer et al., 2022).
- **Adaptability:** The capacity to make incremental adjustments in management or operations in response to changing conditions, while the farm's core structure remains intact (Pfeifer et al., 2022).
- **Transformability:** The ability to make significant, structural changes to the farming system when "business as usual" is no longer viable. This is the capacity for profound reinvention (Pfeifer et al., 2022).

A truly resilient pig system is one that can absorb a shock, adapt its practices, and, if necessary, transform itself to thrive in a new reality.

Establishing Key Metrics and Goals for a Climate-Resilient Pig Farm

To build this multifaceted resilience, farmers need clear, actionable goals and metrics that move beyond mitigation to fully embrace adaptation. These can be organized around several key pillars of the farm system.

Infrastructure and Environmental Management

The physical environment of the pigs is a critical control point for managing climate stress. The goal is to create a stable microclimate that buffers animals from external volatility. The key metrics involved infrastructure and environment management, include:

- Indoor temperature and humidity stability during extreme weather events.
- Percentage of water recycled or harvested on-farm.
- Energy independence, measured by the share of power generated from on-site renewables or secured by an emergency generator (Hörtenhuber et al., 2020).

The goals and strategies, includes:

- Enhance Robustness: Invest in high-quality thermal insulation for all housing, coupled with mechanical ventilation systems. Implement cooling technologies like pig showers or misters for heat abatement (Hörtenhuber et al., 2020; Mbachu, 2024).
- Boost Adaptability: Develop integrated water management plans that include rainwater harvesting and efficient watering systems to conserve resources during droughts (Hörtenhuber et al., 2020; Mbachu, 2024).

Feed and Nutrient Circularity

Feed represents a major vulnerability, as its cost and availability are directly tied to climate-impacted crop yields. The goal is to create a secure and flexible feed supply chain while minimizing waste. Key Metrics involved in feed and nutrition circularity:

- Percentage of feed grown on-farm or sourced locally.
- Nutrient-use efficiency (e.g., nitrogen and phosphorus cycles).
- Reliance on external feed markets versus diversified sources (Hörtenhuber et al., 2020).

Goals and Strategies in feed and nutrition circularity:

- Promote Circularity: Reconnect crop and livestock systems by using manure as fertilizer for on-farm feed production. This closes nutrient loops, reduces costs, and enhances resource efficiency (Pfeifer et al., 2022).

- Build Adaptive Capacity: Cultivate climate-adapted feed crops and maintain access to supra-regional markets to balance on-farm production with external supply, ensuring stability against local droughts or floods (Hörtenhuber et al., 2020).

Genetic and Animal-Level Resilience

The pigs themselves are central to the resilience equation. Decades of breeding for high productivity have often come at the cost of environmental hardiness (Pius et al., 2024). The goal is to balance productivity with innate adaptability.The key metrics involved in genetic and animal-level resilience:

- Use of local or cross-bred pigs with documented heat tolerance and disease resistance.
- Mortality and morbidity rates during periods of heat stress.
- Performance data (e.g., growth rate, fertility) of different breeds under local climate conditions.

The goals and strategies in genetic and animal-level resilience, include:

- Leverage Genetic Diversity: Incorporate genetic material from indigenous breeds known for their adaptation to challenging environments, such as high temperatures and low-quality feed (Pius et al., 2024). This can impart crucial resilience traits into commercial herds.
- Diversify the Herd: Consider keeping multiple breeds or species to spread risk and capitalize on the unique strengths of each (Pfeifer et al., 2022).

Economic and Social Resilience

A farm's resilience is ultimately tied to the people who run it and the economic systems they operate within. Financial and social buffers are just as important as physical ones. The key metrics involved in economic and social resilience, include

- Diversity of farm income streams (e.g., pig production, cash crops, tourism, on-farm processing) (Pfeifer et al., 2022).
- Level of financial reserves or access to insurance and credit (Pfeifer et al., 2022).

- Strength of social capital, measured by participation in farmer networks, access to extension services, and community support.

The goals and strategies involved in the economic and social resilience:

- Build Financial Buffers: Diversify farm enterprises to create multiple revenue streams that are not all equally vulnerable to the same shocks (Pfeifer et al., 2022). Maintain financial savings and explore insurance options to serve as a critical reserve during crises (Pfeifer et al., 2022).
- Invest in Human Capital: Foster a culture of continuous learning and adaptation. Success depends on the availability of knowledge, skills, supportive government policies, and social acceptance of new practices (Mbachu, 2024).

Ultimately, building a climate-resilient pig system is a dynamic process, not a final destination. The nature of climate hazards will continue to evolve, and so too must our definition of resilience (Brooks, 2022). By establishing clear goals and consistently measuring progress across these interconnected pillars, pig producers can move beyond simply surviving climate change to building adaptive, circular, and truly sustainable systems for the future.

2. TECHNOLOGICAL INNOVATIONS IN HOUSING AND ENVIRONMENT MANAGEMENT

The modern livestock farm exists at a complex intersection of global food demand, economic pressure, and environmental responsibility. The industrial drive for cost-efficient, specialized production has often increased vulnerability and come at the expense of animal welfare (Pfeifer et al., 2022). In response, a new generation of technological innovation is reshaping the very structures that house our animals. No longer just shelters from the elements, modern barns are becoming dynamic, responsive ecosystems designed to enhance animal well-being, boost productivity, and safeguard the environment (Neethirajan, 2024). This chapter explores the transformative technologies that are redefining what a farm can be. These advancements include the integration of smart sensors, automated monitoring systems, and data-driven management tools that allow farmers to make precise, real-time decisions. By combining animal-centered design with cutting-edge technology, farms are evolving into more sustainable and ethical systems of production.

Smart Housing and Climate Control

The first line of defense in building a resilient farm is controlling the immediate environment of the animals. Buffering livestock from climate volatility—be it scorching summers or harsh winters—is fundamental to their health and productivity (Hörtenhuber et al., 2020; Neethirajan, 2024).

The foundation of a climate-resilient barn is robust physical infrastructure. Well-insulated housing combined with mechanical ventilation is a critical starting point for both pig and dairy operations (Hörtenhuber et al., 2020; Neethirajan, 2024). In a survey of agricultural personnel, 90% advised using insulation to improve pig housing against climate challenges, while 100% recommended integrated water management strategies, such as pig showers, to combat heat stress (Hörtenhuber et al., 2020; Mbachu, 2024). These climate-controlled barns, while requiring a high initial investment, have a highly positive impact on animal welfare and are seeing growing adoption (Neethirajan, 2024). The goal is to create a stable microclimate that minimizes stress and allows animals to thrive, regardless of the weather outside.

Precision Livestock Farming

The Rise of the Digital Stockperson: Beyond structural integrity, the most profound transformation is happening through the integration of data. Precision Livestock Farming (PLF) uses smart technologies to monitor individual animals, turning anecdotal observation into a stream of actionable, real-time data (Collins & Smith, 2022). The aim is to provide farmers with tools for continuous, remote monitoring of their animals and the farm environment, empowering them to make better, faster decisions (Collins & Smith, 2022).

The array of PLF tools is extensive and growing. In the pig sector alone, technologies include (Collins & Smith, 2022):

- Camera systems to assess weight, behavior, and activity.
- Thermal cameras and non-contact sensors to monitor body temperature.
- Microphones that listen for coughing or distress vocalizations.
- Flow meters to track water intake, an early indicator of health issues.
- Radio Frequency Identification (RFID) tags for individual tracking.

This constant flow of data allows for meticulous management of everything from feed intake to health, playing a crucial role in minimizing methane and ammonia emissions while improving farm efficiency (Collins & Smith, 2022; Neethirajan, 2024). The digital stockperson never sleeps, offering a level of oversight that was previously unimaginable.

Advanced Manure and Air Quality Management

Waste is one of the greatest environmental challenges in livestock farming, but technology is turning it into a resource. The adoption of indoor manure treatment is a pivotal step, as enclosed systems significantly reduce the emission of methane, ammonia, and other pollutants (Neethirajan, 2024). These systems include solutions like composting, mechanical separation, and anaerobic digestion, which can convert manure into valuable biogas (Neethirajan, 2024).

Automation is also revolutionizing daily operations. Systems like V scrapers and belts automate the removal of manure, which reduces labor costs, improves cleanliness, and lowers emissions (Neethirajan, 2024). Even more targeted innovations are emerging, such as the "CowToilet," which collects urine separately from feces to prevent the chemical reaction that produces ammonia (Neethirajan, 2024).

Air quality within the barn is just as critical. Technologies once common in other industries are now being adapted for agricultural use. Electrostatic precipitators use electrical charges to capture fine dust and particulate matter from the air, creating a healthier environment for both animals and workers (Neethirajan, 2024). Air scrubbers offer another powerful solution for removing airborne contaminants, though they require a high initial investment (Neethirajan, 2024).

The Smart Revolution:From Building Better Barns to Building Resilience

The digitalization of the livestock industry presents a monumental opportunity. By integrating these technologies, farmers can maximize efficiency, reduce waste, prevent disease, and elevate animal welfare (Collins & Smith, 2022).

A smart, connected farm allows producers to tackle the complex challenges of sustainable development with a strong evidence base, turning risk into quantifiable opportunity (Collins & Smith, 2022). This technological revolution is not just about building better barns; it is about creating a more resilient, humane, and sustainable future for agriculture.

2.1 Advanced Ventilation and Cooling Systems: Innovations in Passive and Active Cooling Technologies

In the landscape of modern pig farming, the barn is no longer a simple shelter but a sophisticated, climate-controlled environment. As global temperatures rise, managing the thermal environment has become one of the most critical factors in ensuring animal welfare, productivity, and economic stability (Hörtenhuber et al., 2020). Heat stress compromises growth, reproduction, and health, making advanced ventilation and cooling systems an indispensable component of a climate-resilient farm (Hörtenhuber et al., 2020). This chapter delves into the technological innovations that are transforming how we manage the air our pigs breathe and the climate they live in.

The Foundation: Passive Design and Mechanical Ventilation: The first line of defence against thermal stress is intelligent building design. A well-insulated barn acts as a buffer, moderating the impact of extreme outdoor temperatures. When combined with a properly working mechanical ventilation system, even a significant 4.5°C rise in outdoor temperature may only result in a 1.6°C increase inside the pig house (Hörtenhuber et al., 2020). These systems, which control temperature through variable air volume flows, are the bedrock of climate management in confined housing (Hörtenhuber et al., 2020).

However, during prolonged summer heatwaves, their capacity can be limited (Hörtenhuber et al., 2020). This is where more advanced, active cooling technologies become essential to `prevent performance losses, especially for fattening pigs (Hörtenhuber et al., 2020).

Innovations in Active Cooling: When passive measures are not enough, active cooling technologies provide direct relief. These systems are designed to lower the ambient temperature and give animals a way to manage their own thermal comfort.

One of the most effective and widely recommended strategies is the use of evaporative cooling, such as pig showers (Hörtenhuber et al., 2020). These systems periodically spray a fine mist of water, which cools the air and the animals' skin as it evaporates. This simple yet powerful technology is particularly valuable for farms with sufficient water availability and offers a direct way to mitigate the effects of intense summer heat (Hörtenhuber et al., 2020).

The Rise of Smart, Sensor-Driven Control: The true revolution in environmental management comes from the integration of smart technology. Precision Livestock Farming (PLF) utilizes a network of sensors to monitor the barn environment and the animals in real time, enabling a shift from reactive adjustments to proactive, automated control (Collins & Smith, 2022).

A smart agri-system can integrate data from a wide array of sources (Collins & Smith, 2022):

- In-house environmental monitors track indoor and outdoor temperature, light intensity, and humidity.
- Ventilation monitors automatically adjust air flow based on the production stage and stocking density of the pigs.
- On-farm weather stations provide real-time data on air temperature and rainfall, allowing the system to anticipate changes.

This constant stream of data allows the ventilation system to operate with unparalleled precision, ensuring optimal conditions are maintained with maximum energy efficiency. It’s a move away from one-size-fits-all settings to a dynamic system that responds to the specific needs of the animals and the changing climate (Collins & Smith, 2022).

Beyond Cooling: Advanced Air Quality Management: A truly advanced system manages more than just temperature. Air quality is vital for the respiratory health of both pigs and farm workers. Modern barns are beginning to incorporate technologies to actively clean the air.

- Air Scrubbers: These systems draw contaminated air through filters or chemical solutions to neutralize pollutants like ammonia, dust, and odor-causing compounds before releasing the cleaned air back into the barn or outside (Neethirajan, 2024).

- Electrostatic Precipitators: Traditionally used in poultry and swine facilities, this technology uses electrical charges to capture fine dust and other particulate matter from the air, dramatically improving its quality (Neethirajan, 2024).
- Air Velocity Optimization: Strategic ventilation design can also be used to minimize the agitation and suspension of dust, creating a healthier and more stable atmosphere within the barn (Neethirajan, 2024).

By integrating these technologies, the modern pig barn becomes a finely tuned ecosystem. It is a system that not only protects pigs from the immediate threat of heat stress but also provides a healthier, cleaner, and more productive environment. As climate challenges intensify, these innovations are not just advancements—they are the cornerstones of a sustainable and resilient future for pig production.

2.2 Insulated and Resilient Building Materials

The modern farm building is the first line of defence against a climate in flux. It is no longer enough for a barn to simply provide shelter; it must function as a high-performance buffer, shielding animals from the growing volatility of the outside world. As heatwaves intensify and storms become more frequent, the very materials we use to construct these environments are becoming a cornerstone of agricultural resilience (Pfeifer et al., 2022). The goal is to create a stable, safe, and productive microclimate, and that begins with the building envelope itself.

The Critical Role of Insulation

At the heart of a climate-resilient structure is its ability to resist thermal transfer. For pigs, which are particularly sensitive to heat and cannot sweat to cool themselves, this is a matter of welfare and survival (Pfeifer et al., 2022). Sufficiently insulated housing is a foundational characteristic of any pig farm built to withstand climate change impacts (Hörtenhuber et al., 2020). The value of this strategy is widely recognized; in one survey, 90% of agricultural personnel advised using insulation to improve pig housing against climate challenges (Mbachu, 2024).

Proper insulation, when paired with mechanical ventilation, creates a powerful defense against temperature swings. Even with a significant 4.5°C rise in outdoor temperatures, a well-insulated and ventilated pig house may see an internal increase of only 1.6°C (Hörtenhuber et al., 2020). This ability to moderate the internal climate is crucial for maintaining animal health and productivity year-round, protecting livestock from both summer heat and winter cold (Neethirajan, 2024).

Beyond Insulation: Building for Extreme Events

True resilience, however, extends beyond temperature control. Climate change is also bringing an increase in extreme weather events, such as intense rainfall leading to flooded fields and high winds that can compromise structural integrity (Pfeifer et al., 2022). This reality demands a new generation of building materials that are not only insulative but also durable and robust.

While the sources in my knowledge base emphasize the importance of insulation, they also point toward the need for a holistic approach to infrastructure. This includes:

- Structural Integrity: Buildings must be designed to withstand higher wind loads and heavier rainfall. This involves choices in framing materials, roofing, and foundation design that prioritize durability.
- Water Management: With the increasing risk of "excess rainfall" and "flooded fields," infrastructure must incorporate advanced drainage systems, water-resistant materials at ground level, and site planning that diverts water away from critical areas (Pfeifer et al., 2022).
- Energy Independence: A resilient building is not just a physical structure but a functioning system. Since advanced ventilation and cooling systems rely on electricity, a constant power supply secured by an emergency generator is essential to ensure the system doesn't fail during a power outage caused by a storm (Hörtenhuber et al., 2020). In addition, integrating renewable energy sources such as solar panels or biogas systems can further reduce dependency on external power grids. These solutions not only enhance energy security but also contribute to lowering the farm’s overall carbon footprint.

The Human and Economic Dimension

Investing in advanced, resilient infrastructure is a significant financial commitment. Farmers who pursue an "efficiency-based strategy" by investing heavily in good infrastructure can build robust operations, but this can also create a "lock-in" effect, making it difficult to adapt further until the initial investment is recouped (Pfeifer et al., 2022). This highlights the need for building materials and systems that are not only effective but also economically viable and adaptable for the future.

Ultimately, the materials used to build a farm are a direct investment in its future. By prioritizing novel, low-carbon, and highly insulative materials, farmers can construct environments that not only buffer the immediate stress of a hot day but also stand strong against the unpredictable forces of a changing climate, safeguarding the animals, the people, and the viability of the farm for years to come.

2.3 Precision Livestock Farming (PLF) for Climate Adaptation

Precision Livestock Farming (PLF) for Climate Adaptation

The art of raising livestock has always been a delicate balance of experience, intuition, and hard work. But as the climate changes, bringing more frequent and intense heatwaves, the traditional stockperson's eye is no longer enough (Hörtenhuber et al., 2020). Heat stress is a formidable threat, particularly in pig production, where it can silently erode productivity, compromise welfare, and threaten the economic viability of the farm. In this new era, agriculture is turning to a powerful ally: data. Precision Livestock Farming (PLF) is the digitalization of the farm, a transformative approach that uses smart technology to give farmers a deeper, more immediate understanding of their animals and their environment (Collins & Smith, 2022). Through continuous monitoring and real-time data analysis, farmers can detect early signs of heat stress and take swift, targeted action. This proactive management not only minimizes production losses but also enhances animal welfare by ensuring more stable and comfortable living conditions.

The Digital Stockperson: A New Set of Senses

At its core, PLF is about replacing periodic checks and guesswork with continuous, automated monitoring (Collins & Smith, 2022). It equips the modern farm with a network of digital senses, all connected through the Internet of Things (IoT), to capture a constant stream of information that was previously invisible (Neethirajan, 2024). This technological toolkit includes a wide array of devices specifically designed for the pig sector (Neethirajan, 2024):

- Environmental Sensors: These are the farm's nerve endings, constantly measuring indoor and outdoor temperature, humidity, and light intensity. On-farm weather stations track rainfall and air temperature, allowing the system to anticipate external changes .
- Cameras and Thermal Imaging: Standard cameras monitor pig behavior, activity levels, and even body weight, while thermal cameras can detect subtle changes in an animal's body temperature—a direct and early indicator of heat stress (Neethirajan, 2024).
- Individual Monitoring: Technologies like Radio Frequency Identification (RFID) tags, flow meters on water nipples, and load cells on feeders track the individual health and consumption patterns of each animal, flagging any deviation from the norm (Neethirajan, 2024).

AI and Machine Learning: Transforming Data into Predictive Resilience

This torrent of information would be overwhelming without a brain to process it. This is where Artificial Intelligence (AI) and machine learning come in. These sophisticated algorithms analyze the continuous data streams from every sensor and camera, learning the unique patterns of a healthy, productive herd (Neethirajan, 2024).

By integrating this data, the system can move beyond simple monitoring to predictive management. For example, by combining data from the on-farm weather station with in-barn temperature and humidity sensors, an AI model can forecast an impending heat stress event. Before the pigs even show visible signs of distress, the system can automatically trigger an intervention, such as adjusting ventilation monitors or activating cooling systems (Hörtenhuber et al., 2020).

This proactive capability is revolutionary. Machine learning algorithms can analyze real-time video feeds to detect subtle behavioral changes that might indicate the start of a disease outbreak or welfare issues like tail biting (Neethirajan, 2024). When the system detects these indicators, it can instantly alert the farmer via the IoT, allowing for immediate treatment or management changes that can prevent a small problem from escalating into a crisis (Neethirajan, 2024).

The digitalization of the pig industry represents a monumental shift. It offers the opportunity to maximize efficiency, reduce waste, and elevate animal welfare to new heights (Neethirajan, 2024). By leveraging the power of PLF, farmers are not just reacting to the challenges of climate change; they are anticipating them, building resilient, intelligent, and truly sustainable systems for the future.

CONCLUSION

The modern pig farm stands at a critical juncture. Decades of industrial optimization have delivered cost-efficient pork production but have also created systems with inherent vulnerabilities to shocks (Pfeifer et al., 2022). In an era defined by climate change, the threats of heat stress, extreme weather, and resource scarcity are no longer abstract risks but tangible realities that challenge the very foundation of global food security (Pfeifer et al., 2022). The path forward is not about reinforcing the old model but about reimagining what a farm can be. The future of pig farming is not just efficient; it is resilient.

This journey toward resilience begins with a fundamental shift in mindset—away from a narrow focus on withstanding the next crisis and toward a dynamic capacity to navigate a cycle of change. It is a vision built on three pillars: the robustness to absorb shocks, the adaptability to adjust practices, and the transformability to reinvent the system when necessary (Pfeifer et al., 2022).

Achieving this vision requires a synthesis of the physical, the digital, and the biological. The physical foundation is built with resilient infrastructure—well-insulated housing, advanced ventilation, and active cooling systems like pig showers that create a stable microclimate, buffering animals from external volatility (Hörtenhuber et al., 2020). This is the farm’s first line of defense.

Layered on top is the digital nervous system of Precision Livestock Farming. This network of sensors, cameras, and AI-driven analytics transforms the farm into a responsive, intelligent ecosystem. It allows producers to move from reactive problem-solving to proactive management, anticipating heat stress before it strikes and optimizing resource use with unparalleled accuracy.

At the heart of the system are the animals themselves. Resilience must be bred into the herd. This involves looking beyond maximum productivity to embrace the hardiness of local and cross-bred pigs, whose innate ability to tolerate heat and thrive in challenging environments is a vital genetic resource (Hörtenhuber et al., 2020; Pius et al., 2024).

Yet, technology and genetics alone are not enough. The human element is the ultimate driver of resilience. Farmers demonstrate this through diverse strategies, whether by investing in high-efficiency infrastructure, diversifying their enterprises to spread risk, or creating circular nutrient systems . However, the path is fraught with challenges, from financial constraints and knowledge gaps to a simple resistance to change (Mbachu, 2024).

Overcoming these barriers requires a collective effort. True transformation is not achieved in isolation but through a web of collaboration that connects farmers, researchers, policymakers, and industry stakeholders (Mbachu, 2024). It demands supportive policies that incentivize innovation, robust extension services that transfer knowledge, and a shared commitment to a sustainable future (Neethirajan, 2024). Ultimately, the resilience of a farm is a reflection of the farmer's attitude—their innovative spirit, their belief in new principles, and their connection to a supportive community (Pfeifer et al., 2022).

The resilient pig farm of the future is a testament to integration. It is a place where smart technology enhances animal welfare, where genetic diversity strengthens the herd, and where human ingenuity, supported by a collaborative community, turns the challenges of a changing climate into opportunities for a more sustainable and enduring system of food production.

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