



Technology Investment in Smart and Sustainable Agriculture towards Food Security

Dr. Nirmala Devi

Institute of Pharmacy, Bundelkhand University, Jhansi, 284128

*Corresponding Author

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Abstract— *Internet of Things (IoT) has emerged as a transformative force across multiple sectors of the agriculture industry, enhancing both quality and quantity of agricultural yield. Artificial intelligence, integrated with IoT, encompasses soil preparation, cultivation, harvesting, and research-related activities, leading to sustainable productivity improvements. Agriculture automation has enhanced precision in farming operations including irrigation control, pesticide/weedicide/fertilizer management, crop growth monitoring, and environmental control in greenhouse and hydroponics systems. This chapter reviews IoT applications in crop farming, animal farming, farm monitoring and tracking, disease detection in plants and livestock, classification processes of agricultural foods, quality assessment of vegetables and fruits, and rearing activities. Climate-smart agriculture is examined and compared with traditional forms (Agriculture 1.0) regarding efficiency and waste reduction. The chapter discusses benefits, limitations, future directions, and potential development of intelligent farming technologies and IoT (AI-enhanced tools) to make farming more accessible, convenient, and precise, with reference to different countries and their agricultural advancements. Finally, the chapter acknowledges technological limitations and other factors affecting the growth of healthy farming systems. This chapter contributes to understanding AI-enabled IoT in transforming contemporary agriculture through data-driven insights and automation capabilities.*

Keywords— *Climate-smart farming, Artificial intelligence, Internet of Things, Automation, Sustainability, Food security, Carbon sequestration, Satellite imagery, Sensors.*

I. INTRODUCTION

Zero hunger and good health and well-being are Sustainable Development Goals (SDGs) that can be secured through continuous food production and accessibility. Agriculture is the primary and oldest industry in the world. In India, 18% of gross domestic product comes from agriculture, of which approximately 57% originates from rural areas (Reddy and Dutta, 2018). Advancement in agricultural technology with socio-ecological sustainability is depicted across distinct eras: Agriculture 1.0 (pre-industrial era; 1784-1870), Agriculture 2.0 (era of industrial revolution; use of mechanized tools; 1950-1992), Agriculture 3.0 (automation; 1992-2017), Agriculture 4.0 (smart farming; current decade), and Agriculture 5.0 (era of Internet of Things) (Holzinger et al., 2024; Thilakarathne et al., 2025).

The advent of Internet of Things (IoT) based technologies has transformed every industry including agriculture, automating control and monitoring of most aspects of traditional farming. Climate change and greenhouse gas (GHG) emissions are significant challenges in agriculture. Climate-smart agriculture offers a way to address both challenges simultaneously, ensuring adequate food production while protecting the environment. In essence, climate-smart farming aims to make agriculture more sustainable and successfully adaptable to changing climate and other stressors. Public and private authorities are increasingly investing in AI-based initiatives to incentivize traditional agriculture practices through smart technologies and tools.

Climate-smart farming (Agriculture 5.0) enables out-of-season and out-of-region crop yield improvement through greenhouse farming, hydroponics, and livestock yield monitoring and tracking practices (Rubio and Más, 2020). Real-time cloud-enabled smart data sensors (IoT) provide systematic solutions for precision agriculture in food-insecure areas threatened by floods, low rainfall, disease, and pests, which reduce agricultural yield qualitatively and quantitatively (Thilakarathne et al., 2025; Dhanaraju et al., 2022) (Fig. 1).

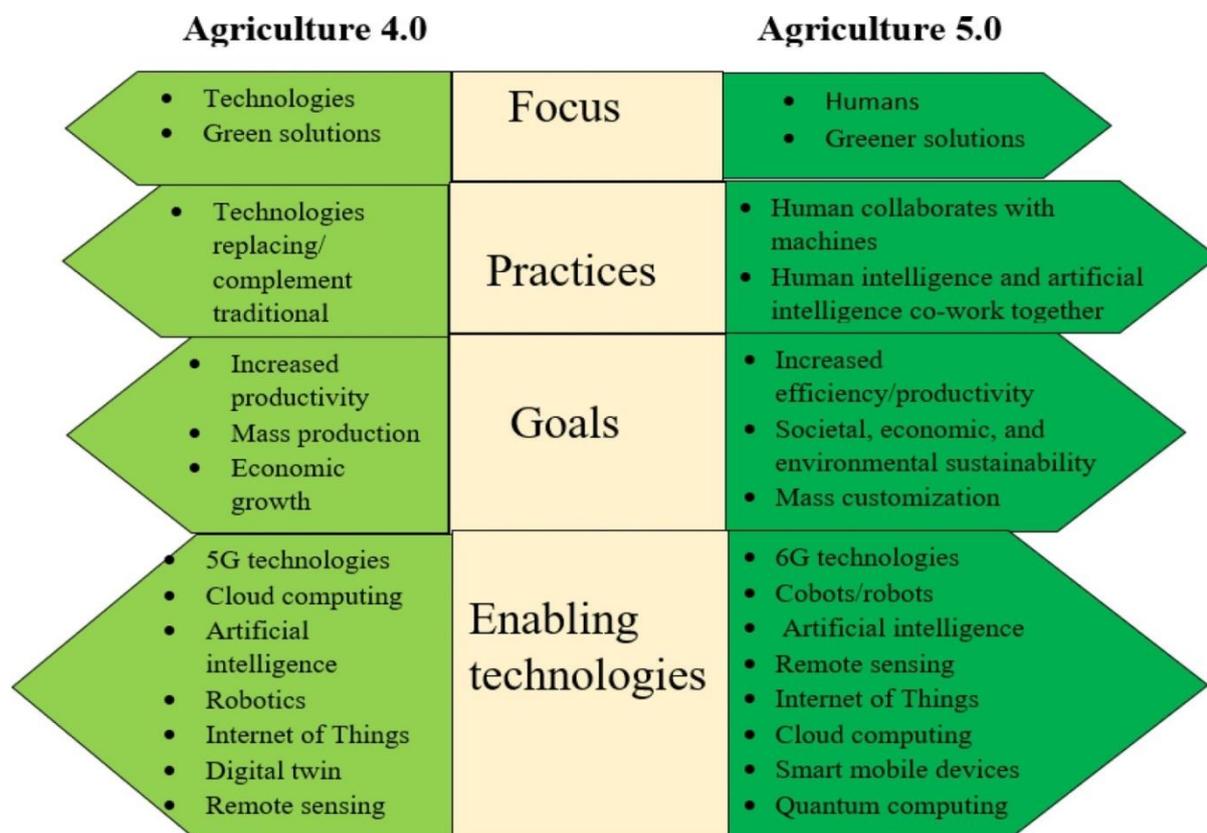


FIGURE 1: Comparison of Latest Advancements in Technologies Agriculture 4.0 vs Agriculture 5.0 (IoT)

IoT technologies can automate tasks and reallocate resources in optimized ways to enhance efficiency and productivity. Precision farming techniques help reduce waste by ensuring optimized resource allocation (Khang et al., 2024). Real-time digital technologies like mobile robotics have enabled better resource management including energy, labor, irrigation, fertilizers, and weedicides/pesticides, while avoiding resource wastage (Alwi and Manocha, 2024). Access to information and technology empowers farmers to integrate technology in open fields as well as kitchen farming, thereby improving their livelihoods. Climate-smart farming has already been adopted in several countries. EU-funded initiatives like the IoF2020 (Internet of Food and Farm 2020) project have demonstrated the potential of IoT in agriculture and developed innovative solutions (Rizan and Siva, 2024; Balasundram et al., 2024; Ragazou et al., 2022).

Companies like CropX specialize in using soil sensors and cloud-based analytics to provide farmers with actionable insights. Israel has a thriving agtech startup scene, with companies like Prospera developing AI-powered platforms that analyze data from IoT devices to optimize crop management. Farm management software that uses IoT to track machinery and worker activity is also a significant part of technological advancement to maximize efficiency and sustainability. AI applications in climate-smart farming utilize machine learning, deep learning, and data analytics to analyze vast amounts of ecological data obtained from satellites, drones, and ground sensors. Precision agriculture techniques such as geostatistics, Global Positioning System (GPS), geographical information system (GIS) remote sensing, and yield monitors have expanded the scope for monitoring and mapping crop phenology parameters and yield (Shanwad et al., 2002).

The use of intelligent air-ground UAVs/UGVs (unmanned aerial/ground vehicles) or drones allows for real-time mapping of biomass and yield, eradication of pests and weeds, and irrigation scheduling of farms. Materially engineered map-based artificial pollinators and pesticide and weedicide sprayers come with controlled spray nozzles (Raparelli and Bajocco, 2019). AI-driven UAV remote sensing, high-resolution visible, multispectral and thermal image cameras, and robotics can assess

crop health and identify changes over time with higher accuracy than traditional remote sensing methods (Barasa et al., 2021; Miller et al., 2021; Tyagi and Tiwari, 2025).

However, smart/digital farming is often linked to technologies like genetic engineering, biotechnology, and artificial fertilizers, which carry potential for high cost, high skill requirements, and uncertainties due to delayed benefits. For example, developing early warning systems for extreme weather (drought, flood, hail) and for pest and disease occurrence presents challenges to potentially climate-smart farming (Mizik, 2021).

Internet of Things devices (sensors or actuators) are digital technologies that can be remotely controlled and connected to each other via the Internet. Monitoring, tracking, controlling, and prediction become more automated, lessening human interventions, costs, power consumption, and water and other resource consumption. Other significant contributions of AI-based IoT include image recognition and bioacoustics analysis, which facilitate species identification and resource distribution, behavior, and movement detection in farms (Brown et al., 2023; Thompson and Lee, 2022). AI models and IoT also help in mapping vegetation fraction, alien-invasive species distribution in fields, and water/nutrient stress monitoring, aiding in the development of proactive conservation measures for stress-resistant crop species (Anderson et al., 2020; Carter and Nguyen, 2023; Madushanki, 2019).

Robotic technology plays an increasingly important role in thinking, perception, decision-making, and multitasking capabilities, enabling farmers to undertake repetitive, tedious, and dangerous agricultural tasks (Adamides, 2020; Elijah et al., 2018). Technological advancement 5.0 (Internet of Things) integrates farming with industry in a symbiotic way, holding immense potential to enhance quality and quantity of agri-food such as plant and animal products (edible or non-edible), including meat, eggs, milk, honey, silk, wool, leather, and other products, in a sustainable manner (Wolfert and Isakhanyan, 2022; Williams et al., 2024) (Fig. 2).

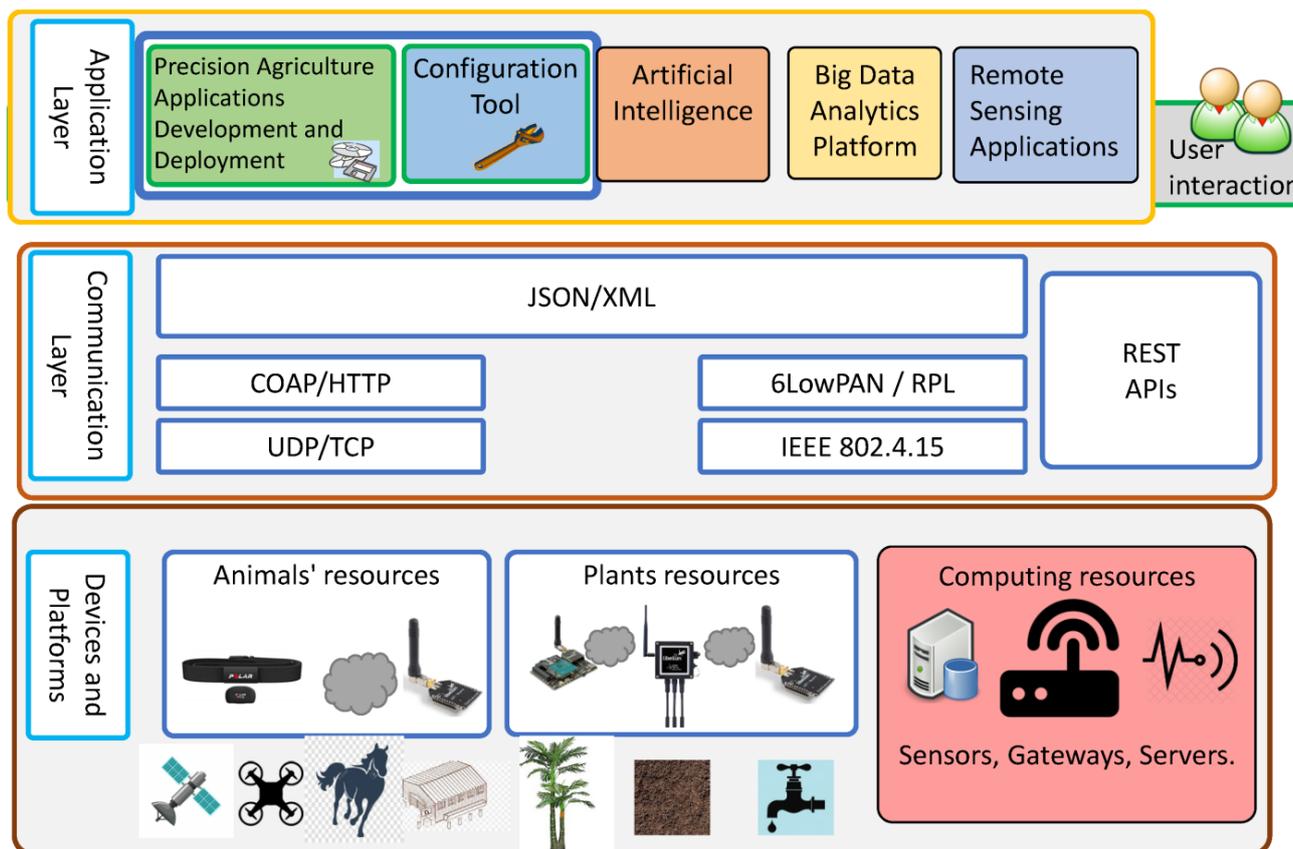


FIGURE 2: Representation of Three Main Layers of Developing Internet of Things (IoT) and IoT-Enabled Strategies and Methodologies Currently Employed in Precision Agriculture

This chapter aims to explore and analyze applications of Internet of Things in farming, discuss challenges associated with its implementation, and propose future directions for integrating AI with emerging technologies. Throughout the chapter,

emphasis is placed on how AI can contribute to sustainable farming management and inform policymakers, researchers, and farmers about the opportunities and limitations of AI-driven approaches.

II. AI TECHNOLOGIES IN FARMING MANAGEMENT

Artificial intelligence (AI)-driven technologies have dramatically transformed real-time management of crop production, soil improvement, pest/weed control, and environmental management (Eli-Chukwu, 2019). Remote sensing, satellite imagery, and unmanned aerial vehicles (UAVs) equipped with AI algorithms represent some of these advancements (Kurz et al., 2022). By analyzing factors such as temperature, humidity, and wind speed, AI provides early warning systems that help mitigate risks. Furthermore, deep learning AI models play a role in monitoring farm health by detecting diseases and pest infestations. For example, convolutional neural networks (CNNs) have been used to detect beetle infestations (Kumar et al., 2022; Sharma, 2021).

Another emerging application is the use of AI for carbon sequestration modeling and climate change adaptation. AI-enhanced models analyze biomass and carbon fluxes from farms, providing accurate estimates of carbon storage potential. Such insights contribute to climate change mitigation strategies (Tang et al., 2022). The integration of AI with geographic information systems (GIS) and Internet of Things (IoT) sensors enables soil moisture detection, automated irrigation, weeding techniques, spraying pesticides and herbicides using drones, and harvesting and yield mapping (Talaviya et al., 2020). Such predictive capabilities are essential for reducing economic losses. For instance, deep learning models process multispectral and hyperspectral data from remote sensing cameras designed for crop monitoring (Kattenborn et al., 2021).

2.1 Machine Learning and Predictive Analytics in Farming:

Machine learning (ML) and predictive analytics have applications in crop, water, and soil management, along with appropriate management of feeding, reproduction, health, milking, and other resources. Integrating varied and multi-component data related to different parameters such as climate, topography, and soil properties with agricultural land use and crop patterns improves decision-making (GmbH, 2021). Furthermore, integrating advanced technologies like the Internet of Things, remote sensing, and ML algorithms such as decision trees, support vector machines (SVMs), multilayer perceptron (MLP) neural networks, random forests, and extreme gradient boosting (XGBoost) to classify images captured by unmanned aerial vehicles (UAVs) has transformed the agriculture sector (Botero-Valencia et al., 2025).

Recent applications of ML, deep learning (DL), and predictive analytics include:

- **Yield and fertilizer prediction** based on machine learning algorithms, advancing precision agriculture with improved productivity using data mining techniques
- **Deep learning for image-based weed detection**
- **Intelligent crop selection method** based on various environmental factors using machine learning
- **Predicting the effects of climate change on crop yields**
- **Renewable energy predictions** using artificial neural networks (ANN) with stochastic optimization for renewable energy systems
- **Image-based deep neural networks in plant disease detection** using machine learning and remote sensing, for example, recognition of plant diseases by leaf image
- **Phenotypic classification**

2.2 Remote Sensing and AI-Based Image Analysis:

AI-powered multi-temporal Unmanned Aerial System (UAS) data enables crop height monitoring, weed mapping with digital images and automatic spraying decisions, high-throughput phenotyping of crops to accelerate crop breeding, monitoring of disease in the field, estimation of site-specific vegetation monitoring and management using RGB and multispectral images from UAV, and high-resolution UAV-based thermal imaging to estimate instantaneous and seasonal variability of plant water status and yield mapping (Gupta, 2025; Jinha et al., 2021).

Integration of high-resolution remotely sensed data and machine learning techniques enables spatial prediction of soil properties on different terrains and prediction of carbon, nitrogen, and ultimately yield. Precision techniques enhance nutritive value of crops, addressing both qualitative and quantitative parameters. Additional applications include automatic

detection of insect pests, multi-modal sliding window-based support vector regression for predicting biotic and abiotic stress in plants, and automatic fruit defect identification.

2.3 Internet of Things (IoT) and AI Integration:

The future of digital technologies in sustainable farming management systems requires high-level policy frameworks integrating the supply chain with internet platforms for safe and healthy food from farm to fork. Precision agriculture techniques such as remote sensing and GPS optimize resource allocation and improve productivity by collecting data on soil conditions, temperature, nutrient levels, weather patterns, and crop health. This leads to reduced water for irrigation and minimized pesticide and fertilizer usage, reducing environmental impact and lowering costs. Crop monitoring through drones and satellite imagery combined with IoT sensors can monitor crop health, detecting diseases or pests early and allowing timely interventions to minimize crop damage.

AI models and algorithms have the capability to transform agriculture through instantaneous tracking, controlling, and monitoring of direct agricultural activities (allied) and indirect activities (non-allied) such as storage, warehousing, cold storage, transportation, and marketing. Through integration of IoT sensors, artificial intelligence algorithms analyze various environmental characteristics such as temperature, humidity, and gas concentrations (Pandey and Mishra, 2024). Intelligent drones facilitate exhaustive monitoring of fields and farm land topology. Automated controlled sensor-based spraying UAVs enable precise spraying that enhances productivity, reduces chemical waste, improves crop health, and promotes sustainability. Artificial intelligence, ML algorithms, deep learning models, and microprocessors analyze incoming data (Taseer et al., 2024; Rajak et al., 2023).

Application of artificial intelligence in electrical automation in mechanized agriculture is substantial (Rajak et al., 2023; Stephan et al., 2025). Examples include planting, precise spraying using unmanned aerial spraying systems, automated plant leaf disease detection and classification using optimal MobileNet-based convolutional neural networks, and weed classification based on Haar wavelet transform via k-nearest neighbor (k-NN) for real-time automatic sprayer control systems. A CNN-RNN framework for crop yield prediction enables autonomous sensor networks for rural agriculture environments at low cost with energy self-charging capabilities. Crop classification based on temporal signatures of Sentinel-1 observations represents another application. Recent advances in hyperspectral imaging technology have expanded agricultural applications. IoT devices ensure traceability and quality control of harvested crops from fields through processing throughout the supply chain, minimizing waste and ensuring product safety and quality. Data analysis and machine learning algorithms can predict seed germination rates, estimate seed vigor, identify trends and patterns, and optimize resource management.

2.3.1 Smart Irrigation System:

AI-driven use of crop-water stress maps and IoT-based soil moisture sensors optimizes water requirements throughout the season. These devices are enabled with visible and thermal UAV camera imagery. Such systems prevent overwatering or drought stress, ensuring efficient plant growth (Boutagayout et al., 2025; Singh et al., 2021). Development and assessment of field-programmable gate array (FPGA)-based image processing (FIP) systems are useful for measuring moisture content, humidity, and transpiration rate of plants (Rajak et al., 2023).

2.3.2 Real-Time Farm Monitoring and Environmental Sensing:

Geospatial analysis and Internet of Things in environmental monitoring help prevent crop damage due to extreme weather conditions or water shortages. Adapting and building resilience helps farmers cope with climate change impacts such as droughts, floods, and extreme weather events. Sensors deployed in seed storage and growing environments monitor crucial factors including temperature (vital for preventing seed damage and maintaining viability), humidity (excess moisture can lead to mold and decay), light levels (important for germination and early growth), and air quality (detecting harmful gases or pollutants).

IoT-based environmental sensors deployed in farms collect real-time data on temperature, humidity, soil moisture, air quality, and carbon levels. AI processes this data to detect anomalies such as drought stress, pollution, or illegal activities. Drones and satellite imagery enhance monitoring by providing high-resolution visuals of farm cover changes, wildlife movement, and deforestation patterns. In wildfire prevention, AI-powered sensors detect early signs of fire such as temperature spikes and smoke, triggering immediate alerts for rapid response. Similarly, acoustic sensors identify chainsaw

noises or gunshots, helping prevent illegal logging and poaching. For ecosystem management, real-time data from IoT devices support afforestation efforts by optimizing irrigation and tree planting strategies.

2.3.3 Internet of Things in Crop Yield Maximization:

High-definition 3D cameras and imaging sensors capture detailed images of seeds. Artificial intelligence algorithms analyze these images to assess seed size, shape, and color, detect defects or damage, and identify seed varieties. Specialized sensors can analyze the internal composition of seeds: near-infrared spectroscopy (NIRS) can determine moisture content, protein levels, and other chemical properties; electrical conductivity sensors can assess seed viability. Development of portable grain mass flow sensor test rigs and point-of-care diagnostic devices for pathogen detection has advanced significantly.

Low-altitude remote sensing, battery-free wireless smart sensors with Bluetooth connectivity measure soil mechanical resistance, moisture level, pH (soil acidity or alkalinity indicator), nutrient levels (N-P-K), and track soil temperature which affects seed germination and root development. Chemical constituents can be estimated using high-resolution hyperspectral imagery. Automated tilling by robotic systems can adjust tilling depth based on soil density. Co-location opportunities for large solar infrastructures and agriculture in drylands present new possibilities. IoT multiplatform networking with wireless sensors monitors and controls wineries and vineyards. Greenhouse wireless sensor network monitoring system design based on solar energy has been developed. Battery-free radio frequency identification (RFID) sensors ensure food quality and safety. Chipless RFID tags with integrated sensors, such as fully inkjet-printed chipless RFID gas and temperature sensors on paper and humidity passive sensors based on UHF RFID using cork dielectric slabs, represent emerging technologies.

Flexible and shape-morphing plant sensors designed for microenvironment temperature monitoring of irregular surfaces have been developed. Stretchable-polymer-electronics-based autonomous remote strain sensors (SPEARs) enable continuous, precise, autonomous plant growth monitoring of delicate grass leaves throughout the tracking period (Wang et al., 2024).

2.3.4 AI in Fruiting Stage Detection and Harvesting:

Sound absorption for ripeness and unripe classification of fruits optimizes harvest timing, providing farmers with real-time information on crop maturity levels and factors like moisture content, sugar levels, and ripeness (Rajak et al., 2023). This allows farmers to determine optimal harvest time, ensuring maximum yield and quality. IoT-enabled robots and autonomous vehicles can be programmed to perform harvesting tasks with precision and efficiency. These systems can navigate fields, identify ripe crops, and harvest them automatically, reducing labor costs and minimizing crop damage. Sensors mounted on harvesting equipment create yield maps, providing valuable insights into crop performance and helping farmers optimize future planting and harvesting strategies.

2.3.5 AI-Based IoT in Pest and Disease Monitoring:

Toxicological evaluation of insecticides, pesticides, or weedicides requires careful consideration. Agricultural pesticides are both beneficial and harmful to the biosphere. Agricultural pest and disease monitoring based on Internet of Things and unmanned aerial vehicles has advanced significantly. Automated applications of acoustic wireless sensors enable stored product insect detection, pest monitoring, and control. Deep learning and computer vision are transforming entomology. Automatic traps for moth detection in integrated pest management, remote monitoring of European Grapevine Moth (*Lobesia botrana*) populations using camera-based pheromone traps in vineyards, electronic traps for detection and population monitoring of adult fruit flies, and web-based automatic traps for early detection of alien wood-boring beetles have been developed. Artificial neural network-based pest identification and control in smart agriculture using wireless sensor networks, electronic pest repellents, and smart plant-wearable biosensors for in-situ pesticide analysis represent ongoing innovations.

2.3.6 Smart Drones for Farm Surveillance:

Agriculture is labor- and cost-intensive with long waiting periods for returns. Agricultural security challenged by human and animal intrusion is therefore a priority. Cloud computing and machine/deep learning-based smart farm surveillance systems (SFSS) reduce reliance on manual field inspections, saving time and resources. PIR sensors, ultrasonic detectors, and deep learning models enable animal detection with real-time monitoring, data acquisition, and precise analysis for conservation and security. UAVs/UGVs surveillance drones equipped with high-resolution cameras, thermal sensors, and LiDAR technology capture detailed images and maps. Alarm systems, motors, SMS alerts, high-resolution images/videos, and 3D topographical data represent latest advancements for detecting illegal activities, wildlife tracking, assessing farm health, and responding to environmental threats (Delwar et al., 2025). Thermal imaging assists in locating wildfires even in dense

vegetation, enabling rapid response and mitigation efforts. For wildlife monitoring, drones track animal movement, population trends, and migration patterns without disturbing ecosystems.

2.3.7 Carbon Sequestration and Climate Adaptation:

Farming tactics to reduce carbon footprint in semi-arid areas include agroforestry, which integrates trees and shrubs into agricultural systems to improve soil health, sequester carbon, and provide additional income sources. Carbon farming helps soil capture and hold more carbon by reducing greenhouse gas emissions wherever possible. Conservation agriculture minimizes soil disturbance (no-till farming), maintains permanent soil cover (using crop residues or cover crops), and practices crop rotations.

The effects of crystal structure on photovoltaic performance of perovskite solar cells under ambient indoor illumination in greenhouse farming have been studied. Model-based evaluation of greenhouse microclimate using IoT-sensor data fusion enables energy-efficient crop production. Cloud-based IoT platforms enable precision control of soilless greenhouse cultivation. IoT sensors track carbon fluxes, plant growth rates, and soil health to assess carbon sequestration potential. AI models analyze these data points to estimate carbon storage capacities, predict climate change impacts, and optimize planting strategies (Tang et al., 2022). These insights contribute to global climate mitigation efforts and carbon credit programs.

Carbon sequestration and climate adaptation technologies like robotics, satellite imagery, digital twins, and drones equipped with Light Detection and Ranging (LiDAR) technology provide high-resolution mapping of forest biomass, helping estimate carbon stocks accurately. Carbon capture and storage (CCS) through AI-driven models simulate future climate scenarios, aiding policymakers in developing adaptive strategies such as afforestation, reforestation, and sustainable land-use practices.

Direct and indirect agricultural practices have their own carbon footprints in the form of carbon dioxide (CO₂) emission through organic matter decomposition, crop residue burning, fossil fuel burning in equipment or machinery usage; methane (CH₄) from anaerobic conditions in soil, manure and crop residue decay, enteric fermentation, and rice paddies; and nitrous oxide (N₂O) from nitrification fertilizers. Non-dispersive infrared (NDIR), electrochemical, and photoacoustic gas analyzers can detect atmospheric carbon dioxide and methane in soil, vegetation (biomass), and other organic matter. GPS-guided sensors and actuators along with drones map normalized difference vegetation index for crop health monitoring. Smart irrigation systems controlled by IoT sensors optimize water use to enhance yield in drought-prone regions (Ahmed and Shakoor, 2025). Additionally, AI-powered early warning systems help prevent degradation by detecting stress factors like pests, diseases, and extreme weather events. Object detection for agricultural and construction environments using ultrasonic sensors has been developed.

III. FIELD TRACKING AND LIVESTOCK MONITORING

IoT devices (wearable sensors) can track animal health, location, and behavior, allowing farmers to monitor their animals remotely. This helps improve animal welfare through better feed and manure management, enhance productivity, enable early detection and prevention of disease outbreaks, and reduce methane emissions. AI processes this data to track migration patterns, species interactions, and habitat preferences (Ivan et al., 2024; Heinzl and Koch, 2022).

IoT, AI, remote sensing, and GPS technologies monitor animal populations, protect endangered species, and maintain ecological balance. These advanced systems provide real-time insights into wildlife behavior, migration patterns, and habitat changes, enabling data-driven conservation strategies. IoT-enabled GPS collars, bio-loggers, and RFID tags track animal movements, feeding habits, and health conditions. AI processes this data to detect anomalies such as habitat loss or changes in migration routes due to climate change. Camera traps and acoustic sensors powered by AI identify species through image recognition and vocalization analysis, aiding biodiversity assessments. Drones and satellite imaging help monitor large-scale habitat changes, deforestation, and human encroachments. Predictive models use historical data and AI algorithms to forecast threats like poaching, human-wildlife conflicts, and disease outbreaks.

Despite technological advancements, challenges such as connectivity issues, high costs, and ethical concerns regarding animal tagging persist. However, with continued innovation, enhanced site-specific planting strategies through analyzing soil composition, climate patterns, and topography are possible. Machine learning models process these variables to determine optimal tree species for a given location, improving forest resilience and productivity (Singh et al., 2021). In reforestation projects, AI-powered drones assist in seed dispersal, ensuring efficient and precise planting.

Another major AI-driven advancement is automated thinning and harvesting. AI-equipped robotic systems use LiDAR and deep learning algorithms to assess tree maturity, density, and health, guiding selective harvesting while minimizing

environmental impact (Zhang et al., 2023). AI-based predictive modeling further aids in climate adaptation and fire risk management. By analyzing historical climate data, soil moisture levels, and wind patterns, AI forecasts drought stress and wildfire susceptibility, allowing proactive management strategies (Tang et al., 2022; Laktionov et al., 2024). Development of AI-driven robotic systems represents another promising avenue.

IV. POLICY INITIATIVES IN INDIA

The Indian government has recognized the importance of the Internet of Things (IoT) and has launched several initiatives to promote its adoption across various sectors to create a digitally empowered society and knowledge economy (Kurz et al., 2022). The Ministry of Electronics and Information Technology (MeitY), in collaboration with NASSCOM and state governments, has established Centers of Excellence (CoEs) for IoT in locations including Bengaluru, Gurugram, Gandhinagar, and Visakhapatnam. These centers focus on fostering innovation, supporting startups, and developing IoT solutions for various applications.

- **National Digital Communications Policy 2018:** This policy emphasizes enhancing internet and digital engagement through IoT, aiming to create robust digital communications infrastructure.
- **IoT Applications in Agriculture:** The government promotes IoT use in agriculture through programs like the National e-Governance Plan in Agriculture (NeGPA). This includes funding for digital agriculture projects utilizing IoT, AI, and other emerging technologies (Ahirwar et al., 2023; Bamhdi, 2024).
- **Smart Cities Mission:** This mission leverages IoT technologies to improve urban infrastructure and services, including smart parking, intelligent transportation systems, and waste management.
- **Future Skills PRIME:** MeitY has approved funding to create an ecosystem for reskilling and upskilling in emerging technologies, including IoT.
- **Digital Agriculture Mission of India:** This mission focuses on creating a Digital Public Infrastructure (DPI) for agriculture. It aims to provide farmers with digital identities (Farmer IDs) and facilitate data-driven decision-making. Key components include development of an "Agri Stack" and implementation of a nationwide crop survey.
- **National e-Governance Plan in Agriculture (NeGPA):** This program provides funding to state governments for digital agriculture projects, encouraging use of emerging technologies such as AI, machine learning, IoT, and blockchain.
- **Agricultural Mechanization:** The government promotes agricultural mechanization through modern machinery, including "Kisan Drones," via initiatives like the Sub-Mission on Agricultural Mechanization.
- **Digital General Crop Estimation Survey (DGCES):** This survey provides more precise yield estimations.
- **Krishi Decision Support System:** This system aims to unify remote sensing data on crops, soil, and weather to provide farmers with useful information.

V. CHALLENGES AND LIMITATIONS OF AI IN CLIMATE-SMART FARMING

Despite the transformative potential of artificial intelligence (AI) and smart tools (IoT), several challenges and limitations hinder widespread adoption and effectiveness. These challenges range from technological constraints and data quality issues to ethical and economic concerns.

One primary challenge is availability and quality of data. AI models rely on large datasets including satellite imagery, IoT sensor data, and climate records. However, in many regions, data is incomplete, inconsistent, or outdated, affecting accuracy of AI-driven predictions (Tang et al., 2022). Additionally, integrating multi-source data from different sensors and satellites often requires advanced data fusion techniques, which may introduce errors.

Another major limitation is high cost of AI implementation. Developing and maintaining AI-driven climate-smart agriculture systems, such as deep learning models, IoT networks, and cloud computing platforms, requires substantial financial investment. Many developing countries and local agriculture management agencies struggle with costs of acquiring high-resolution satellite data and AI-powered analytical tools (Zhang et al., 2023).

AI models also face computational and infrastructure limitations. Advanced machine learning algorithms such as deep neural networks require significant computing power, which may not be available in remote rural areas with limited connectivity and energy resources (Hernandez et al., 2021). Lack of 5G networks and real-time processing capabilities further restricts AI's operational efficiency.

Another critical concern involves ethical and policy-related issues. Use of AI often involves automated decision-making that may not always align with local conservation goals or indigenous community rights. AI-driven monitoring systems, for example, may misclassify land use changes, leading to conflicts between authorities and local populations (Singh et al., 2021). Additionally, AI models are prone to bias and uncertainty. If AI algorithms are trained on limited or biased datasets, they may produce inaccurate predictions and misinterpret ecological conditions, leading to ineffective conservation strategies and misallocation of resources (Gaveau et al., 2019).

Diverse allied and non-allied agricultural activities in the current scenario are practiced in hybrid mode. Climate-smart agriculture is essential to achieve Sustainable Development Goals (SDGs). Greenhouse gas emissions (methane and nitrous oxide) from agricultural lands are increasing. Traditional farm management approaches often struggle to efficiently monitor and respond to threats due to resource limitations and complexity of ecological systems, leading to food crises (Smith et al., 2020). Climate-smart farming offers an alternative approach to mitigate these challenges.

However, data quality and availability remain significant concerns, as AI models require large datasets for training and validation (Fernandez et al., 2022). Algorithmic biases can affect precision in AI predictions, necessitating use of diverse and representative datasets (Smith et al., 2020; Kumar et al., 2023). Additionally, high costs of implementing AI-based management solutions can limit accessibility, particularly in subsistence farming where farmers prefer traditional methods (Tyagi and Tiwari, 2025). Access to technology, affordability, and digital literacy need to be addressed. Legitimate authoritative initiatives and investments are crucial for promoting smart farming adoption. Ethical considerations including data privacy and potential misuse of AI-based surveillance technologies must ensure careful and responsible deployment (Boateng and Boateng, 2025; Chakraborty and Joshi, 2021; Ahmed and Taylor, 2023). Other challenges include crop distribution and allocation, global temperature change effects on crop yields, and unpredictable climate/weather patterns.

To address these limitations, researchers are working on improving AI transparency, cost-effective implementation strategies, and hybrid approaches that integrate AI with traditional practices. As AI technology advances, overcoming these challenges will be essential to ensuring ecologically sustainable and responsible farming practices.

VI. FUTURE PROSPECTS AND RECOMMENDATIONS

The future of AI holds immense potential for enhancing sustainability, precision monitoring, and disaster prevention. One key future prospect is integration of AI with real-time satellite and drone-based monitoring. High-resolution imagery from AI-powered satellites and UAVs will provide instantaneous crop health assessments, unannounced threat detection, and livestock monitoring (Tang et al., 2023). Adoption of hyperspectral imaging and LiDAR-based AI models will further improve accuracy of species identification and biomass estimation. AI will also play a crucial role in predictive climate modeling, analyzing historical weather data, carbon sequestration patterns, and biodiversity trends to support long-term conservation strategies (Singh et al., 2022).

To maximize AI's potential in agriculture, several recommendations should be considered:

1. **Improved Data Infrastructure:** Establish global AI-driven agricultural databases to ensure high-quality, real-time data accessibility.
2. **Affordable AI Solutions:** Encourage cost-effective AI technologies for developing nations to enhance agricultural conservation efforts.
3. **Ethical AI Implementation:** Ensure AI models are transparent, unbiased, and aligned with indigenous rights and conservation policies.
4. **Cross-Sector Collaboration:** Strengthen partnerships between governments, AI researchers, and environmental organizations for better resource allocation.
5. **Edge AI and 5G Integration:** Deploy low-power AI models and high-speed networks for real-time analysis in remote rural areas.

6. **Capacity Building:** Invest in training programs for farmers and extension workers to enhance digital literacy and technology adoption.
7. **Public-Private Partnerships:** Foster collaborations between government agencies, private companies, and research institutions to accelerate innovation and technology transfer.
8. **Inclusive Technology Design:** Ensure AI and IoT solutions are designed with smallholder farmers in mind, addressing affordability, usability, and relevance to local contexts.

As AI technology continues to evolve, these advancements will significantly improve farm monitoring, carbon sequestration, and biodiversity conservation, making agriculture more resilient to climate change and other challenges.

VII. CONCLUSION

Internet of Things (IoT) and artificial intelligence are transforming agriculture across the globe, offering unprecedented opportunities for precision farming, resource optimization, and sustainable intensification. From soil preparation to harvest, from crop farming to livestock management, from pest detection to carbon sequestration, smart technologies are reshaping every aspect of agricultural production.

The evolution from Agriculture 1.0 to Agriculture 5.0 represents a paradigm shift in how food is produced. Traditional farming methods, while still prevalent in many regions, are increasingly being complemented or replaced by data-driven, automated systems that enhance efficiency, reduce waste, and improve resilience to climate change. Climate-smart agriculture, enabled by IoT and AI, offers a pathway to address the dual challenges of food security and environmental sustainability.

Key applications reviewed in this chapter demonstrate the breadth and depth of technological integration in modern agriculture. Smart irrigation systems optimize water use, reducing both consumption and costs. Remote sensing and UAVs provide real-time crop health monitoring, enabling early intervention against pests and diseases. IoT-enabled livestock tracking improves animal welfare and productivity. AI-powered predictive analytics help farmers make informed decisions about planting, fertilization, and harvesting. Carbon sequestration monitoring contributes to climate change mitigation efforts.

However, significant challenges remain. Data quality and availability, high implementation costs, infrastructure limitations, ethical concerns, and digital divides between developed and developing regions must be addressed to ensure equitable access to these technologies. Policy initiatives like those in India demonstrate governmental commitment to promoting digital agriculture, but more comprehensive and inclusive approaches are needed.

The future of smart farming lies in continued innovation, cross-sector collaboration, and inclusive technology design. As AI algorithms become more sophisticated, sensors more affordable, and connectivity more widespread, the potential for transforming agriculture will only grow. Realizing this potential requires concerted efforts from policymakers, researchers, technology developers, and farming communities worldwide.

In conclusion, investment in smart and sustainable agricultural technologies is not merely an option but a necessity for achieving global food security in the face of climate change, population growth, and resource constraints. IoT and AI, when deployed thoughtfully and equitably, can help create a more resilient, productive, and sustainable agricultural system for future generations.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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