AGRICULTURAL AUTOMATION, CLIMATE CHANGE-ACTION AND FOOD SECURITY: GLOBAL ISSUES & LOCAL PERSPECTIVES

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AGRICULTURAL AUTOMATION, CLIMATE CHANGE-ACTION AND FOOD SECURITY (GLOBAL ISSUES & LOCAL PERSPECTIVES)

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Preface

This book adopts an exegetical approach as well as a pedagogic model, making it attractive agriculture and environmental economics teachers, professional practitioners and scholars. It is eschews pedantry and lays bars the issues in such clarity that conduces to learning. The book elaborates on contemporaneous Agricultural Automation, Climate Change-Action and Food Security issues of global significance and at the same time, is mindful of local or national perspectives making it appealing both to international and national interests. The book explores the ways in which Agricultural Automation, Climate Change-Action and Food Security issues are and should be presented to increase the public's stock of knowledge, increase awareness about burning issues and empower the scholars and public to engage in the participatory dialogue Agricultural Automation, Climate Change-Action and Food Security necessary in policy making process that will stimulate increase in food production and environmental sustainability. Agricultural Automation, Climate Change-Action and Food Security**:** *Global Issues & Local Perspectives* is organized in three parts. Part One deals with The Concept of Agricultural Automation, Part Two is concerned with The Concept of Climate Change-Action and Part Three deals with the Concept of Food Security

Eteyen Nyong; October 2026

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Chapter Four

Transforming Agriculture with Smart Technologies: Benefits,Challenges and Implementation Pathways

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1. Introduction

1.1 Background to the Study

The global agricultural sector faces structural pressures. By 2050, the population may reach nearly 10 billion, raising global demand for agricultural products by 50 percent over present levels and intensifying pressure on already-strained natural resources (FAO, 2017). Dietary shifts toward meat, fruits, vegetables, and processed foods will further drive deforestation, land degradation, and greenhouse gas emissions (FAO, 2017). Agriculture must therefore produce more food on less land with fewer inputs under a changing climate, requiring a threefold increase in wheat output and more than a twofold rise in meat production by 2050 (FAO, 2013; Wolfert et al., 2017). Smart agriculture—also called precision agriculture, digital agriculture, or smart farming—has emerged as a transformative response. It combines sensors, information systems, enhanced machinery, and informed management to optimize production by accounting for variability within agricultural systems (Gebbers&Adamchuk, 2010). Its core principle is to do the right thing, in the right place, at the right time, and in the right amount (Gebbers&Adamchuk, 2010). Its technological foundation includes the Internet of Things (IoT), artificial intelligence (AI), drones and unmanned aerial vehicles (UAVs), sensors, blockchain, satellite-based monitoring, autonomous machinery, digital farm management platforms, and precision aerial spraying (Government Accountability Office [GAO], 2024). Demonstrated benefits include AI-driven yield increases of 12 to 45 percent and input cost reductions of up to 25 percent (Khanna et al., 2026); UAV water savings of up to 96 percent (Embrapa, n.d.) and fertilizer reductions of up to 40 percent (Plant Archives, 2026); IoT-based irrigation productivity gains of 25 percent (Plant Archives, 2026); satellite monitoring for early warning and food security decision-making (GAO, 2024); and blockchain-enabled traceability from farm to fork (Wolfert et al., 2017). Together, these technologies represent a paradigm shift from experience-based to data-driven agriculture (Wolfert et al., 2017) with economic, environmental, and socioeconomic benefits (GAO, 2024). For developing countries, these benefits are particularly consequential: Nigeria faces projected temperature increases of +3.08 to +4.63 degrees Celsius by 2050, erratic rainfall, and floods (Third National Communication of the Federal Republic of Nigeria, 2020), and its capacity to feed a projected

population of more than 400 million by 2050 hinges on transforming agricultural productivity (Audu&Adegbenjo, 2022). Yet the promise remains largely unrealized: only 27 percent of U.S. farms used precision agriculture practices in 2023 (GAO, 2024), while in Nigeria, where over 85 percent of farmers are smallholders, only about 8 percent of smallholders use AI tools, largely within donor-funded or pilot projects (Audu&Adegbenjo, 2022). Barriers include high upfront costs, data ownership concerns, lack of interoperability standards, limited digital literacy, and inadequate rural infrastructure (GAO, 2024).

2. Systematic Literature Review Methodology

This paper is based on a systematic review of peer-reviewed literature, government reports, and international assessment documents published between 2000 and 2025. The following databases were searched: Web of Science, Scopus, Google Scholar, ScienceDirect, IEEE Xplore, and SpringerLink, supplemented by institutional sources including FAO, USDA, GAO, World Bank, CGIAR, and the World Economic Forum. Search terms included combinations of "smart agriculture," "precision agriculture," "digital agriculture," "smart farming," "Internet of Things," "artificial intelligence," "drones," "UAV," "sensors," "blockchain," "robotics," "satellite monitoring," "digital farm management," "precision aerial spraying," "regenerative agriculture monitoring," "security technologies," "climate-smart agriculture," "Nigeria," and "developing countries." Inclusion criteria were: (1) studies that addressed smart agriculture or precision agriculture in the context of productivity, resource optimization, sustainability, climate resilience, and adoption; (2) articles published in English in peer-reviewed journals or by reputable international organizations (FAO, USDA, GAO, World Bank, CGIAR, WEF); (3) studies presenting empirical data, modeling results, case studies, or systematic reviews. Exclusion criteria included: (1) studies focused solely on non-agricultural applications of the technologies; (2) non-peer-reviewed conference abstracts or opinion pieces without data; (3) articles not available in full text. A total of 150 relevant studies were initially identified, of which 80 are cited in this paper based on their relevance, recency, and contribution to key themes. The synthesis follows a thematic approach, organizing findings into three main areas: (a) key smart agriculture technologies and their functions; (b) benefits, adoption status, and challenges across developed and developing contexts, including Nigeria; and (c) policy options, future development trends, and pathways for

sustainable food systems. Where quantitative data are presented (e.g., R^2, RMSE, water savings, yield increases, adoption percentages), they are reported directly from the original sources. The paper does not present primary data collection or original modeling; rather, it synthesizes existing evidence to provide a state-of-the-art review for researchers, practitioners, and policymakers.

3. Analysis of Key Technologies

3.1 Precision Agriculture: Core Concept

Precision farming, also called Precision Agriculture (PA), Smart Farming, or Digital Agriculture, is an innovative farm management technique that uses information and communication technologies to observe spatial and temporal variability within agricultural land and improve crop production (Gebbers&Adamchuk, 2010). Unlike traditional farming, which applies inputs uniformly, precision farming recognizes variation in soil composition, crop development, nutrients, moisture, and pests. Its core principle is to do "the right thing, in the right place, at the right time, and in the right amount." Key components include GIS, GPS, remote sensing, IoT, and AI (Zhang et al., 2002; Ray, 2017; Liakos et al., 2018).

3.2 Agricultural Drones and Unmanned Aerial Vehicles (UAVs)

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are remotely piloted aircraft systems operated without an onboard pilot that have become integral to modern farm operations (Hunt et al., 2010; Zhang & Kovacs, 2012). When equipped with payloads such as high-resolution RGB cameras, thermal imagers, multispectral and hyperspectral sensors, Global Positioning System (GPS) modules, and precision spray systems, UAVs serve as versatile platforms for acquiring high-resolution spatial and crop-health data (Tsouros et al., 2019; Velusamy et al., 2022).

Their agronomic applications are extensive and include continuous crop growth monitoring, assessment of soil status and variability, detection of nutrient deficiencies, early identification of pests and diseases, mapping of weed infestation patterns, irrigation planning, and analysis of intra-field heterogeneity (Tsouros et al., 2019; Radoglou-Grammatikis et al., 2020). UAV platforms are broadly categorized into fixed-wing, rotary-wing (multirotor), and hybrid Vertical Take-Off and Landing (VTOL) systems, which differ markedly in terms of endurance, area coverage, maneuverability, payload capacity, and launch/recovery requirements (Bacco et al., 2018; Tsouros

et al., 2019). When integrated within a broader digital agriculture ecosystem comprising ground-based IoT field sensors, cloud computing infrastructure, and artificial intelligence (AI)-driven analytics, UAVs facilitate the development of intelligent agricultural systems capable of generating actionable, site-specific recommendations for irrigation scheduling, fertilization, and integrated pest management (Radoglou-Grammatikis et al., 2020; Velusamy et al., 2022).

Figure 1. UAV payloads for precision agriculture: Technical diagram - sensor ensuite& Precision Spray System Agriculture. The multirotor platform integrates GPS Module, High-Resolution RGB Camera, Thermal Imager, Multispectral Sensor, Hyperspectral Sensor, and Precision Spray Tank for synchronized data acquisition (Tsouros et al., 2019).

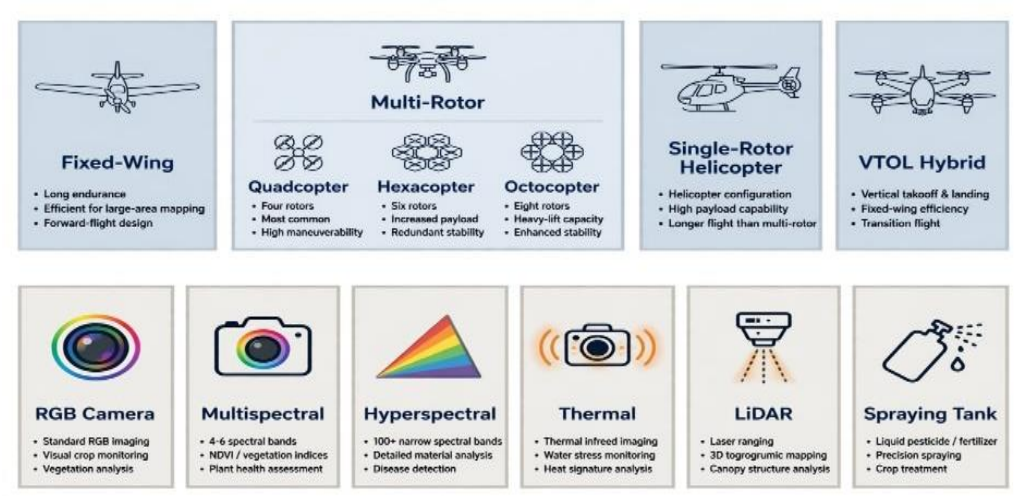


Figure 1. Comparison of quadcopter spraying and fixed-wing mapping platform for precision agriculture.
Source (Bacco et al., 2018; Zhang & Kovacs, 2012)

3.3 Smart Soil Sensors and IoT Monitoring

Internet of Things (IoT)-enabled smart soil sensing technologies have emerged as critical enablers of precision agriculture by providing continuous, real-time information on key edaphic parameters such as soil moisture, temperature, and nutrient status (Farooq et al., 2020; Qazi et al., 2022; Yavalkar, 2026). These data-driven insights allow farmers to optimize agronomic management, thereby enhancing crop yields while promoting efficient resource conservation (Balafoutis et al., 2017; Sarker et al., 2026).

The current ecosystem of soil sensors comprises diverse typologies, including tensiometers, gypsum blocks, time-domain reflectometry (TDR), frequency-domain reflectometry (FDR)/capacitance probes, neutron thermalization, and new proximal sensing techniques including electrochemical NPK sensors (Yavalkar, 2026; Postolache et al., 2023).

As illustrated in Figure 2, these sensors are deployed at varying soil depths and connected to a solar-powered IoT Node / Data Logger via wired connections, which then transmits data via LoRa 915 MHz to a LoRaWAN Gateway for cloud processing.

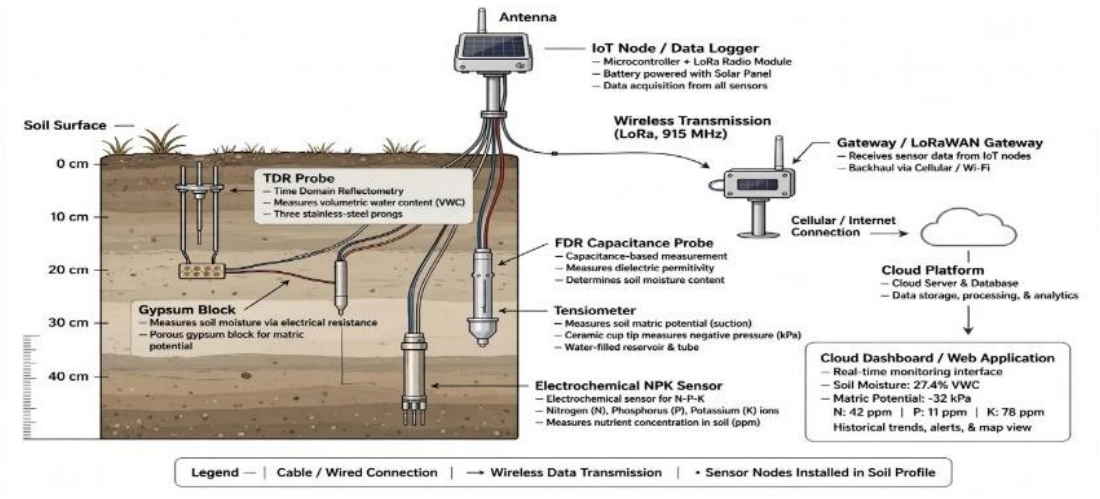


Figure 2. Architecture of an IoT-enabled smart soil sensing system
Source: (Yavalkar, 2026; Postolache et al., 2023)

Practical applications of these sensors extend across multiple domains, including automated smart irrigation scheduling, early disease and stress prediction, site-specific fertilizer management, and precision climate control in greenhouse environments (Farooq et al., 2020; Sarker et al., 2026). Notably, IoT-enabled soil moisture and conductivity monitoring systems have shown strong agreement with laboratory measurements ($R^2 = 0.999$ for EC) and have validated fertilizer-specific responses such as higher EC in Calcium Ammonium Nitrate treated soils (Michigan State University, 2025).

As shown in Figure 3, the system operates on a three-tier IoT architecture: Bottom Tier field sensors measuring volumetric water content, temperature, and N-P-K; Middle Tier gateway and edge processing for data aggregation and low-latency decision making; and Top Tier cloud AI analytics p

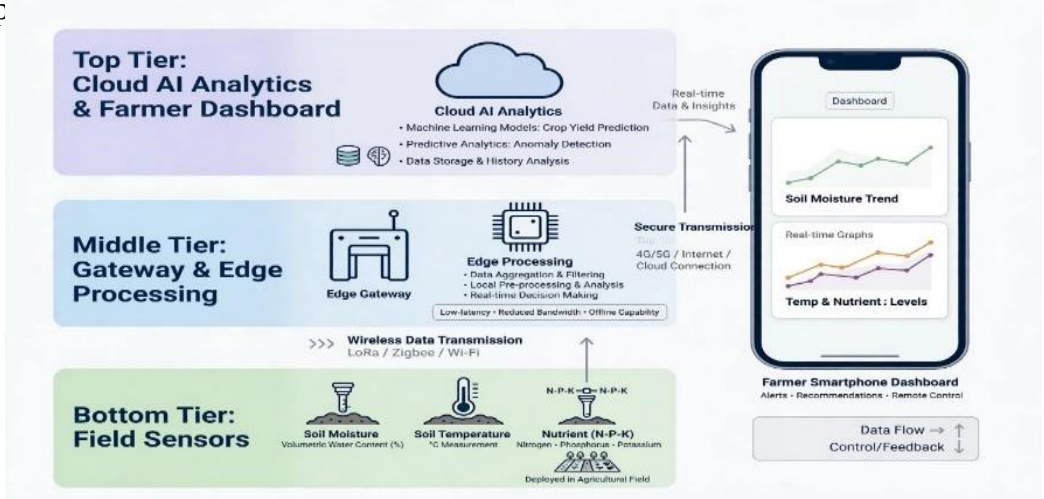


Figure 3. Three-tier IoT architecture for precision agriculture.
Source: Sarker et al., 2026

Bottom Tier: Field Sensors; Middle Tier: Gateway & Edge Processing with secure 4G/5G transmission; Top Tier: Cloud AI Analytics & Farmer Dashboard showing Soil Moisture Trend and Temperature & Nutrient Levels.

Field evaluations of sensor-driven drip irrigation in Bangladesh demonstrated yields on par with intensive conventional practice while saving nearly two-thirds of water and half of fertilizer (Sarker et al., 2026). Collectively, these tools constitute a foundational pillar of climate-smart agriculture, as they facilitate timely, site-specific, and data-driven decision-making that improves resilience and sustainability (Balafoutis et al., 2017; Qazi et al., 2022).

3.4 Autonomous Tractors and Agricultural Robotics

The growing scarcity of agricultural labour coupled with increasing demands for operational efficiency has significantly accelerated the adoption of autonomous machinery in modern farming systems (Lowenberg-DeBoer et al., 2021; Marinoudi et al., 2021). In response to these pressures, leading manufacturers such as John Deere have commercialized fully autonomous tractors integrated with multi-modal sensors, GNSS-based navigation, and artificial intelligence (AI), capable of performing tillage operations with minimal human supervision (John Deere, 2022). The autonomous 8R tractor combines TruSet-enabled chisel plow, GPS guidance system and six pairs of stereo cameras enabling 360-degree obstacle detection, where images are passed through a deep neural network that classifies each pixel in approximately 100 milliseconds to determine continuation or stopp

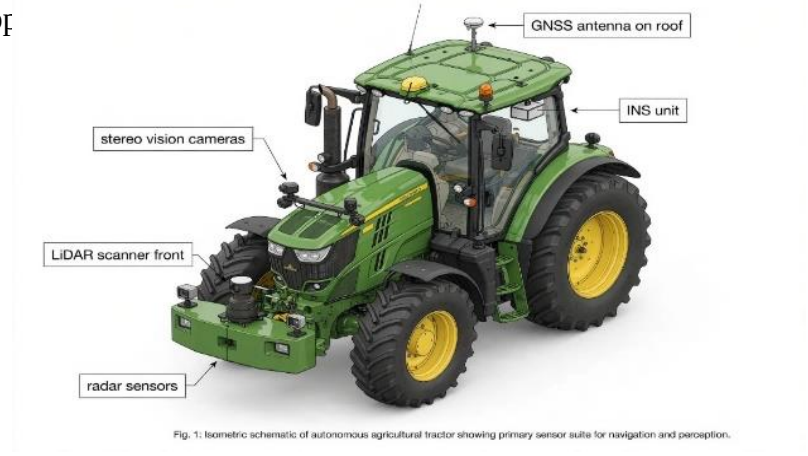


Figure 4: Isometric schematic of autonomous agricultural tractor showing primary suite for navigation and perception.
Source: John Deere, (2022)

Beyond field traction, agricultural robotics encompasses a broader spectrum of applications, including selective pick-and-place operations, continuous crop health monitoring, and large-scale



autonomous harvesting (Oliveira et al., 2021; Shamshiri et al., 2018). For instance, precision weeding robots have demonstrated substantial agrochemical savings; deep-learning based site-specific weed management systems for targeted spraying have been reported to achieve reductions in chemical usage exceeding 90% while maintaining efficacy and improving sustainability (Gerhards et al., 2022; Lottes et al., 2020).

Figure 5: Overview of autonomous robotics applications in modern agriculture
Source: Oliveira et al. (2021)

3.5 Satellite-Based Field Monitoring

Satellite-based remote sensing provides a synoptic, macro-scale perspective of agricultural landscapes, enabling systematic assessment of crop health status, soil conditions, and spatio-temporal field variability (Weiss et al., 2020; Sishodia et al., 2020). Contemporary digital agriculture platforms integrate multi-source satellite imagery to facilitate near real-time crop monitoring, early detection of agronomic anomalies, and evidence-based decision-making (Atzberger, 2013; Weiss et al., 2020).

As shown in Figure 6, operational systems synergistically leverage optical and radar constellations including Sentinel-1 (C-band SAR), Sentinel-2 (multispectral), Landsat-8/9, and MODIS to acquire multi-scale imagery from local to global levels (Atzberger, 2013; Weiss et al., 2020).

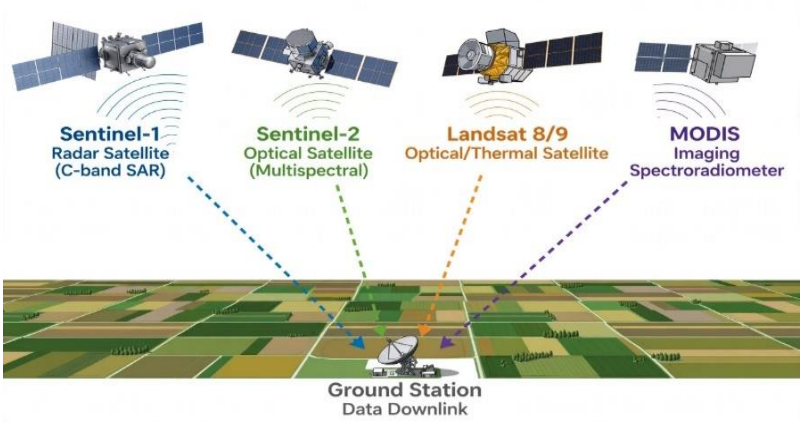


Figure 6: Multi-source satellite constellations for agricultural monitoring. Sentinel-1 radar, Sentinel-2 optical,
Landsat-8/9 optical/thermal, and MODIS spectroradiometer.
Source: Weiss et al. (2020)

This capability is particularly valuable for absentee landowners managing geographically dispersed holdings, as well as for institutional applications such as early warning systems,

rangeland and pasture assessment, and strategic food security planning (Fritz et al., 2019; Becker-Reshef et al., 2020).

A diverse ecosystem of operational monitoring systems has been developed at global, regional, and national scales (Figure 7), including the Anomaly Hotspots of Agricultural Production (ASAP), Early Warning Explorer (EWX), Global Agricultural Geo-Monitoring Initiative (GEOGLAM) Crop Monitors, Global Agricultural Drought Assessment System (GADAS), Agricultural Stress Index System (ASIS), Global Agriculture Monitoring (GLAM), World Food Programme Vulnerability Analysis and Mapping (WFP-VAM), Global Information and Early Warning System (GIEWS), CropWatch, Famine Early Warning Systems Network (FEWS NET), WFP Seasonal Monitor, and the East Africa Crop Monitor (EACM), alongside various national crop monitoring frameworks (Becker-Reshef et al., 2020; Fritz et al., 2019; Becker-Reshef et al., 2010).

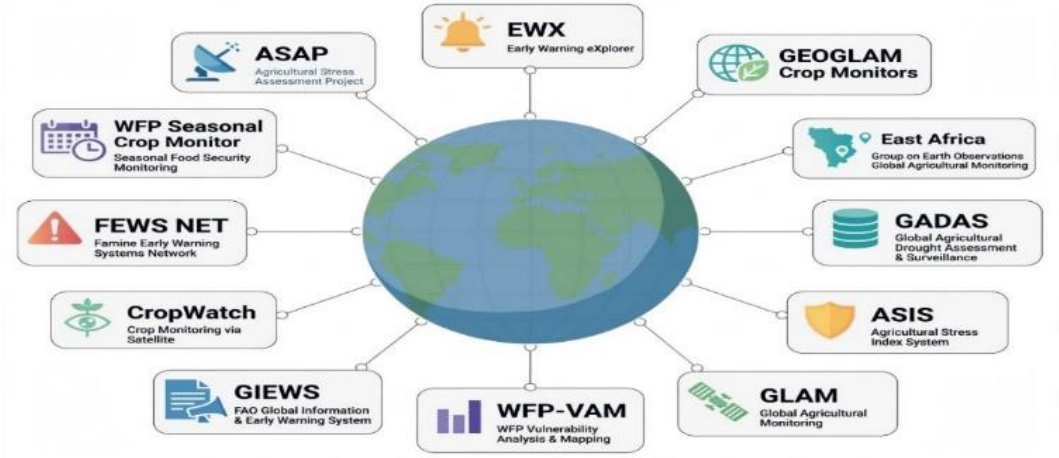


Figure 7: Global ecosystem of operational agricultural monitoring systems at global, regional, and national scales.
Source: Becker-Reshef et al. (2020)

These systems leverage synergistic data streams from optical and radar constellations such as Sentinel-1/2, Landsat-8/9, Moderate Resolution Imaging Spectroradiometer (MODIS), and climate datasets including Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) to support multi-scale monitoring from local to global levels (Atzberger, 2013; Weiss et al., 2020).

3.6 Blockchain for Transparency and Traceability

Blockchain is a tamper-resistant digital ledger with core features of decentralization, consensus, immutability, and cryptographic security (Bohmeeke-Schwafert et al., 2022; Li et al., 2020). It can track orders, payments, accounts, and transactions, and it enables contracts to be executed without intermediaries (Androulaki et al., 2018). In agriculture and food supply chains, blockchain

improves transparency, traceability, origin verification, anti-counterfeiting, quality management, and consumer confidence (Chang et al., 2019; Kumar et al., 2020; Cole et al., 2019) as illustrated by Xiong et al. (2020) in Figure 8. It also supports secure information sharing, trust, coordination, operational efficiency, and sustainable performance (Hastig& Sodhi, 2020; Wang et al., 2019). Barriers include limited understanding, technical limitations, costs, ROI uncertainty, integration difficulties, scalability, throughput, and latency (van Hoek, 2019b; Saberi et al., 2018; Wang et al., 2019a). In Nigeria, blockchain has been linked to improved security, trust, and privacy in marketing-oriented organizations and to anti-corruption and e-procurement transparency (Casino et al., 2019; Anetoh et al., 2025; Oladipupo, 2024; Akaba et al., 2020).

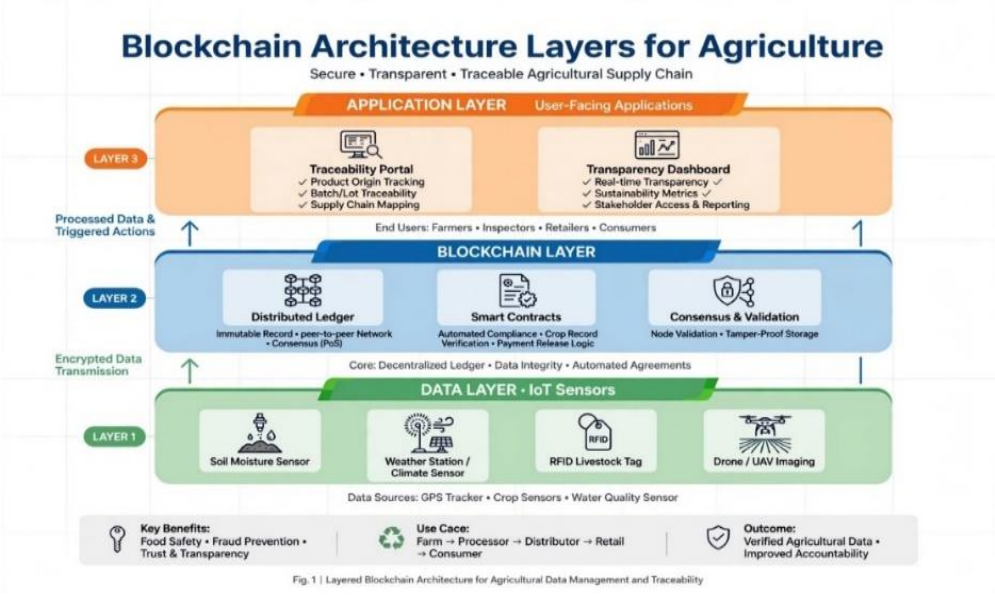


Figure 8: Layered blockchain architecture for agriculture management and traceability
Source: Xiong et al. (2020)

3.7 Digital Farm Management Platforms

Digital farm management platforms are integrated cloud-based and mobile-enabled systems designed to capture heterogeneous farm data and transform raw records into actionable management decisions (Wolfert et al., 2017; Walter et al., 2017). These platforms provide comprehensive decision support across the crop production cycle, encompassing planting recommendations, precision irrigation scheduling, fertilizer planning, input cost and labour tracking, continuous crop health and weather monitoring, predictive analytics for yield estimation and disease forecasting, and linkage to output markets and financial services (Wolfert et al., 2017; Tsan et al., 2019).

As shown in Figure 9, most systems adopt a modular framework consisting of a data capture layer including mobile forms, IoT sensors and remote sensing, a centralized cloud database, and an

analytics and artificial intelligence engine with an advisory dashboard (Wolfert et al., 2017; Basso &Antle, 2020).

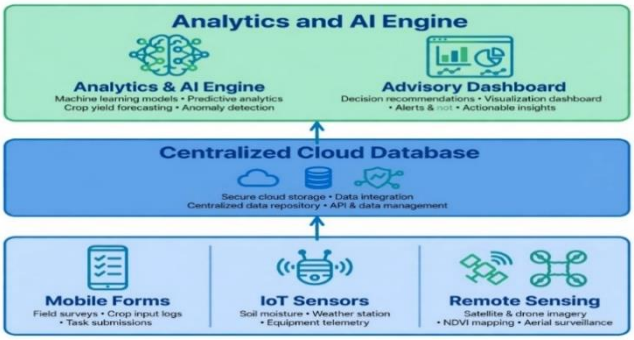


Figure 9: Modular architecture of digital farm management platforms.
Source: Wolfert et al. (2017)

Data capture layer (Mobile Forms for field surveys and task submissions, IoT Sensors for soil moisture/weather/equipment telemetry, Remote Sensing for satellite/drone imagery) flows into Centralized Cloud Database (secure storage, data integration, API management) and up to Analytics & AI Engine and Advisory Dashboard for predictive analytics, yield forecasting, anomaly detection and actionable insights (Wolfert et al., 2017; Basso &Antle, 2020).

Such systems are central to the vision that digital agriculture can help design more sustainable agricultural systems (Basso &Antle, 2020; Walter et al., 2017).

In the Nigerian context, the evolution of these platforms illustrates both potential and fragility. As illustrated in Figure 10, notable models include Hello Tractor, which operates an asset-sharing model often described as "Uber for Tractors" linking tractor owners with smallholders via a booking app (Daum et al., 2021).



Figure 10: Hello Tractor — Uber for Tractors in Nigeria model.
Source: Daum et al. (2021)

Smallholder farmers book on-demand via mobile app with live tracking; tractor owners list services for income; booking agents bridge the digital literacy gap; youth are engaged as trained operators and technicians. The model reduces transaction costs for mechanization but analog complements remain important (Daum et al., 2021).

The evidence shows Hello Tractor reduces transaction costs for mechanization but that analog complements such as booking agents remain important and ICT literacy constraints persist (Daum et al., 2021). Despite innovations, adoption remains constrained by persistent challenges widely documented for sub-Saharan Africa including infrastructure deficits, low digital literacy and uneven connectivity, with only 28% internet access and one-third of the population still out of reach of mobile broadband signals (FAO & ITU, 2022; Tsan et al., 2019). However, a key demographic opportunity exists as youth engagement and mobile expansion create fertile ground for digital scaling (FAO & ITU, 2022).

3.8 AI-Driven Yield Prediction and Modeling

AI integration into agricultural modeling marks a shift from empirical yield forecasting to intelligent, data-driven systems. ML and DL improve predictive accuracy for crop-yield estimation. Traditional ML algorithms—Random Forest, Gradient Boosting, Decision Tree, and Support Vector Machine—achieved strong performance, with Random Forest reaching R^2 values between 0.75 and 0.90, Support Vector Machines up to 0.955, and XGBoost up to 0.953, with a mean $R^2 = 0.83$ and low dispersion (SD = 0.065) (Hernández Hernández et al., 2025; Screpnik et al., 2025).

Deep learning architectures achieved a mean R^2 of 0.914, ranging from 0.87 to 0.95. CNN-based models using UAV imagery reached $R^2 = 0.95$, while LSTM models reached $R^2 \approx 0.94$, reflecting their capacity to capture spatial and temporal dependencies (Nevavuori et al., 2020; Hernández Hernández et al., 2025). A review of 23 studies found that deep learning models achieved average R^2 values between 0.85 and 0.93, compared to 0.60–0.75 for traditional empirical and mechanistic models, with LSTM outperforming process-based models by 73% for maize yield variance prediction (Betew et al., 2026). A systematic review of tomato yield prediction found that 66.67%

of best-performing models were Deep Learning, with LSTM, ANN, and SVR identified as most effective (Odah et al., 2025).

Hybrid models (Figure 11), such as APSIM + Random Forest and CNN + Ensemble Learning, achieved R^2 values between 0.88 and 0.94 and reduced RMSE by 18–25% relative to single-model approaches (Hernández Hernández et al., 2025). A hybrid APSIM + Random Forest model reduced RMSE from 15.51 t/ha to 5.52 t/ha (Li et al., 2023), while UAV remote sensing integrated with PROSAIL–AquaCrop reduced RMSE by 17–25% and increased R^2 by 7–19% (Xu et al., 2026). A TOPSIS-based multi-criteria analysis of 149 studies produced scores from 0.41 to 0.93, with hybrid models dominating the top tier (Hernández Hernández et al., 2025).

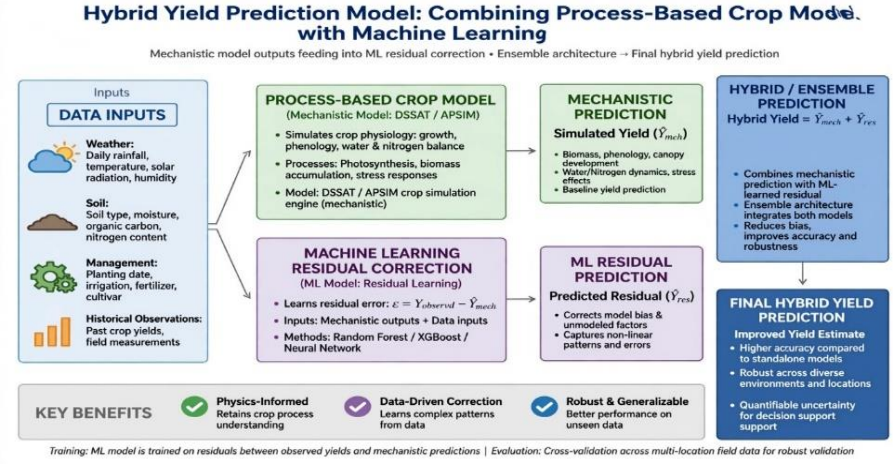


Figure 11: Hybrid yield prediction model
Source: Hernández Hernández et al. (2025)

A review of 106 studies in Mediterranean agroecosystems confirmed strong potential for Random Forest, Support Vector Machine, and Artificial Neural Networks, while noting limited adoption of CNNs and LSTMs due to data and computational constraints (Demissie et al., 2026). IoT and AI can significantly enhance agricultural production estimation (Saini et al., 2025), but continuous and up-to-date research is essential (De Clercq& Mahdi, 2025).

3.9 Regenerative Agriculture Monitoring Tools

Regenerative agriculture is defined as a holistic farming system that prioritizes soil health restoration, biodiversity enhancement, and ecosystem function, merging production with natural resource conservation (LaCanne& Lundgren, 2018; Newton et al., 2020; Schreefel et al., 2020). Its principles are centrally grounded in minimizing soil disturbance, maintaining continuous soil

cover, maximizing crop diversity, and integrating livestock, with soil organic matter as the foundational metric (Lal, 2020; Schreefel et al., 2020).

Monitoring the effectiveness of regenerative practices requires integrated tools that capture physical, chemical, and biological soil health indicators. As illustrated in Figure 1, the Soil Health Institute recommends a minimum suite of three widely applicable measurements across North America: soil organic carbon concentration via dry combustion, carbon mineralization potential via 24-hour CO2 burst, and aggregate stability as a proxy for soil structure and erosion resistance (Bünemann et al., 2018; Norris et al., 2020).

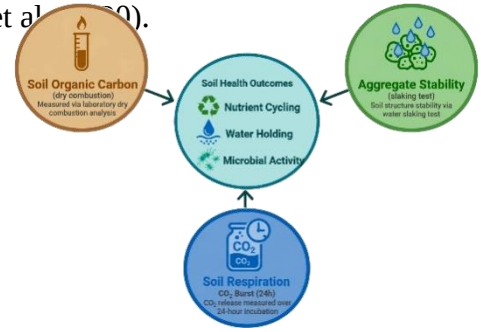


Figure 12. Minimum suite of soil health indicators for regenerative agriculture monitoring.
Source: Bünemann et al., 2018

Soil Organic Carbon (dry combustion analysis), Soil Respiration CO2 Burst (24h incubation measuring CO2 release), and Aggregate Stability (slaking test) converge on Soil Health Outcomes: Nutrient Cycling, Water Holding, and Microbial Activity.

These indicators are responsive to regenerative management and link directly to nutrient cycling, water holding capacity, and microbial activity.

Contemporary monitoring increasingly leverages digital and geospatial tools to scale field assessments. As shown in Figure 2, remote sensing platforms including Sentinel-2, Landsat-8/9, and MODIS enable synoptic monitoring of cover crop biomass, tillage intensity, and vegetation phenology, while decision

support tools (DSTs) developed under projects such as TUdi allow farmers to input georeferenced photos and sensor data to track erosion, compaction, carbon, and soil biology at field level (Weiss et al., 2020; Basso &Antle, 2020).

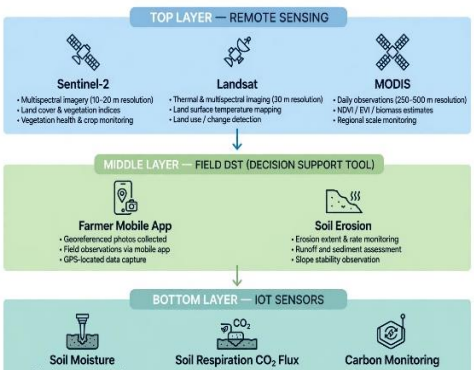


Figure 13. Geospatial and Decision Support Tool (DST) framework for regenerative agriculture monitoring.
Source:Weiss et al., 2020

The bottom layer integrates IoT-based soil sensors and real-time carbon flux monitoring systems that provide continuous data on soil moisture, CO2 flux, and carbon sequestration potential, supporting adaptive management and verification for carbon markets (Basso &Antle, 2020; Wolfert et al., 2017).

3.10 Security Technologies

Automated security technologies protect agricultural operations from theft, vandalism and trespass. Smart technologies include motion and perimeter sensors, GPS tags, and CCTV, integrated through IoT controllers and cloud platforms (Farooq et al., 2020; Qazi et al., 2022; Wolfert et al., 2017).

As illustrated in Figure 14, these tools form an integrated perimeter-to-cloud architecture where wireless devices enable real-time monitoring and secure communication.. The system integrates motion sensors, infra-red movement sensors, CCTV cameras with Wi-Fi video stream, and tractor-mounted GPS tags connected via ZigBee/LoRa and LTE to a central IoT controller and encrypted cloud platform for remote monitoring and alerts via user dashboard/mobile app.



Figure 14. IoT-based automated farm security architecture
Source: Qazi et al. (2022)

These tools alert farmers to boundary fence breaches, control site access, tackle rural crime, and make stolen goods easier to recover through cloud-linked smart trackers. IoT-based solutions are

being developed to automatically monitor farms with minimal human involvement, where wireless devices enable real-time crop and animal monitoring and the connection with cloud computing and big data analytics supports security (Farooq et al., 2019; Farooq et al., 2020). Modern IoT-equipped smart agriculture frameworks use low-powered wireless sensors to remotely report field conditions and AI to enable better predictions and autonomous responses (Qazi et al., 2022).

In practice, farmyard security relies on mains or battery-operated perimeter alarms, infra-red movement sensors, and CCTV to deter thieves, alongside removal of GPS receivers from tractors when not in use, PIN protection, indelible marking and secure storage (NFU Mutual, 2024; Farmers Weekly, 202

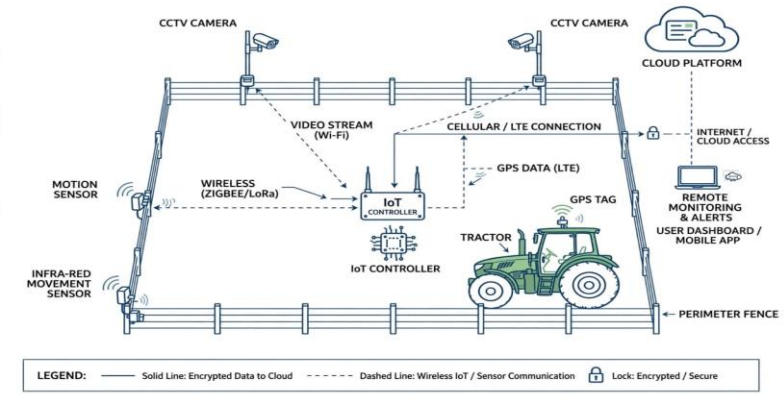


Figure 15: Farm security tools – theft prevention system
Source: NFU Mutual, (2024)

As shown in Figure 15, operational implementation includes discreet, battery-powered Thatcham-approved trackers with smartphone-based virtual fencing and theft-mode recovery features.

It consists of Farmyard theft prevention system. 1) Discreet GPS tracker on tractor (IP67, battery-powered, Thatcham-approved, hidden under chassis); 2) Smartphone app with virtual fence alerts and 60-second pings in theft mode with live location tracking and 24/7 police liaison; 3) PIN protection on GPS receiver with anti-tamper lock; 4) Secure storage shed with CCTV and keypad entry (Farmers Weekly, 2023; NFU Mutual, 2024).

Table 1: Summary of Key Technologies

Technology	Core Function	Application Examples	Key Constraints
Drones/UAVs	Aerial monitoring and spraying	Crop health, pest detection, precision spraying	Cost, regulation, battery/flight time
Sensors/IoT	Real-time field data	Smart irrigation, nutrient monitoring	Connectivity, calibration, maintenance
Autonomous machinery	Automated field operations	Self-driving tractors, robotic harvesting	Cost, complexity, labor displacement
Satellite monitoring	Macro-scale crop and climate monitoring	Early warning, food security	Data interpretation, resolution, access
Blockchain	Traceability and trust	Supply chain transparency, anti-counterfeiting	Scalability, cost, standards, understanding
Digital platforms	Data integration and decision support	Farm records, credit scoring, market linkage	Trust, digital literacy, infrastructure
AI/ML	Prediction and decision support	Yield forecasting, disease detection	Data quality, computing needs, validation
Regenerative monitoring	Soil, carbon, water, biodiversity tracking	MRV, soil health, carbon credits	Standardization, cost, measurement accuracy
Security tech	Farm protection	Perimeter alerts, equipment tracking	Cost, rural connectivity

4. Discussion of Application Statuses of These Technologies

4.1 Global and Developed-Country Application Status

Precision agriculture has been available since the 1990s, yet adoption remains uneven. In the United States, only 27% of farms used precision agriculture practices in 2023 (GAO, 2024; USDA, 2023). Adoption is stronger among large farms, those with better capital access, and regions with reliable connectivity and technical support. Satellite-based monitoring systems are operational at global and regional scales, and digital platforms, autonomous tractors, and drone-based services are commercially available. Policy support, standards, and research and development have accelerated innovation in developed countries. However, even there, high upfront costs, data ownership concerns, lack of standards, and complexity continue to limit broader uptake.

4.2 Application Status in Developing Countries and Nigeria

In developing countries, the adoption of precision agriculture is constrained by the dominance of smallholder farming, limited capital, weak infrastructure, and scarce technical support. Nigeria illustrates both the opportunity and the challenge. Agriculture contributes about 24% to GDP, accounts for about 80% of total food production, employs over 35% of the labor force, and is dominated by smallholders cultivating less than 2 hectares. Despite this, precision agriculture adoption in Nigeria is estimated at less than 10%, and Nigeria-specific empirical research remains scarce. The country also faces significant climate risks, including projected temperature increases of +3.08 to +4.63°C by 2050, erratic rainfall, and floods.

Precision agriculture offers a pathway to address these challenges through sensing, mapping, analytics, and automation. These technologies contribute to the “CSA Triple Win” of productivity, adaptation, and mitigation and ultimately support sustainable food systems characterized by food security, resilience, and low emissions. Implementation in Nigeria requires attention to sensors, drone and satellite data, data analytics, and machine learning. Sensors measure soil moisture, temperature, pH, EC value, and fertilizer adequacy; data analytics software analyzes and presents this data to farmers; drone and satellite data gather information on plant density, productivity, and

water content; and machine learning increases productivity, facilitates data interpretation, and helps determine water needs, manage fertilizers, and identify pests and diseases.

Digital farm management platforms show mixed but instructive results. Thrive Agric pivoted in 2020 from retail crowdfunding to an Agricultural Operating System funded by banks and now serves 1.3 million farmers, whereas Farm Crowdy, which stayed on crowdfunding, shut down in December 2024 due to defaults and regulatory issues. Hello Tractor works as an "Uber for tractors," Crop2Cash creates credit scores from farm activity, and ReLeaf links farmers to factories. The main challenges remain trust, poor roads, poor storage, and low digital literacy, but the opportunity is large because over 60% of Nigerian farmers are under 35 and use smartphones.

4.3 Observed and Expected Benefits

Smart agricultural technologies offer economic, environmental, and socioeconomic benefits. Economically, they improve crop yields through location-based techniques while saving labor and optimizing inputs such as water, fertilizers, pesticides, and energy. This lowers production costs, increases input-use efficiency, and improves farmer profitability. Environmentally, they avoid excessive agrochemical use by applying chemicals according to crop needs, reducing soil, water, and air pollution. They conserve water through better irrigation management and support sustainable agriculture by minimizing resource waste and preventing ecosystem degradation. Socioeconomically, precision technologies improve farmer safety by reducing direct contact with pesticides and dangerous activities, reduce physical labor through automation, and contribute to food security by improving agricultural output.

Specific benefits include increased productivity and profits, enhanced resource management, improved pest and disease detection, and greater labor efficiency. IoT-driven irrigation systems and digital pest traps allow real-time monitoring, so farmers can adjust growing conditions immediately (Topraq, 2025). Precision agriculture improves resource management by enabling precise application of water, fertilizer, and feed (GAO, 2024). It reduces fertilizer, herbicide, fuel, and water use and addresses water scarcity (GAO, 2024). Smart technologies increase the speed and accuracy of pest detection, including through AI-based tools such as the T-Trap Digital

Pheromone Trap (Topraq, 2025). Robotics helps solve staff shortages, rising costs, and human error (Dobson, 2025).

4.4 Policy and Implementation Pathways

The U.S. Government Accountability Office (2024) identified three policy goals to address adoption challenges and enhance benefits. First, encourage greater adoption and use through incentives, financial support, loan guarantees, grants, better benefit-cost quantification, promotion, outreach, and expanded Extension services. Second, encourage further innovation through research and development, in-ground sensors, remote imagery, and standards that improve equipment interoperability. Third, manage greater amounts of data through enhanced data analysis, AI and machine learning, data-sharing governance, easy-to-understand data license agreements, and codes of conduct.

For Nigeria, tailored strategies are critical because smallholder farmers dominate production. Strategies must account for local contexts and resource constraints (2025 Ag Tech Tools, p. 29). Priority areas include affordable sensor packages, drone and satellite data services, mobile-based analytics, machine learning for water and fertilizer management, extension support, financial inclusion, mobile money integration, and data governance. The conceptual framework for precision agriculture in Nigeria shows how these technologies contribute to the "CSA Triple Win" and support sustainable food systems (FAO, 2013; Wolfert et al., 2017).

4.5 Synthesis of Application Status

Application status varies sharply by region, farm size, infrastructure, and policy environment. Developed countries have more commercialized technologies, stronger data infrastructure, and higher adoption among large farms, though overall adoption remains modest. Developing countries, including Nigeria, are in an emerging phase characterized by pilot projects, mobile-enabled platforms, and targeted use among younger, smartphone-using farmers. The technology exists, but adoption depends on finance, trust, standards, connectivity, digital literacy, and supportive policy.

5. Existing Challenges and Pathways for Adoption

5.1 Existing Challenges

Several challenges limit broader adoption of precision agriculture.

1. **High upfront acquisition costs.** The latest technologies can be prohibitively expensive, especially for farmers with limited resources or capital (GAO, 2024). This is acute for smallholder farmers who dominate production in many developing countries (2025 Ag Tech Tools).
2. **Farm data sharing and ownership issues.** Farmers often do not trust how data is collected and managed. Terms and conditions for data use should be simple, transparent, and accountable (GAO, 2024).
3. **Lack of standards.** The absence of uniform standards hampers interoperability. Different precision agriculture technologies cannot work together easily, and data quality is difficult to assess (GAO, 2024).
4. **Limited adoption rates.** Precision agriculture has been available since the 1990s, yet only 27% of U.S. farms used these practices in 2023 (GAO, 2024; USDA, 2023). In Nigeria, adoption is estimated at less than 10%, with scarce Nigeria-specific empirical research (2025 Ag Tech Tools, p. 32).
5. **Complexity and technical knowledge requirements.** Precision agriculture technologies can be complex and require significant technical knowledge. This creates barriers for farmers with limited digital exposure, training, and support services (GAO, 2024).
6. **Infrastructure and socioeconomic constraints in Nigeria.** Trust, poor roads, poor storage, and low digital literacy remain major challenges, even though mobile money is strong and many farmers are young smartphone users.
7. **Blockchain-specific barriers.** These include limited understanding, technical limitations, costs, ROI uncertainty, integration difficulties, traceability needs, and concerns about product safety, quality failure, and counterfeiting (van Hoek, 2019b; Zhao et al., 2019; Cole et al., 2019).

5.2 Pathways for Adoption

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The pathways for adoption involve three policy goals—encouraging greater adoption through incentives, finance, loan guarantees, grants, benefit-cost evidence, outreach, and extension; encouraging further innovation through R&D, sensors, remote imagery, and interoperability standards; and managing greater data volumes through analytics, AI/ML, data-sharing governance, simple license agreements, and codes of conduct—while for developing countries like Nigeria, tailored strategies must prioritize affordable sensors, drone/satellite data, mobile analytics, machine learning for water and fertilizer management, extension support, financial inclusion, mobile money, and data governance so that precision agriculture supports the CSA Triple Win of productivity, adaptation, and mitigation.

6.0 CONCLUSION

In conclusion, smart agriculture offers transformative potential to address food security, environmental sustainability, and climate resilience. The technologies exist, and the evidence demonstrates their effectiveness. However, adoption depends on finance, trust, standards, connectivity, digital literacy, and supportive policy. Without deliberate effort to address these barriers, the benefits of smart agriculture risk accruing only to those with existing resources and infrastructure, leaving the world's most food-insecure regions further behind. The pathways for adoption are clear, but they require sustained commitment from policymakers, researchers, practitioners, and the private sector to ensure equitable access and maximize benefits across diverse farming systems.

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