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Data-Driven Policymaking for Sustainable Agribusiness Development: An Analysis on Leveraging AI and Digital Technologies

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Abstract— *The global agricultural sector faces an unprecedented convergence of challenges: population growth, accelerating climate variability, and chronic food insecurity. Artificial intelligence (AI) and digital technologies have emerged as transformative instruments capable of reshaping agribusiness value chains and enabling evidence-based policymaking at scale. This paper examines how data-driven policymaking can advance sustainable agribusiness development in Nigeria—Africa's largest economy—with particular focus on how AI technologies proven in the United States, the Netherlands, Japan, and Australia can be directly replicated and adapted for the Nigerian context. Nigeria's agricultural sector, contributing 24.8 percent of GDP and employing over 70 percent of the rural population, stands at a critical inflection point characterized by profound dualities of latent potential and systematic underperformance. The paper maps specific replication pathways across six priority domains: satellite crop monitoring, AI-powered market intelligence, precision agriculture for smallholders, agricultural finance and index insurance, supply chain optimization, and national data infrastructure. Drawing on proven pilot programs already operational in Nigeria, the paper presents eight integrated, actionable policy recommendations spanning data infrastructure establishment, national governance frameworks, digital extension services, AI innovation funding, broadband connectivity, and evidence-based monitoring architecture. Together, these constitute a coherent digital transformation agenda capable of closing Nigeria's productivity gap and positioning the country as a continental leader in sustainable agribusiness development.*

Keywords— Agribusiness, Artificial intelligence, Data-driven policy, Digital agriculture, Food security, Nigeria, Precision agriculture, Agricultural policy, Digital transformation, Smallholder farmers.

I. INTRODUCTION

Agriculture remains the backbone of global economic development, providing livelihoods for an estimated 2.5 billion people and contributing approximately 4 percent of global GDP (World Bank, 2023). Despite its foundational importance, the sector faces an unprecedented convergence of structural pressures that conventional farming systems are increasingly ill-equipped to manage. The Food and Agriculture Organization of the United Nations (FAO) estimates that global food production must increase by at least fifty percent from 2012 levels to meet projected demand by 2050—a target that is widely acknowledged to be impossible to achieve through traditional farming methods alone (Fadiji et al., 2023). This imperative is compounded by accelerating climate variability, which threatens the stability of agricultural production across all major food-producing regions, and by the uneven distribution of agricultural productivity gains across the global South.

The concept of data-driven policymaking—the systematic use of empirical data, digital monitoring systems, and predictive analytics to inform agricultural governance decisions—has emerged as a critical response to these challenges. Razak et al. (2024) characterize this shift as the convergence of precision agriculture, big data infrastructure, and intelligent decision systems into what they term "smart farming," a paradigm that treats agricultural management as an information-intensive enterprise rather than a labor-intensive one. The implications for policy are profound: where traditional agricultural policy relied on infrequent census data, anecdotal extension reports, and lagged economic indicators, data-driven governance creates the potential for real-time, adaptive management of entire agricultural systems.

The Fourth Industrial Revolution has produced a suite of transformative technologies—artificial intelligence, machine learning, Internet of Things (IoT) sensors, satellite imagery, and big data analytics—that have already demonstrated measurable and replicable results in developed economies (Kisliuk et al., 2023). The challenge for developing nations is no longer one of technological feasibility but of institutional design, policy architecture, and the strategic adaptation of proven tools to local contexts. This paper undertakes precisely that task, providing a direct technology-by-technology mapping of how tools proven in the United States, Netherlands, Japan, and Australia can be replicated and institutionalized in Nigeria.

II. The Nigerian Agricultural Context: Paradox of Potential and Underperformance

Nigeria presents a compelling and urgent case study for digital agricultural transformation. As Africa's largest economy, with a GDP exceeding USD 477 billion (National Bureau of Statistics, 2023), Nigeria's agricultural sector operates at a scale and strategic importance that make its productivity deficits a matter of national and continental significance. Agriculture contributes 24.8 percent of GDP and employs over 70 percent of the rural population, making it simultaneously the largest sector of the economy and the primary livelihood of the most economically vulnerable Nigerians (Kisliuk et al., 2023).

The sector is characterized by profound dualities that reflect systemic governance and investment failures rather than intrinsic limitations. Nigeria possesses 84 million hectares of arable land, yet only 40 percent is under cultivation. Approximately 60 million farmers participate in the agricultural economy, yet average maize yields languish at 1.8 MT/ha against a global average of 5.7 MT/ha—a productivity gap of more than threefold (USDA Economic Research Service, 2023). Perhaps most starkly, Nigeria spends USD 3–5 billion annually importing food staples—rice, wheat, sugar, fish—that it has the agro-ecological capacity to produce domestically. This import dependency represents not only an economic cost but a structural vulnerability to global commodity price volatility and supply chain disruption (Pervez et al., 2026).

The smallholder structure of Nigerian agriculture is both a defining characteristic and a core policy challenge. Smallholder farmers, operating on average plots of less than two hectares, account for approximately 80 percent of total food production (Hampel & Fabulya, 2024). Yet these farmers are systematically excluded from the financial services, market intelligence, agronomic support, and technological tools that would enable productivity improvements. The extension-to-farmer ratio of 1:3,000 against a recommended international benchmark of 1:500 illustrates the severity of institutional underinvestment in smallholder support (Pervez et al., 2026). Only fifteen percent of smallholder farmers currently use any form of digital agricultural tool, reflecting both infrastructural constraints and the absence of appropriately designed digital services.

Akintuyi (2024) noted that Nigeria has enacted successive ambitious agricultural policy frameworks—the Agricultural Transformation Agenda (2011–2014), the Green Alternative (2016–2020), and the current Agricultural Sector Action Plan (2022–2027)—each of which has explicitly acknowledged digital technologies as transformative enablers. Yet less than forty percent of programmatic commitments under these frameworks have been implemented as designed, with data and monitoring deficiencies consistently identified as the primary contributing factor (Nwachukwu et al., 2021). The gap between policy ambition and agricultural outcomes is therefore fundamentally a governance and data architecture gap—one that advanced digital technologies are uniquely positioned to close.

III. Objective

The specific objective of this paper is to explore the potentials of data-driven policymaking in agribusiness, focusing on the role of advanced technologies in addressing key challenges and providing actionable recommendations for policymakers to harness these technologies effectively in the Nigerian context.

IV. Literature Review

4.1 Data-Driven Policymaking: Conceptual Framework

Data-driven policymaking in the agricultural context refers to the systematic integration of real-time and near-real-time data streams from satellites, IoT sensors, mobile devices, market platforms, and administrative systems into the evidence base that informs policy design, resource allocation, monitoring, and adaptive management (Akintuyi, 2024). It represents a qualitative shift from the episodic, retrospective evaluation model that has characterized agricultural governance in most developing nations toward a continuous, prospective, and responsive governance architecture.

Ikubanni et al. (2025) document how deep learning and machine learning systems have achieved performance equivalent to or exceeding human expert judgment across core agricultural decision domains—including crop disease diagnosis, yield forecasting, soil analysis, and irrigation management—demonstrating that AI is no longer an experimental technology in agriculture but a mature one. The policy challenge is therefore one of institutionalization: embedding these tools within governance frameworks, regulatory structures, and public service delivery systems in ways that are equitable, accountable, and sustainable.

The enabling infrastructure for data-driven agricultural policymaking comprises four interdependent layers: (1) data collection infrastructure—sensors, satellites, mobile platforms, and administrative systems that generate the raw data inputs; (2) data integration and analytics platforms—systems that aggregate, clean, and analyze data from multiple sources to produce actionable intelligence; (3) knowledge translation systems—extension services, decision-support tools, and mobile applications that translate analytical outputs into farmer-level recommendations; and (4) governance and regulatory frameworks—the institutional structures, data ownership regimes, and accountability mechanisms that ensure the system operates equitably and generates public value. Nigeria's challenge is that it possesses nascent versions of each layer but lacks the integration architecture that would make them collectively functional (Babar & Akan, 2024).

4.2 AI Technologies Transforming Global Agriculture

Several leading agricultural economies have each pioneered distinct digital agriculture approaches that together constitute the global frontier of AI-enabled agribusiness. Their aggregate experience forms the replication blueprint for Nigeria's digital transformation agenda.

4.2.1 Netherlands: Greenhouse AI, Robotics, and Data-Intensive Horticulture

The Netherlands, despite covering only 41,543 km², is the world's second-largest agricultural exporter by value—an achievement entirely attributable to AI-driven greenhouse technology and data-intensive production management (Ministry of Agriculture, Nature and Food Quality, Netherlands, 2023). Dutch greenhouse systems employ continuous AI optimization of temperature, humidity, CO_2 concentration, and lighting based on real-time crop response data, achieving 90 percent reductions in water use and 30 percent reductions in greenhouse gas emissions per unit of production compared to open-field equivalents. The Topsector Agri & Food—a structured public-private innovation fund with data-guided investment priorities—has been central to this achievement, demonstrating the governance model rather than merely the technology as the transferable asset for developing nations (Murindanyi et al., 2024).

4.2.2 Australia: Satellite Monitoring and Climate-Adaptive Analytics

Australia's vast geographic scale and extreme climate variability have driven innovation in satellite-based remote sensing and AI-enhanced climate analytics (Nawaz et al., 2025). The Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) produce monthly AI-enhanced crop condition reports with national coverage, achieving a 25 percent improvement in grain production forecast accuracy compared to traditional survey methods (ABARES, 2022; Grains Research and Development Corporation, 2023). The return on investment from digital agriculture investments in the Australian grains sector is documented at AUD 4.70 per dollar invested—one of the highest ROI ratios recorded for any agricultural technology category. The Australian model is particularly relevant for Nigeria because it demonstrates the policy and institutional architecture—not merely the technology—required to translate satellite data into actionable agricultural governance intelligence.

4.3 Proven Nigerian Pilots: Evidence of Feasibility

Critically, the replication case for AI in Nigerian agriculture is not theoretical. A series of pilots has already demonstrated technical feasibility and impact within Nigeria's specific infrastructural and institutional context, providing the empirical foundation for national scaling. The USAID Feed the Future Nigeria (2019–2023) deployed AI-enhanced satellite monitoring across the Guinea Savanna zone, achieving 85 percent accuracy in crop stress detection 4–6 weeks before visual symptoms appeared in the field—a lead time sufficient to enable preventive agronomic interventions (USAID, 2023). The FEPSAN soil sensing pilot (2023) demonstrated that AI-enhanced low-cost spectroscopy devices (under USD 200 per unit) could provide laboratory-equivalent soil nutrient analysis, enabling precision fertilizer recommendations that reduced input costs by 25–35 percent while maintaining or improving yields. The Honeywell/LSADA cold chain IoT pilot in Lagos (2022) identified that 60 percent of post-harvest losses were attributable to predictable failure patterns, and AI-enabled cold chain management delivered a 40 percent reduction in tomato and vegetable losses over an 18-month period. The Esoko West Africa market intelligence model, applicable to the Nigerian context, has demonstrated that AI price forecasting can deliver 9–14 percent higher farm-gate prices for subscribing farmers through improved market timing (IFPRI, 2020). These results collectively demonstrate that the enabling conditions for AI-driven agricultural transformation in Nigeria already exist; what remains is the institutional will and policy architecture to scale proven approaches from pilots to national scale.

4.4 Data-Driven Policymaking in Agriculture: Global Evidence

The academic literature on data-driven agricultural policymaking has grown substantially over the past decade, reflecting both the rapid maturation of enabling technologies and the increasing urgency of global food security challenges. Babar and Akan (2024) provided a foundational review of big data in smart farming, documenting the transition from farm-level precision agriculture tools toward integrated data ecosystems that span the entire agrifood supply chain. Their framework identifies data connectivity, interoperability standards, and governance architecture as the critical bottlenecks limiting the scaling of smart farming approaches—findings that remain highly relevant to the Nigerian policy context.

Hampel and Fabulya (2024) carried out a survey on the application of deep learning across agricultural domains, documenting performance benchmarks that consistently demonstrate AI systems achieving accuracy rates of 85–99 percent in crop disease detection, yield prediction, and soil classification tasks. Their analysis highlights the rapid democratization of deep learning tools through open-source frameworks and cloud computing platforms, substantially reducing the technical barriers to AI deployment in agricultural research and extension contexts. This democratization underpins the replication logic of this paper: the core technologies are no longer proprietary or capital-intensive, but the institutional frameworks for their deployment remain underdeveloped in most African agricultural contexts.

The FAO's State of Food and Agriculture report (2022) examines automation and digital transformation across the agrifood system, concluding that the productivity and sustainability gains from digital agriculture are substantial and well-documented, but that their distribution is highly unequal—accruing disproportionately to large commercial farms in high-income countries while smallholder farmers in low and middle-income countries remain largely excluded. The report identifies three categories of intervention required to achieve inclusive digital transformation: infrastructure investment, governance frameworks that protect smallholder interests, and locally adapted digital tools designed for low-bandwidth and low-literacy contexts. This tripartite framework directly informs the policy architecture proposed in this paper.

4.5 AI and Precision Agriculture: Evidence from Developed Economies

The empirical literature on AI applications in developed country agriculture is extensive and consistently documents significant productivity, efficiency, and sustainability gains. The USDA Economic Research Service (2023) documents precision agriculture adoption trends across US farms, finding that farms adopting AI-enabled precision tools achieve yield improvements of 10–15 percent alongside input cost reductions of similar magnitude, with the strongest adoption rates among large commercial operations. Deere & Company's (2022) sustainability reporting provides corporate-level evidence of the scale of precision agriculture impact, documenting substantial improvements in fuel efficiency, input use efficiency, and yield predictability attributable to machine learning-enabled farm management systems.

The Australian grains sector provides particularly robust return-on-investment evidence. GRDC (2023) documents a AUD 4.70 return per dollar invested in digital agriculture across the grains sector, based on a portfolio-level analysis of precision agriculture, remote sensing, and AI decision-support tools. Nawaz et al. (2025) provided complementary evidence at the policy level, documenting that AI-enhanced crop condition monitoring has improved the accuracy and timeliness of agricultural policy decisions—including drought assistance allocation, export strategy, and infrastructure investment—in ways that generate measurable economic value at the national scale.

The Netherlands provides the most extreme case of AI-enabled agricultural transformation, with a country of 17 million people generating agricultural exports valued at over EUR 100 billion annually. The Ministry of Agriculture, Nature and Food Quality (2023) documents how the Topsector Agri & Food public-private innovation framework has structured this transformation, channeling data-guided investment into greenhouse technology, robotics, and precision horticulture over a sustained multi-decade period. The Dutch case is instructive not primarily for its technologies—which are largely beyond immediate replication in Nigerian conditions—but for its governance model: the systematic use of data to identify investment priorities, monitor outcomes, and adaptively manage public and private agricultural R&D expenditure (Pervez et al., 2026).

4.6 Digital Agriculture in Sub-Saharan Africa: Opportunities and Constraints

The literature on digital agriculture in Sub-Saharan Africa reflects both the transformative potential and the acute implementation challenges specific to the regional context. Brewster et al. (2020) examine IoT deployment in African agricultural contexts, identifying connectivity infrastructure, energy access, and digital literacy as the primary constraints limiting adoption, while arguing that the modular, low-cost character of modern IoT technology makes it fundamentally compatible with smallholder agricultural systems when appropriately designed. Their emphasis on the necessity of robust data governance frameworks—particularly around data ownership, consent, and benefit-sharing—directly anticipates the governance architecture challenges that Nigeria must address.

IFPRI (2020) evaluates the Esoko market information system across West Africa, one of the most extensively studied digital agriculture interventions in the region. The evaluation documents consistent improvements in farm-gate prices of 9–14 percent for subscribing farmers, attributable to improved market timing enabled by AI-driven price forecasting and SMS-delivered market intelligence. Critically, the evaluation also documents the conditions necessary for sustained impact: reliable mobile connectivity, farmer trust in the system, and price information that is genuinely actionable given available transport infrastructure. These conditional findings are directly relevant to Nigeria's policy design.

Nwachukwu et al. (2021) provide the most directly relevant analysis for the Nigerian agricultural policy context, examining implementation gaps across three successive national agricultural policy frameworks. Their analysis identifies four recurring failure modes: inadequate baseline data to set measurable targets; absence of real-time monitoring systems to track performance; insufficient institutional capacity to translate monitoring data into policy adjustments; and misalignment between policy objectives and the incentive structures of implementing agencies. These findings constitute a diagnostic framework that directly motivates the data infrastructure and governance architecture recommendations advanced in this paper.

USAID's evaluation of the Feed the Future Nigeria digital agriculture (2023) provides the most directly applicable evidence base for national scaling, documenting that AI-enhanced satellite monitoring achieved 85 percent accuracy in crop stress detection 4–6 weeks before visual symptoms appeared—sufficient lead time to enable meaningful agronomic intervention. The evaluation also documents the institutional requirements for sustainability: integration with national agricultural monitoring systems, capacity building within FMARD and state agricultural development programs, and data-sharing frameworks that ensure satellite intelligence reaches extension agents and farmers in actionable form.

V. POLICY ARCHITECTURE FOR DIGITAL AGRICULTURAL TRANSFORMATION

The literature on policy architecture for digital agricultural transformation in developing economies converges on several key design principles. First, data infrastructure investment must precede or accompany digital service deployment: AI systems trained on inadequate or outdated data produce systematically inaccurate outputs that undermine rather than support agricultural decision-making. Second, governance frameworks that address data ownership, privacy, and benefit-sharing are necessary conditions for farmer participation and private sector investment that sustain digital agricultural ecosystems. Third, digital extension platforms must be designed for the actual connectivity, literacy, and device landscape of target farmers—which in the Nigerian context means SMS, USSD, and voice interfaces rather than smartphone apps. Fourth, evidence-based policy monitoring—the systematic use of digital data to evaluate performance in real time—is both a prerequisite for adaptive management and a mechanism for building the political accountability that sustains long-term investment in agricultural transformation.

The FAO (2022), World Bank (2023), and IFPRI (2020) collectively document that the countries achieving the most significant digital agricultural transformation gains share a common policy architecture: integrated national data infrastructure, structured public-private innovation funding, mandatory evidence-based monitoring, and governance frameworks that explicitly protect smallholder interests. Nigeria's ASAP 2022–2027 implicitly acknowledges this architecture but lacks the specific institutional mechanisms required to operationalize it. This paper provides those mechanisms.

VI. GLOBAL AI TECHNOLOGIES: WHAT WORKS AND WHY IT CAN WORK IN NIGERIA

6.1 Technology-to-Policy Mapping

The following section presents a direct technology-by-technology mapping of proven global AI agricultural tools and their specific replication pathways for Nigeria. Table 1 provides a summary overview of the four country models and their primary transferable elements.

TABLE 1
INTERNATIONAL AI TECHNOLOGY MODELS AND NIGERIA REPLICATION PATHWAYS

Country	Core AI Technology	Proven Outcome	Nigeria Replication Pathway
United States	ML platforms, precision agriculture, AI crop insurance	60 percent large farm adoption; 15–20 percent insurance accuracy gain	Integrate FMARD/NBS/NASRDA data into unified AI analytics platform
Netherlands	Greenhouse AI, robotics, IoT sensor networks	World's second-largest exporter; 30 percent GHG reduction per unit	Launch Topsector-equivalent NGN 50 billion public-private AI Innovation Fund
Japan	WAGRI data commons, smartphone disease AI	30 percent labor reduction; agronomist-equivalent diagnosis	Build NADI as Nigerian WAGRI; deploy SMS/USSD disease AI nationally
Australia	Satellite remote sensing, climate analytics	25 percent forecast accuracy gain; AUD 4.70 ROI per dollar invested	Institutionalize USAID pilot's 85 percent-accurate satellite crop monitoring

Note: Data sourced from USDA Economic Research Service (2023), Ministry of Agriculture, Nature and Food Quality, Netherlands (2023), Japanese Ministry of Agriculture, Forestry and Fisheries (2023), ABARES (2022), and GRDC (2023).

VII. THE NIGERIAN AGRIBUSINESS LANDSCAPE: SIX PRIORITY TECHNOLOGY REPLICATION DOMAINS

Based on the international evidence review and the demonstrated feasibility of Nigerian pilots, six priority domains are identified for technology replication and policy investment. Table 2 summarizes the key characteristics and investment requirements across these domains.

TABLE 2
SIX PRIORITY TECHNOLOGY REPLICATION DOMAINS FOR NIGERIA

Domain	Core Technology	Pilot Evidence	Estimated Investment	Expected Impact
Satellite Crop Monitoring	NASA MODIS, ESA Sentinel, EU Copernicus with AI analytics layer	USAID FtF: 85 percent accuracy, 4–6 weeks lead time	NGN 3–5 billion/year operating	National early warning and budget allocation intelligence
AI Market Intelligence	Time-series price forecasting, SMS/USSD delivery	Esoko model: 9–14 percent farm-gate price improvement	Low capital; private sector led	Reduced market information asymmetry
Precision Agriculture	Drone-as-a-Service, AI soil sensors, smartphone disease AI	FEPSAN: 25–35 percent fertilizer cost reduction	Scalable from NGN 500 million	Input cost reduction; yield improvement
Agricultural Finance & Insurance	AI credit scoring, index-based insurance	IFC pilots: improved uptake and basis risk reduction	Regulatory framework + infrastructure	Expanded smallholder credit access
Post-Harvest & Supply Chain	IoT cold chain, AI demand forecasting, blockchain	Honeywell/LSADA: 40 percent loss reduction in 18 months	NGN 5–10 billion national	20–40 percent post-harvest loss reduction
National Data Infrastructure (NADI)	Federated data platform, multi-agency integration	Modelled on Japan WAGRI / Australia ABARES	NGN 15–20 billion over 3 years	Enabling foundation for all five domains above

VIII. CHALLENGES AND BARRIERS TO IMPLEMENTATION

Replication of global AI technologies in Nigeria is achievable but faces six categories of barriers that must be addressed in parallel with technology deployment. Table 3 provides a structured assessment of each barrier, its current severity, and the recommended mitigation approach.

TABLE 3
KEY IMPLEMENTATION CHALLENGES, SEVERITY, AND MITIGATION APPROACHES

Challenge	Current Status	Severity	Mitigation Approach
Rural Connectivity	21 percent rural internet penetration; 60 percent unreliable power	Critical	AgriConnect Initiative: 4G in all agricultural LGAs by 2027; Starlink satellite backup
Digital Literacy	15 percent smallholder digital tool adoption; 1:3,000 extension ratio	Critical	Digital Agriculture Certificate; Youth Agribusiness targeting; gender equity provisions
Data Governance	No farm-level data ownership framework; NDPR lacks agricultural provisions	High	Agricultural Data Governance Framework under Nigeria Data Protection Act 2023
R&D Financing	0.2 percent of agricultural GDP versus 1 percent Maputo Declaration benchmark	Critical	NGN 50 billion Agricultural AI Innovation Fund; blended finance instruments
Institutional Silos	FMARD, NBS, NASRDA, NiMet data not integrated; no common API	High	NADI platform with multi-agency governance board under executive mandate
Technology Adaptation	Off-the-shelf tools not designed for low-literacy, low-bandwidth contexts	Moderate	NADEP platform with SMS/USSD/voice interfaces in Nigerian languages

IX. POLICY RECOMMENDATIONS

The following eight recommendations form a mutually reinforcing policy agenda. Each directly addresses the gap between a proven global technology and its deployment at Nigerian scale. Together, they constitute the institutional and investment architecture required for a national digital agricultural transformation.

9.1 Establish the National Agricultural Data Infrastructure (NADI)

The Federal Government should establish NADI—a federated, interoperable data platform aggregating inputs from FMARD, NITDA, NBS, NASRDA, and NiMet, hosted by FMARD with technical management by NITDA. Modelled on Japan's WAGRI and Australia's ABARES system, NADI would provide the foundational data integration layer that all subsequent AI applications require. Based on developed country benchmarks, this infrastructure investment is expected to generate 10–25 times returns in agricultural productivity improvements over a decade.

9.2 Conduct a National Agricultural Census and Annual Digital Survey

Nigeria must commission the first comprehensive agricultural census since 2011, followed by an annual digital survey using Computer-Assisted Personal Interview technology and GPS-georeferenced sampling. Without current baseline data, any AI system trained on Nigerian conditions will be operating on decade-old inputs, systematically compromising the accuracy and policy relevance of its outputs. This is the foundational data investment that enables evidence-based resource allocation across all subsequent interventions.

9.3 Enact an Agricultural Data Governance Framework

Building on the Nigeria Data Protection Act 2023, a sector-specific Agricultural Data Governance Framework should address farm data ownership rights, consent mechanisms for smallholder data collection, data-sharing obligations for agritech companies operating in Nigeria, and benefit-sharing arrangements ensuring farmers receive fair compensation for the commercial use of their operational data. The framework should be developed through participatory consultation with farmer organizations, agritech companies, and civil society, and reviewed every three years in light of technological change.

9.4 Integrate Digital Agriculture into Tertiary and Vocational Education

Agricultural curricula at all tertiary and vocational levels must be revised to incorporate digital agriculture competencies. A six-month Digital Agriculture Certificate—integrating drone operation, sensor technology, data analysis, and digital extension methodology—should be deployed through agricultural universities and the national extension network. Curriculum design must explicitly address gender equity, given the disproportionate barriers women farmers face in accessing digital agricultural tools and services.

9.5 Establish Evidence-Based Policy Monitoring Architecture

All major agricultural policy programs must incorporate a Theory of Change with measurable digital indicators, a pre-registered evaluation design, and a real-time data monitoring framework drawing on NADI data. A Policy Analytics Unit should be established within FMARD, staffed with data scientists and agricultural economists, publishing quarterly evidence digests and annual performance reports. A public data portal should enable civil society and researchers to access de-identified data for independent evaluation, creating the accountability structure necessary to sustain long-term investment in agricultural transformation.

9.6 Launch the Agricultural AI Innovation Fund

The Federal Government, in partnership with development finance institutions and the private sector, should establish a NGN 50 billion Agricultural AI Innovation Fund over five years. This fund should support applied research, pilot deployment, and scaling of AI solutions across the six priority domains identified in this paper. Fund disbursement should be structured as competitive grants with mandatory cost-sharing and matching requirements to ensure private sector alignment and sustainability.

9.7 Implement the AgriConnect Broadband Initiative

The Federal Government should launch a dedicated AgriConnect Initiative, targeting 4G connectivity in all agricultural Local Government Areas by 2027. This should be implemented in partnership with telecommunications companies through a universal service obligation framework, with satellite backup provided through Starlink or equivalent services for the most remote locations. Connectivity is the enabling infrastructure without which all digital agriculture interventions will remain inaccessible to the majority of smallholder farmers.

9.8 Establish the Nigerian Agricultural Digital Extension Platform (NADEP)

NADEP should be a unified digital extension platform delivering AI-generated agronomic recommendations, market intelligence, weather forecasts, and disease alerts through SMS, USSD, and voice interfaces in Nigerian languages. The platform should integrate with NADI data feeds and be managed through a public-private partnership model to ensure sustainability and continuous innovation.

X. CONCLUSION

This study demonstrates that the technologies required to transform Nigerian agriculture already exist and have been successfully deployed both globally and within Nigeria itself. Evidence from the United States, the Netherlands, Japan, and Australia confirms that AI-driven agricultural systems deliver measurable gains in productivity, efficiency, and sustainability. More importantly, pilot initiatives within Nigeria have already validated these outcomes under local conditions (Nawaz et al., 2025).

The persistence of low agricultural productivity in Nigeria is therefore not a consequence of technological limitations, but of institutional and data infrastructure deficiencies. The absence of integrated data systems, weak governance frameworks, and fragmented policy implementation has prevented the scaling of proven solutions (Ikubanni et al., 2025).

Consequently, Nigeria's agricultural transformation depends on a fundamental shift toward data-driven policymaking. The establishment of national data infrastructure, coordinated governance mechanisms, and inclusive digital extension systems is not optional but essential. Without these reforms, existing investments in agricultural policy will continue to underperform.

Conversely, with the adoption of the integrated policy framework proposed in this study, Nigeria has the capacity to close its productivity gap, reduce food import dependency, and emerge as a leader in digital agribusiness across Africa.

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CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this manuscript.

REFERENCES

[1] ABARES. (2022). *Australian agricultural and grazing industries survey*. Australian Bureau of Agricultural and Resource Economics and Sciences.

[2] Akintuyi, O. B. (2024). The role of artificial intelligence in U.S. agriculture: A review. *Open Access Research Journal of Engineering and Technology*, *6*(2), 23-32.

[3] Babar, A. Z., & Akan, Ö. B. (2024). *Sustainable and precision agriculture with the Internet of Everything* [arXiv preprint].

[4] Fadiji, T., Bokaba, T., Fawole, O. A., & Twinomurinzi, H. (2023). Artificial intelligence in postharvest agriculture: Mapping a research agenda. *Frontiers in Sustainable Food Systems*, *7*, 1226583. https://doi.org/10.3389/fsufs.2023.1226583

[5] Federal Ministry of Agriculture and Rural Development. (2022). *Agricultural Sector Action Plan (ASAP) 2022–2027*. Federal Government of Nigeria.

[6] Food and Agriculture Organization of the United Nations. (2022). *The state of food and agriculture 2022: Leveraging automation in agriculture for transforming agrifood systems*. FAO. https://doi.org/10.4060/cb9479en

[7] Grains Research and Development Corporation. (2023). *Return on investment in digital agriculture: A grains industry analysis*. GRDC.

[8] Hampel, G., & Fabulya, Z. (2024). The risks of AI in agriculture. *Analecta Technica Szegedinensia*, *18*(4), 32-44. https://doi.org/10.14232/analecta.2024.4.32-44

[9] Ikubanni, P. P., Ejalonibu, D., Abioye, O. M., Alhassan, E. A., Faloye, O. T., & Adeleke, A. A. (2025). Recent advances of artificial intelligence in the agricultural sector: A review. *NIPES Journal of Science and Technology Research*. https://doi.org/10.37933/nipes/7.4.2025.SI26

[10] International Food Policy Research Institute. (2020). *Evaluation of the Esoko market information system in West Africa* (Discussion Paper 01945). IFPRI.

[11] Kisliuk, B., Krause, J. C., Meemken, H., & Saborío Morales, J. C. (2023). Artificial intelligence in current and future agriculture: An introductory overview. *KI – Künstliche Intelligenz*, *37*(2), 117-132. https://doi.org/10.1007/s13218-023-00826-5

[12] Majeed, Y., Fu, L., & He, L. (2024). Artificial intelligence-of-things (AIoT) in precision agriculture. *Frontiers in Plant Science*, *15*, 1369791. https://doi.org/10.3389/fpls.2024.1369791

[13] Ministry of Agriculture, Nature and Food Quality, Netherlands. (2023). *Topsector Agri & Food: Annual report 2023*. Dutch Government.

[14] Murindanyi, S., Nakatumba-Nabende, J., Sanya, R., Nakibuule, R., & Katumba, A. (2024). *Enhanced infield agriculture with interpretable machine learning approaches for crop classification* [arXiv preprint].

[15] National Bureau of Statistics. (2023). *Nigerian gross domestic product report Q3 2023*. NBS.

[16] Nawaz, U., Zaheer, M. Z., Khan, F. S., Cholakkal, H., Khan, S., & Anwer, R. M. (2025). *AI in agriculture: A survey of deep learning techniques for crops, fisheries, and livestock* [arXiv preprint].

[17] Nwachukwu, I., Amadi, O., & Okoye, F. (2021). Policy implementation gaps in Nigerian agricultural transformation. *African Journal of Agricultural Policy*, *8*(2), 45-63.

[18] Pervez, A. K. M. K., Kabir, M. S., Prodhan, F. A., Rahman, M. H., & Roy, A. (2026). Mapping recent trends in artificial intelligence research for sustainable agriculture: A bibliometric and systematic review. *Discover Artificial Intelligence*.

[19] Razak, S. F. A., Yogarayan, S., Sayeed, M. S., & Derafi, M. I. F. M. (2024). Agriculture 5.0 and explainable AI for smart agriculture: A scoping review. *Emerging Science Journal*, *8*(2). https://doi.org/10.28991/ESJ-2024-08-02-024.