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AGRICULTURE BEYOND TRADITIONAL MODELS:

INTELLIGENT SYSTEMS, RESOURCE CYCLES, AND SYSTEMIC ADAPTATION

EDITOR
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PREFACE

Agricultural systems are undergoing a profound transformation driven by rapid technological advancements, environmental pressures, and the need for sustainable resource management. In this context, traditional models of agriculture are increasingly being re-evaluated, giving way to more integrated, data-driven, and adaptive approaches that respond to the complexities of contemporary food production.

This volume, *AGRICULTURE BEYOND TRADITIONAL MODELS: INTELLIGENT SYSTEMS, RESOURCE CYCLES, AND SYSTEMIC ADAPTATION*, brings together a collection of scholarly contributions that explore these emerging transformations. The chapters address key themes such as the integration of artificial intelligence, the Internet of Things, and machine learning in developing climate-adaptive farming systems. In addition, the discussion of digital agriculture highlights the opportunities and policy challenges associated with technological adoption in developing economies. The examination of resource recovery and waste transformation further reflects the growing importance of circular approaches in enhancing sustainability within agricultural production systems.

By adopting an interdisciplinary perspective, this volume integrates insights from agricultural science, data-driven technologies, environmental sustainability, and resource management. It contributes to academic discourse while also offering practical implications for researchers, policymakers, and practitioners seeking to navigate the transition toward more resilient and intelligent agricultural systems.

It is hoped that this book will serve as a valuable resource for scholars and professionals interested in the future of agriculture, while encouraging further exploration of innovative and sustainable pathways for global food systems.

Editorial Team
May, 2026
Türkiye

CHAPTER 1
INTEGRATIVE AGRICULTURE 5.0 SYSTEMS: AI, IOT AND MACHINE LEARNING FOR CLIMATE-ADAPTIVE CROP AND LIVESTOCK FARMING

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INTRODUCTION

Today, the world's food production systems are under immense pressure owing to factors such as rising population figures, climate change, and resource scarcity. Although the rate at which global populations grow is reducing in comparison to previous decades, there are still projections that the world population will keep growing through mid-century, meaning there will be sustained long-term demands for food and agriculture products (OECD/FAO, 2025). Meanwhile, the effects of climate change are continuing to affect agriculture. This includes changing rainfall patterns, increasing global temperatures, and an increase in the occurrence of severe weather events (OECD/FAO, 2025), all of which could negatively impact agricultural productivity. In light of these issues, innovation in agriculture, as exemplified in the concepts of Agriculture 5.0, would be essential.

Agriculture 5.0 has been coined to represent the use of modern technologies in combination with sustainable practices as illustrated in Figure 1. Specifically, the term Agriculture 5.0 was inspired by Industry 5.0 developed by the European Commission. In the industrial sector, Industry 5.0 focuses on human-machine cooperation and resilience, along with sustainability in general instead of efficiency (European Commission, 2022). Similarly, in agriculture, it represents the transformation of productivity-oriented systems into holistic models that take care of environmental impact, social inclusion, and sustainability (Javaid et al., 2023; Brunori et al., 2025). Artificial intelligence (AI), IoT, and ML are among core enabling technologies.

The use of Crop-Livestock Integrated Setting (CLIS) offers an appropriate setting for the implementation of Agriculture 5.0. They are practiced on a global scale and contribute immensely to agriculture. The complexity associated with CLIS results from the interaction between crops, livestock, soils, and climate and poses serious management issues. Digital technologies can be used to enhance the functionality of CLIS through improved monitoring, prediction, and decision-making abilities, but they also raise concerns regarding data ownership and governance (Herrero et al., 2020; Berisha et al., 2026).

1. THE ARCHITECTURE OF AGRICULTURE 5.0: A CONCEPTUAL FRAMEWORK

Agriculture 5.0 must be viewed not only as a technology but rather as a layered sociotechnological system where the digital technology is embedded in farming, ecology, and institutions. The model discussed in this section is composed of four layers (Figure 2) which help to categorize the technological elements discussed in this chapter.

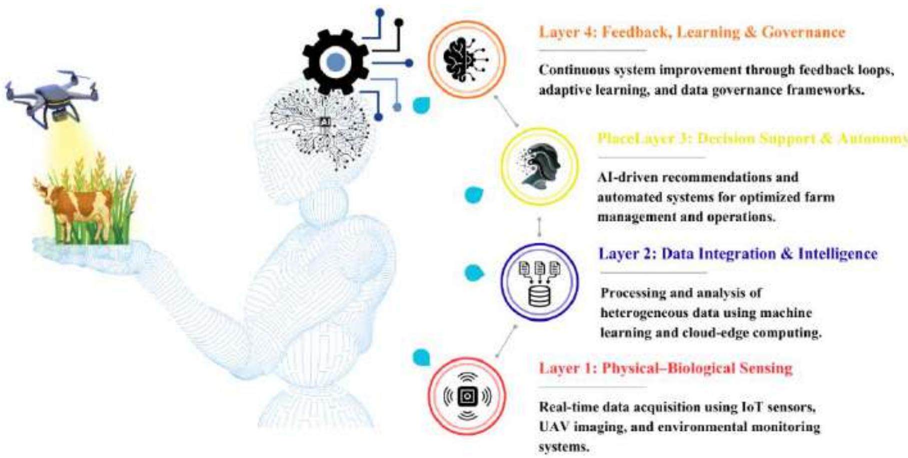

Figure 1. Architecture of Agriculture 5.0

1.1 Layer 1: Physical–Biological Sensing

The basis of Agriculture 5.0 is founded on data that has been collected using the physical-biological sensing system. The use of advanced Internet of Things (IoT)-based technologies such as soil moisture sensors, multispectral imaging using Unmanned Aerial Vehicles (UAVs), animal health trackers, and weather stations ensures the continual and timely monitoring of agricultural conditions. According to recent reports by the International Telecommunication Union (ITU), there has been an explosion in the number of connected devices globally, totaling billions, and the trend will be maintained due to developments in edge computing, low power sensors, and wireless communications (ITU, 2024; ITU, 2025). This increasing network is enabling the implementation of smart sensing technologies in agriculture.

1.2 Layer 2: Data Integration & Intelligences

Sensor outputs are typically characterized by noise, heterogeneity, and high dimensions. To derive valuable information, machine learning algorithms, including classical algorithms such as Random Forests and Support Vector Machines (SVMs), and more sophisticated deep learning approaches, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs), are employed for transforming sensor inputs into usable knowledge. Recent studies demonstrate that the fusion of IoT sensor networks and machine learning algorithms allows for constant monitoring, environmental parameter prediction, and decision-making in precision agriculture (Miller et al., 2025). Moreover, contemporary smart farming solutions have started leveraging cloud and edge computing capabilities to efficiently process sensor inputs, perform scalable analyses, and make real-time inferences at the edge (Tariq et al., 2025).

1.3 Layer 3: Decision Support and Autonomy

The decision support and automation systems transform the information gained from the intelligence layer into practical farm management decisions. Such decision systems may consist of farmer advisory solutions and automated actuators, including the application of fertilizers with variable rates, intelligent irrigation systems, and robotic milking machines. Recent studies have found that agricultural advisory systems incorporating AI and IoT technologies are more common in today's farming sector, as such systems lead to greater efficiency in resource utilization, increased productivity of labor, and sustainable farming techniques (Verdouw et al., 2021; Zhang, 2025). Automation systems, especially systems of precision irrigation and livestock management, have shown significant value in achieving optimal resource use and productivity.

1.4 Layer 4: Feedback, Learning, and Governance

The results achieved through decision support systems and autonomous systems are constantly fed back into machine learning algorithms, facilitating the process of iteration and improvement of these models. The process of such feedback leads to the creation of an adaptable system similar to the principle of closed-loop controls in engineering, which works due to improvements through additional input. Aside from learning aspects, another component of the aforementioned layer is associated with governance issues, including questions of data ownership, interoperability, algorithm transparency, and regulation. As research shows, it becomes clear that with the development of digital agriculture platforms, questions of data management and sharing become crucial to consider. Otherwise, the issue arises that digitalization may not yield benefits for farmers but only for large agribusiness companies (Klerkx et al., 2019; Brunori et al., 2025; Berisha et al., 2026).

2. ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) IN CROP AND LIVESTOCK MANAGEMENT

Artificial intelligence and machine learning play a significant role in Agriculture 5.0 as they facilitate evidence-based decisions from agriculture. As is evident in Table 1 below, different models of AI/ML prove efficient in carrying out various agricultural activities including diseases identification, forecasting production and precision farming.

Table 1. AI and Machine Learning Model in Agriculture 5.0

AI / ML Approach	Task	Reference
Convolutional Neural Network (CNN)	Plant disease identification from leaf images	Mohanty et al., 2016
Long Short-Term Memory (LSTM)	Crop yield time-series forecasting	(Khaki et al., 2020)
Random Forest (RF)	Soil fertility / property classification or mapping	Padarian et al., 2020

AI / ML Approach	Task	Reference
Transformer (Vision)	Multi-spectral crop mapping from UAV	(Guo et al., 2025)
Generative AI (LLM)	Farmer advisory chatbot (local language)	(Ravindran et al., 2026)
Reinforcement Learning	Autonomous irrigation scheduling	Saikai et al., (2023)
Hybrid Transformer-CNN	Real-time plant disease detection under field conditions (robust to noise, lighting variations)	Zeng et al. (2025)
Hybrid CNN + Temporal Attention	Real-time soil moisture & temperature prediction for precision agriculture	Suresh et al., (2025)
Large Language Model (AgriGPT)	Agricultural reasoning, multi-hop Q&A, and farmer advisory	Yang et al. (2025)
Hybrid Reinforcement Learning + LLM	Crop management optimization (fertilization & irrigation)	Chen et al. (2025)
Hybrid CNN-Transformer	Calving time prediction in dairy cattle (precision livestock farming)	Zhao et al. (2025)
Support Vector Machine (SVM)	Livestock behavior classification	Dhakshinamoorthy et al. (2025): SVM for cattle behavior
Thermal Image CNN + Sensor Fusion	Livestock mastitis detection	Asogan et al. (2025)
Deep Neural Networks (DNN)	Smart livestock monitoring	Shin et al. (2025)
CNN + Audio Feature Extraction	Early disease cough/abnormal sound detection	Manikandan & Neethirajan (2025)

2.1 Artificial Intelligence (AI) and Machine Learning (ML) in Crop Management

Utilizing AI/ML technology in agricultural crop production is advancing at a fast rate since 2022 owing to increased data labeling, enhanced hardware capabilities, and increased use of cloud training platforms. In this part, we explore five key areas of application.

Disease and Pest Detection

Computer vision algorithms have revolutionized the diagnosis of plant diseases by allowing real-time automated disease detection through image recognition. Deep learning, specifically CNNs, has been found to be highly effective in the identification of diseases in crops across different plant species in controlled as well as field conditions. The recent reviews reveal that CNN-based algorithms are far superior to other types of algorithms used in plant pathology based on their diagnostic performance when trained on large and annotated image datasets (Kamilaris & Prenafeta-Boldú, 2018; Zeng et al., 2025). Apart from the application of machine learning in detecting plant diseases, it also finds extensive applications in the detection of pests on the landscape level, providing the means for early detection. By combining satellite imaging along with other factors, like weather data, early prediction and monitoring of potential pests is possible. For example, the Food and Agriculture Organization developed the Fall Armyworm Monitoring and Early Warning System (FAMEWS), which integrates field-based observation with geospatial analysis to facilitate early warning and monitoring of risks related to pests in several countries (Buchaillot et al., 2022).

Yield Forecasting

Yield prediction is still one of the key problems in agronomy, and the development of artificial intelligence techniques such as deep learning and transformers has considerably improved the accuracy of prediction. LSTM neural networks are widely applied to predict the yields from multi-year satellite time series data and meteorology data, outperforming conventional process-based models when large data availability is available (Ashfaq et al., 2025a).

The most recent study published in 2025 presents trends in developing hybrid and transformer-based approaches, which are capable of combining spatial-temporal features for predicting crop yields. CNN models combined with attention or transformers showed increased generalizability for predicting crop yield across different agro-climatic zones (Zeng et al., 2025; Chen & Huang, 2025). The approach can efficiently use various sources of data such as satellite imagery, UAV images, and climate information.

With smaller spatial resolution, the combination of high-resolution images captured using UAVs with Vision Transformers (ViTs) is making it possible to estimate yields and zones at the sub-field level for precision agriculture (Zhang et al.,2022) . In general, the use of deep learning, attention networks, and multiple data sources is ensuring that yield forecasting will be an important part of Agriculture 5.0.

Precision Nutrient and Irrigation Management

The development of AI-driven variable rate technology (VRT) for nutrient application is commercially mature. The Operations Center by John Deere, which covers more than 300 million acres worldwide, uses gradient boosting algorithms to recommend nitrogen fertilizer rates at 5 meters intervals based on historical crop yield maps, soil electrical conductivity, and near real-time normalized difference vegetation index (John Deere, 2026). Trials conducted in the US Midwest demonstrated that AI-VRT nitrogen recommendations cut overall nitrogen application rates by 12–18%, maintaining or increasing crop yields while cutting nitrous oxide emissions (Xu et al., 2024 ; Wang, 2025).

In irrigation applications, reinforcement learning (RL) has proven especially effective. RL agents, trained within digital twins of soil-plant-atmosphere systems, learn irrigation policies that optimize crop yields subject to water availability constraints. In recent years, reinforcement learning–based irrigation control has been tested on cotton farms, resulting in higher water use efficiency than traditional evapotranspiration–based scheduling methods without sacrificing yield (Chen et al., 2023; Chen et al., 2025; Saikai et al., 23).

Generative AI and Farmer Advisory Systems

Current developments in generative artificial intelligence have led to the development of large language models (LLMs), which can provide a scalable solution for providing knowledge advisory services to farmers in agriculture. LLM-based advisory services can aggregate various datasets such as agronomy practice, weather, and farmer knowledge databases to offer personalized agronomic advices in plain language. The latest studies on AI in agriculture in 2025 have pointed out the importance of using AI-powered conversation assistants to increase the access to agronomic advisories, especially in resource-poor environments by developing mobile apps and messaging software. Studies have found that AI conversation-based advising is likely to improve the accuracy and efficiency of the advice compared to traditional extension advising programs, with significant reduction in the costs required for spreading the information (Chen & Huang, 2025; Brunori et al., 2025). LLM-based advisory systems will form an important part of the Agriculture 5.0 approach, which will emphasize evidence-based data support services tailored to human needs.

2.2 IoT and AI in Precision Livestock Farming

From rule-based alerts to true predictive capabilities powered by AI, precision livestock farming (PLF) has seen considerable development. It now involves combining the use of the Internet of Things with machine learning to track the well-being and performance of livestock.

Wearable Biometric Monitoring

The use of wearable biometric technologies is essential to precision livestock farming since it makes it possible to monitor continuously the health and behavior of livestock animals through the use of IoT-based sensors like ear tags, rumen boluses, and accelerometers. The data collected by these devices about animal behavior, rumination, and body temperature are analyzed by machine learning algorithms, providing better results in the detection of estrus and health problems compared to the classical approach based on observations (Shin et al., 2025).

Moreover, the incorporation of biometric data together with climatic factors like the Temperature-Humidity Index (THI) contributes to heat stress prediction and adaptation of animals to adverse climatic changes by applying AI models, including LSTM neural networks (FAO, 2024).

Automated Health Surveillance

One important application of precision livestock farming is the early detection of diseases through continuous health monitoring with the help of AI-based systems. Some of the latest research studies reveal the effectiveness of machine vision and deep learning algorithms such as CNNs and LSTM models in recognizing cattle lameness based on gait pattern recognition through video data and sensors (Schlageter-Tello et al. (2014) ; Zhang et al., 2023).

For early detection of respiratory illness in pigs, the technology of multimodal sensing including microphones, thermal imaging, and vision-based monitoring techniques plays an important role as it helps detect symptoms in pigs in their very initial stages (before the symptoms become evident). The sound-based system has been proved highly effective in recognizing patterns related to respiratory illness and distress (Reza et al., 2025).

Smart Feeding and Precision Nutrition

Feeding systems that have been automated rely on ML for optimizing the (Total Mixed Ratio) TMR formulation of individual animals. The Calm feeding robot developed by Lely, coupled with an ML model, alters the ration formulation depending on milk yield, animal body mass, and reproductive status to reduce costs per kg of milk generated. A meta-analysis of 24 farms in Europe that use feeding robots powered by artificial intelligence revealed that the average feed cost was reduced by 8.4%, while nitrogen output was decreased by 11.2% when compared to conventional group-based feeding systems (Espinoza-Sandoval et al., 2024).

3. INTEGRATIVE AI–IOT FRAMEWORK FOR INTEGRATED CROP–LIVESTOCK SYSTEMS

The greatest impact that Agriculture 5.0 can make is not by applying its technological advances individually to crop or animal farming, but through integrating the systems of crops and animals using common data platforms and decision-making algorithms. The concept of integrated crop-livestock systems (ICLS) relies on synergies like manure serving as fertilizer for the crops and residue from crops feeding the animals.

3.1 Shared Data Architectures

In an effort to efficiently manage integrated crop-livestock farming systems, there have been efforts made towards development of interoperable data infrastructure that will integrate the flow of data regarding crops and livestock. Some recent developments that have been noted include the Animal Data Exchange framework developed by International Committee for Animal Recording and the Agricultural Interoperability Network (AgIN) initiative launched by Agricultural Industry Electronics Foundation in 2025. The developments will facilitate data interoperability and help in integrating data on soil, crops, and livestock leading to improved efficiency and decision-making in Agriculture 5.0 systems (ICAR, 2025).

3.2 Co-optimization Algorithms

The co-optimization of crops and livestock in mixed farming is challenging because of the various feedback mechanisms and objectives involved, such as achieving the highest possible yields while at the same time reducing the environmental impact of the process. Multi-objective evolutionary algorithms (MOEAs) have been considered in previous studies on agriculture as a good approach to finding compromise solutions to achieve trade-offs between conflicting objectives in an integrated farming system, especially when used together with multi-source sensor data. For instance, recent studies have reviewed the approaches where optimization algorithms and digital twin technology were used as part of the decision support for integrated agricultural activities such as soil management, growth of crops, and livestock monitoring.

In general, digital twin technology allows the creation of dynamic virtual models of farm systems using Internet of Things technologies, machine learning methods, and modeling approaches. The integration of such an approach provides a framework that enables the simulation and evaluation of management options prior to implementation (Awais et al., 2025; Tagarakis et al., 2024; Wang, 2024).

3.3 Nutrient Cycling and Circular Economy

One of the key synergies in integrated crop-livestock production systems involves efficient nutrient cycling from animal manure to crop fertilizers. AI specifically ML algorithms, has been used more often to predict the nutrient content of soil using information about climatic conditions and soil composition together with sensor information to provide site-specific fertilizer recommendations that decrease synthetic fertilizers' need and environmental effects. Recent studies have shown the application of ML algorithms with the help of spectral analysis and sensors to predict soil macronutrient concentration, thus providing an opportunity to increase the efficiency of fertilization procedures. More sophisticated techniques that combine hyperspectral imagery with advanced deep learning algorithms have shown superior results in predicting the concentration of nitrogen and phosphorus in soil, which shows significant potential for nutrient prediction in real-time (Vullaganti et al., 2025; Vullaganti et al., 2026).

4. CLIMATE ADAPTATION MECHANISMS IN AGRICULTURE 5.0

Agricultural climate adaptation involves the dual processes of mitigation (decreasing agricultural impacts on climate change) and adaptation (modifying agricultural systems to cope with changing climates). Agricultural 5.0 technologies deal with both aspects using several intersecting approaches.

4.1 Dynamic Crop Calendars and Phenology Monitoring

Phenology and dynamic crop calendars have become increasingly accessible due to the advances in remote sensing and artificial intelligence.

For instance, satellite-based remote sensing combined with decision support system tools like DSSAT using MODIS products, such as MCD15A3H (for leaf area index) was found to be able to estimate the phenological variables of crops such as LAI and biomass, with great accuracy (R^2 = 0.90), across multiple growing seasons. This has contributed towards improving the crop monitoring and management practices in Pakistan, as well as other countries with similar agroecosystems (Amin et al., 2025). Furthermore, phenological metrics derived from satellite imagery based on harmonized data from Landsat and Sentinel-2 satellites were employed to determine the field-level planting date for crops like corn and soybean, which is found to explain nearly 77% of the variance in planting dates at field-level, and was consistent with agricultural progress reports (Zhou et al., 2024).

4.2 Water Stress Management

It is projected that water stress will become a prevalent hindrance to the success of agriculture due to climate change because of growing competition for limited water sources and changing hydrologic patterns, with projections indicating that close to 33 % of irrigated crop output has been experiencing extremely high water stress levels and could climb towards 40 % by 2040. (World Resources Institute, 2019; 2024). The deployment of IoT-based precision irrigation techniques, utilizing soil moisture sensors, weather information, and ET models, represents one such response to water stress that has been advocated in Agriculture 5.0. Irrigation schemes powered by machine learning, relying on both satellite imagery and in situ sensor networks, have shown promise as means of optimizing irrigation scheduling and increasing the efficiency of water utilization in farming activities. For example, irrigation management based on satellite-powered machine learning algorithms was found to offer better estimates of crop water demand and irrigation decisions for cotton farms than traditional irrigation scheduling systems (Nasim & Khurram, 2025). Moreover, a meta-analysis of smart irrigation technology found that irrigation systems employing either sensors or machine learning consistently outperformed irrigation systems managed manually by farmers in terms of irrigation efficiency (Wolfert et al., 2017).

4.3 Carbon Sequestration and GHG Monitoring

AFOLU (Agriculture, Forestry, and Other Land Use) activities account for roughly 21-23% of total greenhouse gas (GHG) emissions from human sources worldwide, indicating the importance of the industry in mitigating climate change (IPCC, 2022). With the emergence of Agriculture 5.0 technology, developments in remote sensing techniques, artificial intelligence, and digital soil maps are now providing better monitoring of soil organic carbon (SOC) content and GHG emissions. Recent studies have shown that machine learning algorithms like Random Forest, in tandem with satellite imagery and environmental factors, can greatly enhance the spatial prediction of SOC content within agricultural fields (Li et al., 2023). While these technologies are gradually being used to develop MRV systems and estimate carbon footprinting, some limitations still need to be overcome in terms of temporal changes and SOC content uncertainties (FAO, 2024).

Methane emission in livestock is another area where there are still major challenges. Recent research shows that methanogenic emissions can be decreased by up to 50% when livestock feeds on seaweed called Asparagopsis (Beulque et al., 2023). Another important innovation in this context includes the development of precision livestock farming systems, which are designed to optimize feeding through sensor data and intelligent decision-making systems, thus leading to improved productivity and lower emissions per unit of output (Wolfert et al., 2017).

4.4 Extreme Weather Response and Resilience

The development of Agriculture 5.0 makes possible the prediction and monitoring of extreme weather in real time through the use of AI and IoT solutions. Floods are common occurrences in areas like the Mekong River Basin, which is why the application of LSTM models in predicting streamflow and floods has proven to be quite accurate (Vu et al., 2023). Although effective in predicting extreme weather events, the influence that LSTM modeling may have on reducing crop losses varies greatly depending on the context.

Likewise, there has been an increasing trend in applying machine learning models for predicting frost in orchard systems through the use of meteorological information and sensor networks.

Through this method, not only can frost prediction be improved, but also actions taken to protect crops from cold stress can become automated (Hua et al., 2025).

5. BARRIERS TO ADOPTION, ETHICAL CONSIDERATIONS, AND GOVERNANCE

Despite the significant demonstrated capabilities of these technologies, the large-scale adoption of Agriculture 5.0 technologies is hindered by significant structural, ethical, and political barriers. It is essential to thoroughly evaluate these barriers in order to strategically plan policies that will support the adoption of these technologies in an equitable and inclusive manner.

5.1 Digital Infrastructure and Connectivity Gaps

In general, Agriculture 5.0 technologies require the availability of reliable connectivity in real time in order to efficiently transmit data. In 2024, there are about 2.6 billion individuals worldwide who lack reliable internet connectivity (International Telecommunication Union, 2024). In 2025, an estimated 2.2 billion individuals worldwide remained without internet access (International Telecommunication Union, 2025). The availability of reliable broadband is particularly problematic in rural agricultural areas. Currently, only 24% of rural areas in Sub-Saharan Africa have reliable 4G network availability required for the transmission of data in IoT technologies. Edge computing can mitigate the lack of reliable cloud connectivity in Agriculture 5.0 technologies. However, the hardware required is quite expensive, ranging between US$150 and US$800 per node, which is beyond the average annual income of agricultural households earning less than US$1,500 - 2,000. (World Bank, 2026).

5.2 Data Sovereignty and Ownership

Agricultural data, including crop performance history, soil maps, and livestock health records, is valuable. Platform corporations, for example, John Deere, Bayer/Climate FieldView, Trimble, usually have a license agreement that allows them to use the anonymized and aggregated data. Therefore, the question is who will benefit from the value created by the farmer's data.

The EU Data Governance Act is a promising approach for setting the rights for the farmer's data, including the Agricultural Data Spaces initiative. However, no global standard is yet developed (Brunori et al., 2025; Berisha et al., 2026).

5.3 Algorithmic Bias and Model Transferability

There is a possibility of ML models performing poorly in the Global South, given their training in large-scale farming in the Global North. A systematic review by Botero-Valencia et al. (2025) revealed that 74% of published agricultural deep learning studies used data from only three countries, i.e., the USA, China, and Netherlands. This brings forth questions of model generalizability. Algorithmic recommendations may be biased towards high-input farming, which would be disadvantageous to smallholder farmers who do not have access to such resources.

5.4 Sociotechnical Lock-in and Farmer Agency

However, there is a threat that as Agriculture 5.0 systems increasingly take over decision-making through automation, there will be a loss of skills for the farmer. When there are system failures, such as sensors or connectivity failures, there is a threat that a farmer who has become accustomed to using recommendations from AI systems may not have the skills to effectively manage a farm using their own skills. The philosophy of Agriculture 5.0 recognizes human skills as a key concern, as stated in Botero-Valencia et al. (2025).

5.5 A Governance Framework for Equitable Agriculture 5.0

The governance structure that is fit for supporting an Agricultural 5.0 would need to cover four aspects: (i) data rights and standards for data interoperability to enable farmers to own and benefit from data; (ii) algorithmic accountability measures that require algorithmic explainability and bias assessments; (iii) access equity measures to ensure that public funding for digital support infrastructure is equitably distributed among smallholder and female farmers; and (iv) environment-related measures to prevent the misuse of AI for optimizing input use in ways that compromise ecosystem service delivery. The United Nations' Committee on World Food Security (CFS) has started to develop voluntary guidelines for Digital Food and Agriculture that cover some of these aspects (CFS, 2023).

CONCLUSION AND FUTURE DIRECTIONS

This chapter has provided an extensive overview of Agriculture 5.0 as an integrative approach combining AI, IoT, and machine learning to support climate-adaptive integrated crop-livestock systems. Firstly, the convergence of IoT, machine learning, and edge computing has opened a new frontier in agricultural precision. Secondly, the integration of crop and livestock production through digital platforms enabled by co-optimization algorithms, digital twins, and circular nutrient management remains a relatively underexplored frontier compared to single-commodity systems. The ICLS studies reviewed here demonstrate that intelligent data systems can significantly amplify benefits in nutrient cycling, income diversification, and carbon sequestration.

Lastly, the reviewed literature clearly shows that technological performance alone does not determine adoption. Success hinges on robust connectivity infrastructure, institutional trust, equitable data governance, algorithmic fairness, and the preservation of farmer agency. Future Agriculture 5.0 initiatives must therefore involve social scientists and ethicists from the design stage, rather than treating societal dimensions as an afterthought.

Looking ahead, several promising technologies could shape the next phase of Agriculture 5.0. Foundation models: large, multi-modal AI systems pre-trained on diverse agricultural data hold promise for developing universal agronomic reasoning engines that can be fine-tuned locally with minimal additional data. Quantum optimization algorithms may help overcome computational limits in large-scale, multi-objective farm management, while the combination of synthetic biology and AI-driven precision fermentation could enable on-farm production of biological crop protectants and feed additives, further integrating digital intelligence with biological processes.

The agricultural sector stands at a critical inflection point.

While the technologies reviewed in this chapter have reached sufficient maturity to deliver transformative outcomes, the primary constraints are now institutional, financial, and political. Bridging the gap between technological possibility and equitable, climate-smart agricultural transformation remains one of the defining challenges for agricultural science in the twenty-first century.

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CHAPTER 2
DIGITAL AGRICULTURE IN DEVELOPING ECONOMIES: OPPORTUNITIES, CHALLENGES, AND POLICY IMPLICATIONS

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INTRODUCTION

Agriculture continues to be a cornerstone of economic development, social stability, and food security in many developing countries. It provides livelihoods for a large proportion of rural populations, especially smallholder farmers, who are often the most vulnerable to economic shocks and climate variability (Taye & Ambaye, 2023; Olajide et al., 2024). Despite its critical role, agricultural productivity in these regions remains constrained by structural challenges such as fragmented supply chains, inadequate infrastructure, limited access to credit, and lack of timely market information (World Bank, 2023; Gangwar et al., 2024).

Digital agriculture, defined as the integration of information and communication technologies (ICT), artificial intelligence (AI), remote sensing, Internet of Things (IoT), and big data analytics into farming practices, has emerged as a transformative solution to these challenges (FAO, 2023; Manzoor et al., 2025). These technologies enable farmers to access real-time information on weather patterns, crop health, market prices, and financial services, thereby improving decision-making, reducing losses, and increasing productivity (Munyua et al., 2024; Yuan & Sun, 2024). Digital agriculture also facilitates precision farming, automation, and optimized resource utilization, contributing to climate-smart and sustainable agricultural practices (Kumar & Singh, 2023; Zhang et al., 2025).

Moreover, digital technologies have significant implications for financial inclusion and market integration. Mobile banking, digital credit platforms, and e-marketplaces allow smallholder farmers to access financial services and reach broader markets, potentially improving income stability and investment capacity (Jack & Suri, 2014; Zhou et al., 2024). These developments help address systemic inequalities by enabling more equitable access to resources, knowledge, and opportunities, although challenges in access and adoption remain (Oluwatayo & Yusuf, 2023; Pappa et al., 2024).

However, adoption of digital agriculture in developing economies is uneven. Key barriers include limited digital infrastructure, low digital literacy among farmers, high costs of technology adoption, and gaps in policy and regulatory frameworks (Olajide et al., 2024; Nyamao & Muriuki, 2024).

Gender disparities, social exclusion, and rural-urban divides further exacerbate adoption challenges, making inclusivity a critical consideration for sustainable digital transformation (Oluwatayo & Yusuf, 2023; Degila et al., 2023).

This chapter seeks to provide a comprehensive review of digital agriculture in developing economies, examining the opportunities it presents, the challenges to adoption, and the policy measures required to enhance its effectiveness. This chapter aims to inform stakeholders including policymakers, researchers, and practitioners, on how to leverage digital agriculture for productivity enhancement, market efficiency, financial inclusion, and sustainable rural development.

1. LITERATURE REVIEW

The concept of digital agriculture is closely linked to the broader framework of agricultural innovation systems. These systems emphasize the interactions between farmers, research institutions, policymakers, and private sector actors in promoting technological change and agricultural development (Klerkx et al., 2019).

Two major theoretical perspectives explain the adoption of digital technologies in agriculture. The first is the Diffusion of Innovation Theory which suggests that new technologies spread gradually among users based on perceived benefits, communication channels, and social networks. The second is the Technology Acceptance Model which argues that adoption depends largely on perceived usefulness and ease of use (Davis, 1989).

Empirical studies demonstrate that digital tools can improve access to agricultural information and reduce market inefficiencies. For example, mobile phone technologies have been shown to reduce price dispersion and improve farmers' access to market information (Aker, 2011). Similarly, digital advisory services have been found to enhance farmers' knowledge and productivity by providing timely recommendations (Fabregas et al., 2019).

2. CONCEPTUAL FOUNDATIONS OF DIGITAL AGRICULTURE

Digital agriculture represents a transformative approach to farming that integrates digital technologies and data-driven decision-making across the agricultural value chain. It encompasses the use of mobile applications, precision farming tools, Internet of Things (IoT) devices, remote sensing, artificial intelligence (AI), and big data analytics to improve agricultural productivity, sustainability, and resilience (FAO, 2023; Zhang et al., 2025).

Definition and Scope

Digital agriculture can be defined as the application of digital tools and platforms to monitor, analyze, and manage agricultural operations in order to enhance productivity and efficiency (Munyua et al., 2024). Its scope includes digital advisory services, e-marketplaces, precision agriculture technologies, digital finance, and supply chain management solutions (Manzoor et al., 2025; Yuan & Sun, 2024). The adoption of these tools enables farmers to access timely information on weather, soil conditions, pest outbreaks, and market prices, facilitating informed decision-making and resource optimization (Kumar & Singh, 2023).

Key Components of Digital Agriculture

a. Digital Advisory Services: Mobile-based platforms provide farmers with real-time recommendations for crop management, pest control, and climate adaptation strategies (Degila et al., 2023).
b. Precision Agriculture: Sensors, drones, GPS-guided equipment, and satellite imagery enable precise application of inputs such as fertilizers and irrigation, reducing waste and improving yields (Zhang et al., 2025).
c. Financial Technologies: Mobile banking, digital credit, and insurance platforms facilitate financial inclusion, enabling farmers to invest in inputs and manage risks effectively (Jack & Suri, 2014; Zhou et al., 2024).
d. Digital Market Platforms: Online marketplaces connect farmers directly with buyers, reducing information asymmetry, transaction costs, and postharvest losses (Taye & Ambaye, 2023).

Theoretical Perspectives

Understanding the adoption of digital agriculture requires conceptual frameworks that explain technology uptake and behavioral change:

a) Diffusion of Innovation Theory: Explains how innovations spread through populations based on relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003).
b) Technology Acceptance Model (TAM): Highlights perceived usefulness and ease of use as critical factors influencing adoption of digital tools (Davis, 1989).
c) Socio-technical Systems Perspective: Emphasizes the interaction between technology, social actors, and institutional structures in shaping adoption and outcomes (Rotz et al., 2019).

Digital Agriculture in Developing Economies

In developing countries, digital agriculture adoption is influenced by infrastructure, literacy, access to devices, and institutional support (Olajide et al., 2024; Nyamao & Muriuki, 2024). While mobile-based solutions for market information and weather forecasts have gained traction, integration of advanced technologies like AI and IoT remains limited due to high costs and technical skill requirements (Munyua et al., 2024; Zhang et al., 2025).

Digital agriculture in these economies holds promise for improving productivity, enabling climate-smart practices, enhancing market participation, and supporting inclusive growth. However, challenges in adoption highlight the importance of policy support, capacity building, and infrastructure development to fully realize its potential (Oluwatayo & Yusuf, 2023; Manzoor et al., 2025).

3. EVOLUTION AND TRENDS IN DIGITAL AGRICULTURE

The evolution of digital agriculture has been driven by rapid advancements in information and communication technologies, mobile computing, and data analytics. Historically, agricultural innovation in developing economies focused on improving inputs, crop varieties, and extension services.

The integration of digital tools represents a paradigm shift, enabling more precise, data-driven, and scalable interventions (FAO, 2023; Manzoor et al., 2025).

Global Developments

In developed countries, digital agriculture has advanced rapidly, encompassing AI-driven predictive analytics, autonomous machinery, satellite-based crop monitoring, and blockchain-enabled supply chains (Smith et al., 2025; Zhang et al., 2025). These innovations have enhanced productivity, optimized resource use, improved traceability, and facilitated sustainability by providing decision support systems for farmers and agribusinesses (Kumar & Singh, 2023).

Adoption in Developing Economies

Adoption of digital agriculture in developing economies is growing, albeit unevenly. Mobile-based platforms providing weather forecasts, market prices, and advisory services are increasingly utilized across Sub-Saharan Africa, South Asia, and parts of Latin America (Degila et al., 2023; Nyamao & Muriuki, 2024). These platforms have improved farmer decision-making, reduced postharvest losses, and expanded access to markets. However, advanced tools like IoT sensors, AI-powered monitoring, and precision farming are still limited due to high costs, technical skill requirements, and inadequate infrastructure (Munyua et al., 2024; Zhang et al., 2025).

Emerging Technologies

Recent trends indicate a shift toward integrating multiple technologies to create comprehensive digital agriculture ecosystems:

Artificial Intelligence (AI) and Machine Learning: Used for pest detection, yield prediction, and farm management optimization (Smith et al., 2025; Yuan & Sun, 2024).

Remote Sensing and Satellite Imagery: Monitoring crop health, soil moisture, and weather patterns (Gangwar et al., 2024).

Blockchain: Enhancing transparency, traceability, and trust in agricultural supply chains (Manzoor et al., 2025).

Internet of Things (IoT): Smart sensors for irrigation, nutrient monitoring, and livestock management (Kumar & Singh, 2023).

Key Drivers of Evolution

Mobile Connectivity: Widespread mobile phone adoption enables access to digital services (Jack & Suri, 2014; Degila et al., 2023).

Data Analytics and Cloud Computing: Facilitate processing of large datasets for actionable insights (Munyua et al., 2024).

Policy and Institutional Support: Government initiatives and public-private partnerships promote adoption of digital tools (Manzoor et al., 2025).

Climate and Market Pressures: Farmers increasingly adopt digital solutions to manage risk and optimize production (Gangwar et al., 2024; Zhang et al., 2025).

Implications

The evolution of digital agriculture has transformed how farmers, agribusinesses, and policymakers interact with agricultural data. Enhanced decision-making, predictive insights, and real-time monitoring create opportunities for improved productivity, market participation, financial inclusion, and climate resilience (Yuan & Sun, 2024; Zhou et al., 2024). However, equitable access remains a challenge, necessitating targeted interventions to bridge the digital divide (Oluwatayo & Yusuf, 2023).

Digital agriculture has increasingly gained attention as a transformative approach not only to improve agricultural productivity and market efficiency but also to promote environmentally sustainable food systems in emerging economies. A growing body of literature highlights the diverse technologies available—including artificial intelligence (AI), the Internet of Things (IoT), precision agriculture tools, mobile-based advisory platforms, and digital marketplaces—and examines their potential to optimize resource use, reduce environmental impacts, and enhance resilience to climate change (Gumbi et al., 2026; Zhang et al., 2024).

4. DIGITAL AGRICULTURE AND ENVIRONMENTAL SUSTAINABILITY

Digital agriculture contributes to environmental sustainability by improving resource-use efficiency, reducing waste, and minimizing ecological footprints. Technologies such as precision irrigation, soil and nutrient monitoring, and AI-based predictive modeling help farmers apply water, fertilizers, and pesticides more judiciously, mitigating soil degradation, water contamination, and biodiversity loss (Wolfert et al., 2017; Duguma & Bai, 2025).

Digital tools also enhance market efficiency while indirectly supporting environmental goals. By facilitating real-time access to market prices and demand forecasts, mobile-based platforms reduce overproduction, post-harvest losses, and waste along value chains (Ayim et al., 2022; Finger et al., 2019). E-marketplaces and contract farming systems streamline supply chains, which reduces unnecessary transportation and associated greenhouse gas emissions (Zhang et al., 2024).

Impacts on Productivity, Food Security, and Environmental Resilience

Digital agriculture supports sustainable productivity and food security while promoting resilience to environmental shocks. Precision agriculture and IoT-enabled sensors enable farmers to monitor soil health, water availability, and crop stress, optimizing input use and reducing environmental degradation (Gumbi et al., 2026). In India, platforms such as e-NAM (National Agriculture Market) enhance yields while reducing inefficiencies that contribute to soil exhaustion and resource depletion (Kumar & Singh, 2022). Similarly, mobile-based fertilizer distribution systems in Nigeria, such as the Growth Enhancement Support Scheme (GESS), improve input efficiency and reduce environmental overuse.

These interventions also address the four pillars of food security; availability, access, utilization, and stability, while integrating environmental considerations. Improved logistics and market information reduce post-harvest losses, promoting food availability and decreasing unnecessary land clearing or resource exploitation (World Bank, 2020).

Digital advisory and e-payment platforms enhance access and economic stability, allowing smallholders to adopt sustainable practices without sacrificing income (Ayim et al., 2022). AI-guided crop diversification and nutrient monitoring enhance utilization by promoting environmentally resilient and nutrient-rich crops (FAO, 2021). Stability is supported through climate-smart forecasting, early warning systems, and adaptive management that mitigate the impacts of pests, droughts, and market fluctuations (Gumbi et al., 2026).

Moreover, food security in emerging economies is deeply intertwined with environmental sustainability. Unsustainable practices threaten ecosystem services essential for crop productivity, while climate variability, land degradation, and water scarcity exacerbate food insecurity (IPCC, 2023). Digital agriculture can help align productivity gains with environmental stewardship, ensuring that increases in food availability do not come at the expense of natural resource depletion.

Socio-Economic and Environmental Considerations

Adoption of digital agriculture remains uneven due to socio-economic factors, which can also influence environmental outcomes. Women, for instance, often have limited access to digital devices, advisory services, and financial platforms, restricting both productivity and sustainable land management practices (Rotz et al., 2019; GSMA, 2021). Digital literacy gaps in low-income regions further constrain environmentally beneficial technology adoption (Manzoor et al., 2025). Inclusive capacity-building is therefore critical to ensure that digital interventions promote both equity and environmental sustainability.

Governance, Policy, and Institutional Influences

Effective governance and institutional support are essential for integrating digital agriculture into environmentally sustainable food systems. Clear regulatory frameworks, public-private partnerships, and supportive policy environments facilitate the adoption of precision and climate-smart technologies.

Countries with strong policy backing, such as China and India, demonstrate higher adoption rates and improved environmental outcomes alongside productivity gains (Wolfert et al., 2017; Kumar & Singh, 2022). Policy alignment is thus critical for scaling digital agriculture in a way that balances food security, economic development, and ecological resilience.

5. OPPORTUNITIES OF DIGITAL AGRICULTURE

Digital agriculture offers numerous opportunities for enhancing productivity, market efficiency, financial inclusion, and sustainability in developing economies. By leveraging digital tools, farmers, agribusinesses, and policymakers can optimize resource use, improve decision-making, and strengthen resilience to climate and economic shocks (FAO, 2023; Zhang et al., 2025).

Enhanced Productivity and Precision Farming

Digital tools enable precision agriculture practices that optimize input use, reduce wastage, and increase crop yields. Sensors, drones, and satellite imagery allow for precise monitoring of soil moisture, nutrient status, and pest infestations, enabling farmers to apply fertilizers, water, and pesticides efficiently (Kumar & Singh, 2023). These technologies reduce production costs and environmental impact while maximizing output.

Improved Market Access and Information

Digital platforms provide farmers with real-time information on market prices, demand trends, and buyer contacts, reducing information asymmetry and transaction costs (Taye & Ambaye, 2023). E-marketplaces and mobile-based platforms connect farmers directly to buyers, expanding market reach and improving income stability. Recent developments in AI-driven market prediction models allow farmers to plan crop production more strategically (Liu et al., 2023).

Financial Inclusion and Risk Management

Access to digital financial services, including mobile banking, digital credit, and insurance products, empowers farmers to manage risks, invest in inputs, and scale operations (Zhou et al., 2024). These services are particularly transformative for smallholder farmers in developing economies, providing access to capital that was previously limited due to geographic or institutional constraints (Adeoti et al., 2023).

Climate Resilience and Sustainable Practices

Digital agriculture enhances climate resilience by providing timely information on weather events, droughts, and pest outbreaks, enabling farmers to adopt adaptive strategies (Singh et al., 2024). Precision irrigation, AI-guided crop planning, and soil health monitoring contribute to sustainable farming practices and help mitigate the environmental impacts of agriculture (Chen et al., 2023).

Data-Driven Decision Making

Digital tools allow for the collection and analysis of large datasets on farm performance, supply chains, and environmental conditions. This enables evidence-based decision-making at both farm and policy levels, improving efficiency, accountability, and the targeting of interventions (Patel et al., 2023).

6. CHALLENGES AND CONSTRAINTS OF DIGITAL AGRICULTURE

Despite the significant opportunities, the adoption of digital agriculture in developing economies faces multiple challenges and constraints. These barriers affect smallholder farmers, agribusinesses, and policymakers, limiting the full potential of digital innovations (Degila et al., 2023; Olajide et al., 2024).

Infrastructure and Connectivity

Limited access to reliable electricity, internet connectivity, and mobile networks restricts the adoption of digital tools, especially in remote rural areas (Nyamao & Muriuki, 2024; Adeoti et al., 2023).

Poor infrastructure reduces the efficiency of IoT devices, mobile platforms, and cloud-based services, hindering timely information delivery and data analysis.

Digital Literacy and Capacity

Low levels of digital literacy among smallholder farmers constrain the effective use of digital technologies (Oluwatayo & Yusuf, 2023). Training and capacity-building initiatives are often inadequate, resulting in underutilization of digital tools and misinterpretation of advisory information (Patel et al., 2023).

High Cost of Technology Adoption

Advanced digital tools, such as AI-driven analytics, drones, and precision farming equipment, remain expensive for smallholder farmers in developing economies (Chen et al., 2023; Singh et al., 2024). Without subsidies, financing mechanisms, or public-private partnerships, many farmers are unable to afford these technologies.

Policy and Regulatory Challenges

Inconsistent policies, lack of regulatory frameworks, and insufficient government support limit the adoption of digital agriculture (Manzoor et al., 2025). Data privacy, intellectual property rights, and cybersecurity issues remain poorly addressed, reducing trust in digital platforms (Smith et al., 2025).

Social and Cultural Barriers

Gender disparities, social exclusion, and traditional farming practices can impede adoption. Women farmers and marginalized groups often face limited access to mobile devices, training programs, and market networks (Oluwatayo & Yusuf, 2023; Adeoti et al., 2023). Cultural resistance to new technologies can further slow adoption and reduce participation.

Sustainability and Maintenance Issues

Digital agriculture tools require regular maintenance, software updates, and technical support. Lack of local service providers and technical expertise can lead to underutilization or abandonment of technologies (Degila et al., 2023; Munyua et al., 2024).

7. DIGITAL DIVIDE AND INCLUSIVITY ISSUES

While digital agriculture offers substantial benefits, disparities in access, adoption, and utilization highlight significant digital divide and inclusivity challenges in developing economies. These challenges limit equitable access to resources, information, and opportunities, often exacerbating existing socio-economic inequalities (Oluwatayo & Yusuf, 2023; Degila et al., 2023).

Gender Disparities

Women farmers frequently face limited access to digital technologies due to socio-cultural norms, lower literacy levels, and restricted ownership of mobile devices (Adeoti et al., 2023). As a result, they may not fully benefit from digital advisory services, e-market platforms, or mobile finance solutions, reducing their competitiveness and income potential (Munyua et al., 2024).

Rural-Urban Gaps

Digital infrastructure in rural areas often lags behind urban centers, resulting in uneven access to mobile networks, internet connectivity, and ICT services (Nyamao & Muriuki, 2024). Farmers in remote areas are thus at risk of being excluded from timely market information, advisory services, and e-commerce platforms (Patel et al., 2023).

Socio-Economic Barriers

High costs of digital devices, internet subscriptions, and subscription-based agricultural platforms create barriers for smallholder farmers with limited financial resources (Chen et al., 2023; Singh et al., 2024). Marginalized groups, including low-income households and ethnic minorities, are disproportionately affected, reinforcing structural inequalities.

Literacy and Capacity Constraints

Low levels of digital literacy and technical skills impede the effective use of digital agriculture tools. Farmers may struggle to interpret advisory information, utilize mobile applications, or operate smart devices, reducing adoption rates and the effectiveness of digital interventions (Oluwatayo & Yusuf, 2023; Patel et al., 2023).

Strategies to Enhance Inclusivity

Addressing digital divide challenges requires multi-faceted approaches, including:

i. Targeted Training Programs: Digital literacy and capacity-building initiatives for women, youth, and marginalized communities (Patel et al., 2023).
ii. Affordable Technologies: Subsidies, low-cost devices, and community-shared digital infrastructure to expand access (Adeoti et al., 2023).
iii. Policy Interventions: Inclusive policies promoting equitable access to ICT services and digital agriculture platforms (Manzoor et al., 2025).
iv. Public-Private Partnerships: Collaboration between governments, NGOs, and technology providers to deliver inclusive digital solutions (Munyua et al., 2024).

8. IMPLICATIONS FOR AGRICULTURAL VALUE CHAINS

Digital agriculture has profound implications for agricultural value chains, particularly in developing economies where smallholder farmers dominate production. By leveraging digital tools, stakeholders can improve efficiency, transparency, market access, and overall performance across the value chain (FAO, 2023; Zhang et al., 2025).

Improved Market Linkages

Digital platforms facilitate direct connections between farmers, input suppliers, buyers, and processors, reducing the number of intermediaries and enhancing price discovery (Taye & Ambaye, 2023).

E-marketplaces and mobile applications enable smallholders to sell their produce directly, thereby increasing profitability and reducing postharvest losses (Liu et al., 2023).

Supply Chain Transparency and Traceability

Blockchain technology and digital record-keeping allow for enhanced transparency in the supply chain. Farmers, distributors, and consumers can track the movement of products from farm to market, ensuring quality control and reducing fraud (Rao et al., 2023). This traceability is particularly critical for exports and high-value crops where quality standards are strictly enforced.

Data-Driven Decision Making for Stakeholders

Digital tools enable stakeholders to collect, analyze, and use data across the value chain for operational decisions, such as optimizing logistics, predicting demand, and managing inventory (Patel et al., 2023). These insights help reduce waste, improve production planning, and increase overall efficiency.

Financial Integration Across the Value Chain

Digital financial services support transactions, credit access, and risk management for all actors in the value chain (Adeoti et al., 2023). Mobile banking and digital payment platforms facilitate timely payments, reduce transaction costs, and enhance trust among stakeholders.

Capacity Building and Knowledge Sharing

Digital agriculture promotes knowledge sharing across value chains through online advisory services, training modules, and community forums. This helps improve technical skills, adoption of best practices, and coordination among stakeholders (Patel et al., 2023; Singh et al., 2024).

Challenges to Value Chain Integration

While digital tools provide numerous benefits, integration across value chains faces challenges including uneven access, infrastructure gaps, low digital literacy, and regulatory barriers (Degila et al., 2023; Manzoor et al., 2025). Targeted policies and investment in capacity building are essential to ensure inclusive participation.

9. POLICY AND INSTITUTIONAL FRAMEWORKS

Effective policy and institutional support are critical for the adoption, scaling, and sustainability of digital agriculture in developing economies. Policies shape the enabling environment for infrastructure, access to finance, digital literacy, data governance, and innovation, while institutions provide coordination, training, and technical support (Manzoor et al., 2025; FAO, 2023).

National Digital Agriculture Policies

Several countries in Africa, Asia, and Latin America have developed national strategies that integrate digital tools into agricultural development plans. These policies aim to improve productivity, market access, and resilience, while ensuring that smallholder farmers can participate equitably in digital ecosystems (Adeoti et al., 2023; Chen et al., 2023).

Regulatory Frameworks

Clear regulatory frameworks for digital agriculture are essential to address data privacy, cybersecurity, intellectual property rights, and digital transactions (Smith et al., 2025). Governments need to establish guidelines for the ethical use of AI, IoT, and other technologies, while promoting interoperability and standardization across digital platforms (Rao et al., 2023).

Institutional Support

Institutions such as agricultural extension agencies, research organizations, and farmer cooperatives play a key role in facilitating digital adoption. They provide training, technical assistance, and knowledge sharing to improve digital literacy and skills (Patel et al., 2023). Public-private partnerships (PPPs) further strengthen institutional capacity by combining resources, expertise, and technological solutions for inclusive adoption (Munyua et al., 2024).

Incentives and Financing Mechanisms

Policy incentives, subsidies, and financing programs encourage investment in digital tools and services. Examples include grants for precision agriculture equipment, tax benefits for ICT service providers, and digital credit schemes for smallholders (Adeoti et al., 2023; Manzoor et al., 2025). Financial support reduces barriers to adoption and promotes long-term sustainability.

Multi-Level Governance

Coordination between national, regional, and local government authorities ensures consistency and effectiveness of digital agriculture policies. Multi-level governance enables alignment of resources, infrastructure, and technical support to maximize impact, particularly for smallholder farmers in remote areas (Oluwatayo & Yusuf, 2023; Nyamao & Muriuki, 2024).

10. FUTURE PROSPECTS AND EMERGING ISSUES

The future of digital agriculture in developing economies is shaped by rapid technological advancements, evolving policy landscapes, and emerging socio-economic and environmental challenges. These trends present both opportunities and considerations for sustainable adoption and impact (FAO, 2023; Zhang et al., 2025).

Integration of Artificial Intelligence and Machine Learning

AI and machine learning are expected to play an increasingly important role in predicting crop yields, pest outbreaks, and market trends. Predictive analytics will allow farmers and policymakers to make proactive, data-driven decisions, reducing risks and improving efficiency (Yuan & Sun, 2024; Liu et al., 2023).

Expansion of IoT and Smart Farming Technologies

Internet of Things (IoT) devices, including soil sensors, drones, and automated irrigation systems, will continue to enhance precision farming and resource optimization. Future integration of IoT with AI and big data analytics will create intelligent farm management systems tailored to local conditions (Kumar & Singh, 2023; Chen et al., 2023).

Blockchain and Supply Chain Innovations

Blockchain technology will increasingly enable transparency, traceability, and trust in agricultural supply chains. As smallholder farmers gain access to digital marketplaces, blockchain can ensure fair pricing, verify product quality, and reduce transaction risks (Rao et al., 2023).

Climate Change Adaptation and Resilience

Emerging digital solutions will support climate-smart agriculture by providing real-time climate data, predictive models, and adaptive management tools. These innovations will help farmers respond to climate variability and extreme weather events more effectively (Singh et al., 2024; Chen et al., 2023).

Financial and Policy Innovations

The evolution of digital finance, including mobile credit, insurance, and payment systems, will continue to facilitate smallholder investment and risk management. Coupled with supportive policies and institutional frameworks, these financial innovations will encourage inclusive adoption of digital agriculture (Adeoti et al., 2023; Manzoor et al., 2025).

Social and Ethical Considerations

As digital agriculture expands, issues related to digital equity, privacy, data governance, and ethical AI use will become increasingly important. Ensuring equitable access for women, youth, and marginalized groups will remain a priority, alongside responsible use of digital technologies (Oluwatayo & Yusuf, 2023; Smith et al., 2025).

11. POLICY IMPLICATIONS

The findings of this study underscore the need for comprehensive and context-specific policy frameworks to unlock the full potential of digital agriculture in developing economies. Effective policy interventions should address structural, institutional, and socio-economic barriers while fostering innovation, inclusivity, and sustainability across the agricultural value chain.

First, governments must prioritize investment in digital and rural infrastructure, including reliable electricity, broadband connectivity, and mobile network expansion. Strengthening digital infrastructure is foundational to enabling access to ICT-based agricultural services, particularly for smallholder farmers in remote areas.

Second, capacity building and digital literacy programs are essential to enhance farmers' ability to adopt and effectively utilize digital tools. Policies should support extension services, training programs, and farmer field schools that integrate digital competencies, with targeted initiatives for women, youth, and marginalized groups to ensure inclusivity.

Third, policymakers should promote affordable access to digital technologies through subsidies, tax incentives, and innovative financing mechanisms such as digital credit schemes and public-private partnerships. Lowering the cost barrier will encourage wider adoption of advanced tools such as precision agriculture technologies, IoT devices, and AI-driven platforms.

Fourth, there is a need to establish robust regulatory and governance frameworks that address data privacy, cybersecurity, digital transactions, and intellectual property rights. Clear guidelines will enhance trust among users and stakeholders while ensuring the ethical and responsible use of digital technologies in agriculture.

Fifth, policies should support the development of integrated digital ecosystems by encouraging collaboration among governments, private sector actors, research institutions, and development organizations. Such partnerships can drive innovation, improve service delivery, and ensure scalability of digital solutions.

Sixth, addressing the digital divide and social inclusion must be a central policy priority. Gender-responsive policies, equitable access to digital devices, and inclusive program design are critical to ensuring that vulnerable populations benefit from digital agriculture.

Finally, policymakers should align digital agriculture strategies with broader goals of climate resilience and sustainable development. Integrating digital tools into national agricultural and environmental policies can enhance resource-use efficiency, reduce environmental impacts, and strengthen resilience to climate variability.

In conclusion, a coordinated policy approach that combines infrastructure development, capacity building, regulatory support, and inclusive strategies is essential for scaling digital agriculture and maximizing its contribution to productivity, food security, and sustainable rural development in developing economies.

CONCLUSION

Digital agriculture presents transformative opportunities for developing economies, offering enhanced productivity, improved market access, climate resilience, and financial inclusion. By leveraging technologies such as AI, IoT, blockchain, and mobile-based platforms, stakeholders across the agricultural value chain can optimize resource use, reduce risks, and increase efficiency (FAO, 2023; Zhang et al., 2025).

However, adoption is constrained by challenges including limited infrastructure, low digital literacy, high technology costs, policy gaps, and social inequalities. Addressing these challenges requires multi-level policy interventions, targeted capacity-building programs, investment in digital infrastructure, and inclusive strategies to ensure equitable access for women, youth, and marginalized groups (Oluwatayo & Yusuf, 2023; Munyua et al., 2024).

Emerging trends in AI, IoT, blockchain, and predictive analytics promise further innovations that can enhance sustainability, traceability, and resilience. Policy frameworks and institutional support play a critical role in facilitating adoption, scaling up innovations, and promoting responsible use of digital technologies (Manzoor et al., 2025; Smith et al., 2025).

In conclusion, while digital agriculture holds immense potential to transform agricultural systems in developing economies, its benefits can only be fully realized through a holistic approach that combines technology, policy, capacity building, and inclusivity. Strategic investment, public-private collaboration, and continuous innovation will be essential to harness the full potential of digital agriculture for sustainable development and food security.

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CHAPTER 3
TRANSFORMATION OF AGRICULTURAL WASTES TO ACTIVATED CHARCOAL FOR USE IN ANIMAL AGRICULTURE

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INTRODUCTION

The expansion of agricultural production has naturally resulted in increased quantities of wastes from both plant and animal agricultural systems. Nigeria is endowed with abundant quantities of agricultural residues (livestock and crop residues) which pollute our environment and are yet to be harnessed to useful products. A research on agricultural wastes such as pig dung and palm oil wastes is desirable because of their contribution to environmental degradation and the need to convert them to value-added products such as activated charcoal (AC) for inclusion in animal feeds. This is important because amongst all the inputs required for poultry production, feed makes up about 70% of the total cost of production (Esiobu *et al.,* 2014), and any effort in reducing the cost by applying feed additive will be a step in the right direction. Agricultural residues are being considered the most promising materials for the production of activated charcoal because they are cheap, readily available, renewable and do not require very elaborate process as precursors from industries and fossil fuel.

Activated charcoal (AC) also known as biochar is a solid, porous, tasteless and black carbonaceous material (AAFCO, 2012) produced from a variety of carbon containing materials including agricultural residues and wastes. It is manufactured by a two-step process of carbonization followed by oxidation (activation) in an inert gas (example steam) chamber (Hagemann *et al.,* 2018). Activated charcoal is widely accepted as an essential tool in disease management in human and veterinary medicines where it is used as universal poison antidote (Hagemann *et al.,* 2018). It is effective in the elimination of mycotoxins, such as aflatoxins as well as pesticide residues that occasionally contaminate feed ingredients (Huwig *et al.,* 2001; Bhatti *et al.,* 2018).

Hien *et al.* (2018) studied the effects of AC on growth performance, blood parameters and fecal bacteria of noiler chickens and raised the birds to maturity. At 12th week, the results showed that the addition of AC in their feed did not affect the feed intake, weight gain and feed conversion efficiency. However, it appeared that the birds fed activated charcoal were stronger and healthier than those without access to AC. Intake of activated charcoal did not influence numbers of red and white blood cells nor hemoglobin.

However, content of plasma triglycerides was reduced in noiler fed activated charcoal. The addition of AC into the noiler feed reduced total coliforms in litter from 1.4×10^6 to 5.1×10^5 CFU/g and *E. coli* from 1.7×10^6 to 8.2×10^5 CFU/g which was in accordance with Prasai *et al.* (2017) who reported that biochar inhibited growth of microbial pathogens.

Durunna *et al.* (2018), reported improved growth rate and reduced flatulence, fly population, and litter odour at varied inclusion levels of wood charcoal in the feed of broiler birds. Mongo *et al.* (2020) researched on the effect of activated charcoal derived from coconut (*Cocos nucifera*) shell on the growth performance of broiler chickens at 0.2 and 0.6% inclusion in a maize-soybean diet. The results indicated improvements in feed intake, live weight gain and feed conversion as the level of charcoal in the diet increased. Feed intake was increased by 6.3%, live weight gain by 14%, and feed conversion was improved by 9%, at 0.6% charcoal inclusion. In this study, activated charcoal produced from agricultural wastes through pyroltic carbonization was included in noiler feed to investigate the effect on performance, carcass characteristics, haematology and serum biochemical indices of noiler chickens.

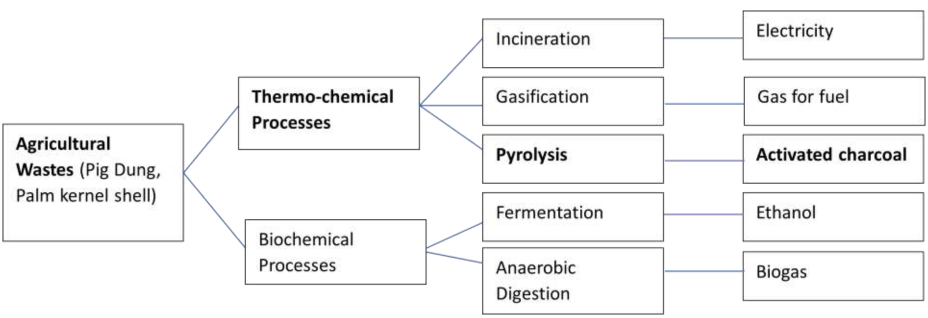

Fig. I: Biomass transformational pathways.

1. MATERIALS AND METHODS

1.1 Place of Study

The study was carried out at the Teaching and Research Farm of Michael Okpara University of Agriculture Umudike, Abia State. Umudike is located within the South East agro-ecological zone of Nigeria with geographical coordinates of 5.4801° N and 7.5437° E.

1.2 Ethical approval

Ethical approval was obtained from college of Veterinary Medicine Michael Okpara University of Agriculture, Umudike and was approved in line with the guidelines for the care, use and management of animals.

1.3 Activated carbon preparation

Palm kernel shell and palm fruit fibre were collected from a palm oil mill located at Amaba while freshly voided pig dung was collected into a plastic container using a parker from a pig farm at Ndolu all within Umudike. Each material was sun-dried to a constant weight and crushed manually to reduce the particle size before being blended at a ratio of 4:3:3 weight for weight for pig dung, palm kernel shell and palm fruit fibre, respectively as described by Ohanaka *et al.* (2021)

The physical method of preparation of AC which involved thermal decomposition or carbonization of the precursors followed by steam activation was employed in the study according to Gunamartha and Widana (2018). The blended biomass material was weighed using HN 289 digital scale (Omron Co., Ltd, Japan) and transferred to a clay pot of about 30 litres volume for carbonization. The pot containing the precursor was tightly covered except for a small vent that allowed limited entry of oxygen into the mixture. The pot was heated on open fire for combustion until no more smoke was produced. At this point, water was introduced quickly on to the char and the pot covered immediately and tightly. The addition of water was to end carbonization and generate steam to achieve activation of the carbon. Thereafter, the pot was tightly closed and brought down from the fire and left to cool completely. Thereafter, the charcoal product was taken out, rinsed with cold water to remove ash and other debris and air dried. The dried AC was then transferred to a wooden mortar and ground with pestle into fine powder and stored in an air tight plastic container and was used for dietary supplementation.

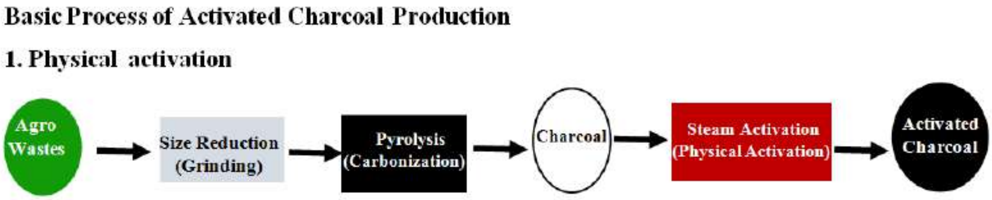

Fig. II: Flow chart for carbonization and physical activation in preparation of activated charcoal.

Fig III Activated charcoal sample

Fig. IV: Mature noiler chickens

1.4 Experimental Animal and Design

Ninety-six (96) day old noiler birds with average body weight of 36.9 grams were used for the study. The noiler birds were purchased from an accredited day old distributor in Umuahia, Abia State. They were housed in a constructed wooden poultry pen, and given water and feed ad libitum. The noiler birds were brooded for 2weeks before they were randomly allocated into 4 groups (T_1- T_4) of 24 birds each with 3 replicates 8 birds each and fed with commercial diet (Chikun® starter mash). From the 4^{th} week, the noiler birds were fed with Chikun® finisher mash and water ad-libitum in a completely randomized design as follows:

GROUP T_1: Received water and feed as control (starter/ finisher)

GROUP T_2: Received water and feed supplemented with 0.5kg of activated charcoal per 100kg of feed.

GROUP T_3: Received water and feed supplemented with 1.0kg of activated charcoal per 100kg of feed.

GROUP T_4: Received water and feed supplemented with 1.5kg of activated charcoal per 100kg of feed.

1.5 Data Collection

Growth performance, body weight, feed intake and feed conversion ratio

The initial weights of the birds were recorded at the beginning of the experiment and subsequently at 4, 5, 6, 7 and 8 weeks. Daily weight gain was obtained by dividing the difference between the initial live weight and final live weight by the age of birds in days. Feed intake was determined on daily basis by subtracting the weight (g) of the left over feed from the weight of the feed initially offered. The feed conversion ratio (FCR) was determined by dividing the total feed intake by the final weight gain.

Determination of haematological and serum biochemical indices

5ml of blood was collected at 56 days of the experiment from the wing vein of three noiler birds per treatment into K3 Ethylene-diamine tetra-acetic acid (EDTA) and plain bottles for haematological and serum biochemical analyses, respectively. The erythrocyte was counted using the haemocytometer method as describe by Schalm *et al.* (1975) while the hemoglobin concentration was determined according to the techniques described by Cole (1986). In determining the packed cell volume (PCV), the Wintrob microheamatocrit tube was filled with blood by capillary action up to two thirds (2/3). The samples were spun in a centrifuge for 5 minutes at 10,000 rpm and the PCV was read and recorded in percentage using a microheamatocrit reader. Other hematological indices namely, MCH, MCV and MCHC were calculated according to the formulae reported by Schalm *et al.* (1975). The Mean Cell Hemoglobin was determined as MCH (pg) = Hb x 100/RBC, the Mean Cell Volume as MCV (fl) = PCV x 100/RBC and Mean Cell Hemoglobin Concentration as MCHC (g/dl) =Hbx100/PCV (Schalm *et al.,* 1975). The leukocyte or white blood cell count was obtained using a haemocytomer after a 1: 20 dilution in Natt and Hendricks diluents to obtain a 1:20 blood dilution (Schalm *et al.*, 1975). The white blood cell was differentiated into granulocytes (heterophils), lymphocytes, monocytes, eosinophils and basophils with the aid of automated WBC differential machine (Model: Durga, China).

The blood samples contained in plain bottles were centrifuged at 3000 rpm for 10 minutes to obtain clear sera which were transferred into fresh plain bottles and labelled appropriately. Serum biochemical tests were carried out using Randox commercial test kit following manufacturer's instructions. Parameters analyzed included total protein, bilirubin and cholesterol levels, albumin, globulin, urea, and creatinine concentrations, alanine aminotransferase (ALT), aspartate aminotransferase (AST), and alkaline phosphatase (ALP).

2. RESULTS AND DISCUSSION

2.1 Growth parameters

The growth parameters namely body weight, feed intake, weight gain and feed conversion ratio (FCR) are presented in Table 1 while weekly FCR is presented in Table 2.

Table 1: Growth performance of noiler birds fed with activated charcoal feed blend

	Treatment group				
Parameters	**T_1**	**T_2**	**T_3**	**T_4**	**SEM**
Initial body weight/bird (g)	36.33	35.75	35.75	35.50	0.39
Final body weight/bird (g)	991.75	1045.67	1000.33	1062.33	19.78
Daily feed consumed/bird (g)	205.85	180.87	197.25	195.89	14.17
Daily weight gain/bird (g)	1.88	1.99	1.91	2.03	0.02
Daily feed conversion ratio/bird	2.58	2.15	2.44	2.26	0.15

Values are presented as Mean. S.E.M: Standard Error of mean.

There was no significant ($P > 0.05$) difference in the initial and final body weights of the experimental birds across treated groups compared with the control, indicating that the inclusion of activated charcoal in the diets did not adversely affect the growth performance of the noiler chickens.

The daily feed conversion ratio did not vary significantly (P > 0.05) but was numerically lower in the activated charcoal supplemented groups compared with the control. This signifies better feed utilization in the supplemented groups than the control. The noiler chickens fed control diet consumed more feed than the supplemented groups although not significantly (P > 0.05) different. This result is in accord with the report of Hien *et al.* (2018) who reported that inclusion of 1% activated charcoal in the diet of noiler chickens did not significantly (P > 0.05) affect the daily feed intake, daily weight gain and daily feed conversion ratio.

Table 2: Weekly feed conversion ratio (mean ± SEM) of noiler chickens fed with activated charcoal feed blend

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Week 4	1.96±0.10	2.50±0.42	2.00±0.16	1.96±0.08
Week 5	3.68±0.17	3.14±0.23	3.74±0.24	3.62±0.38
Week 6	4.53±0.36	5.05±0.33	4.73±0.28	4.30±0.32
Week 7	3.04±0.15^{a}	2.99±0.38^{a}	2.54±0.24^{ab}	1.90±0.19^{b}
Week 8	3.73±0.37^{a}	4.45±0.52^{a}	2.09±0.07^{b}	1.95±0.16^{b}

Results are mean ±SE; a, b, c: means on the same column with different superscripts are significantly different (P ≤ 0.05).

The result of the weekly feed conversion ratio of the noiler chickens across the treatments showed no significant differences at weeks 4, 5 and 6 but at week 7 and 8 the supplemented noiler groups especially T4 at week 7 and at week 8 recorded significantly lower feed conversion ratios signifying better feed utilization than the control. This result is in accord with the report of Mongo *et al*. (2020) whose result indicated that inclusion of 0.6% activated charcoal in the diet of broilers improved feed conversion ratio.

2.2 Carcass characteristics

The carcass characteristics (relative organ weight) of the experimental birds are presented in Table 3 and in fig.IV.

Table 3: Carcass characteristics (mean ± SEM) of noiler birds fed with activated charcoal feed blend at 8 weeks

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Live weight (g)	941.33±155.88	855.66±34.37	965.00±51.11	1105.00±177.74
% Carcass weight	89.01±2.40	89.24±1.53	88.86±3.10	86.46±1.11
% Proventriculus	0.50±0.03	0.66±0.01	0.58±0.07	0.61±0.04
% Gizzard	3.38±0.30	3.92±0.23	3.87±0.25	3.73±0.17
% Gizzard + content	4.76±0.32	5.15±0.31	5.30±0.40	5.19±0.08

Values are presented as Mean ± S.E.M: Standard Error of mean.

The result presented in Table 3 showed that feed supplemented with graded levels of activated charcoal had no significant effect on the carcass and organ weights of noiler chickens. Though, the average live weight, carcass yield, weights of the proventiculus and gizzard with/without content of the noiler chickens fed the supplemented diet (T2-T4) were numerically higher, but they did not weigh significantly higher ($P > 0.05$) than the control birds. The weights of these organs (proventiculus, gizzard, spleen, liver and heart) of the treated birds did not vary from those of the control birds, suggesting that the activated charcoal used in this study did not cause any harm to the organs evaluated. This result contrasted the findings of Jiya *et al.* (2013) who reported that there were significant differences in the values of carcass weight, gizzard, heart and spleen weight at 0.5% inclusion of activated charcoal in the feed of broiler chickens.

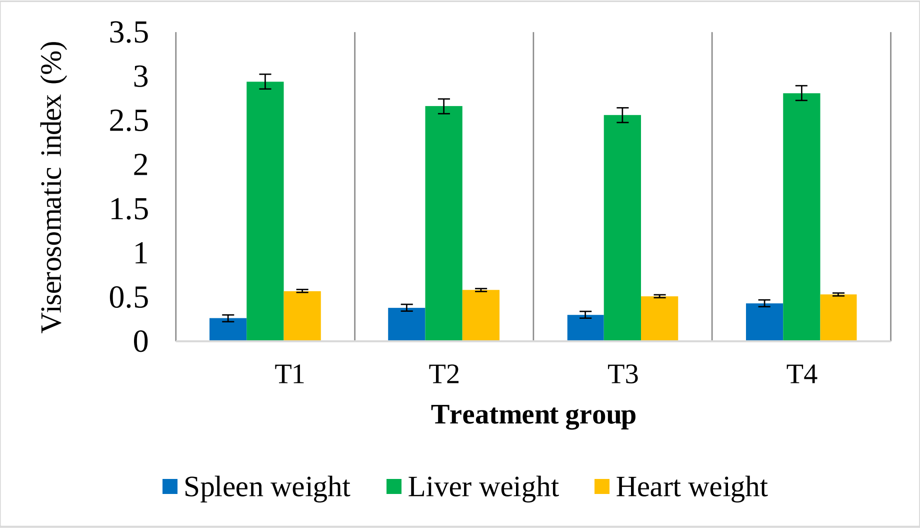

Fig. IV: Comparative organ weights of noiler chickens fed diet supplemented with activated charcoal.

T_1: Control, T_2: 0.5kg of activated charcoal per 100kg of feed, T_3: 1.0kg of activated charcoal per 100kg of feed, T_4: 1.5kg of activated charcoal per 100kg of feed.

2.3 Hematological indices

The hematological profile, erythrocyte indices and differential white blood cell count of the experimental birds are presented in Table 4, 5 and 6 respectively.

Table 4: Hematological profile of noiler fed with activated charcoal feed blend at the end of 8 weeks

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Hemoglobin (g/dl)	12.20±0.11	11.73±0.96	12.40±0.11	11.13±1.04
Packed Cell Volume (%)	26.33±0.33	27.00±2.08	27.66±0.88	24.66±2.33
Red Blood Cell ($\times 10^6 mm^3$)	3.01±0.04	3.05±0.23	3.12±0.08	2.78±0.25
Total White Blood Cell ($\times 10^3 mm^3$)	20.00±0.63	20.03±0.34	19.86±0.76	19.91±0.20

Values are presented as Mean ± SEM (Standard Error of Mean).

The result presented in Table 4, showed that activated charcoal supplemented diet at graded inclusion levels did not affect (P > 0.05) the hematological parameters when compared with the control group. This result is in accord with the report of Hein *et al*. (2018) who reported that inclusion of 1% biochar (activated charcoal) in the diet of noiler did not influence numbers of red and white blood cells nor hemoglobin concentration.

Table 5: Erythrocyte indices of noiler fed with activated charcoal feed blend at 8 weeks

Treatment group				
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
MCV (fl)	90.29±0.82	91.37±0.30	91.60±0.90	91.92±0.16
MCH (Pg)	40.45±0.55	38.36±0.69	39.78±0.73	39.98±0.98
MCHC (g/dl)	46.33±0.30	43.42±0.78	44.88±1.04	45.15±1.17

Values are presented as Mean ± SEM (Standard Error of Mean). MCV= Mean Corpuscular Volume; MCH= Mean Corpuscular Haemoglobin; MCHC= Mean Corpuscular Haemoglobin Concentration.

The erythrocyte indices (MCV, MCH and MCHC) of the noiler chicken fed graded levels of activated charcoal supplemented diet were not altered (P > 0.05) compared with the control group (Table 5). This means that the size of the red cells and their hemoglobin concentration were within normal ranges. This result is in accord with the report of Enyenihi *et al*. (2022) who observed no significant differences (P > 0.05) in the values of the erythrocyte indices (MCV, MCH, MCHC) at 2%, 4%, 6% and 8% inclusion of activated charcoal in the feed of broiler chickens.

Table 6: Differential white blood cell count of noiler fed with activated charcoal feed blend at 8 weeks

Treatment group				
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Lymphocytes	$56.66±0.88^{ab}$	$58.66±0.88^{ab}$	$59.33±0.66^{a}$	$56.00±1.15^{b}$
(%)	$35.66±0.66^{ab}$	$35.00±1.15^{ab}$	$33.33±0.33^{b}$	$36.33±0.88^{a}$
Heterophils (%)	5.00±0.57	4.33±0.33	5.33±0.33	5.33±0.88
Monocytes (%)	2.66±0.33	2.00±0.57	2.00±0.00	2.00±0.57
Eosinophils (%)	0.00±0.00	0.00±0.00	0.00±0.00	0.33±0.33
Basophils (%)				

Results are mean ±SE; a, b, c: means on the same column with different superscripts are significantly different (P ≤ 0.05).

The result presented in Table 6 showed that significant differences existed in the relative numbers of lymphocytes and heterophils among the treated birds, although, no variation ($P < 0.05$) between the treated and the control. The noiler chickens in group T3 recorded higher ($P < 0.05$) mean lymphocyte count (59.33±0.66 %), than T_4 (56.00±1.15 %), whereas, the group T3 recorded lower (33.33±0.33%) relative number of heterophils compared with the higher number (36.33±0.88 %) recorded in T4. However, the relative numbers of monocytes, eosinophil and basophils were the same statistically ($P > 0.05$) with those of the control. This result is in conformity with the report of Hien *et al*. (2018) who observed that intake of biochar did not influence the numbers of white blood cells (monocytes, eosinophil and basophils).

2.4 Serum biochemical indices

The protein metabolism of the noiler chickens are presented in Table 7.

Table 7: Protein metabolism of noiler chickens fed with activated charcoal feed blend.

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Total protein (g/dl)	5.63±0.05^{ab}	5.42±0.02^{c}	5.56±0.01^{b}	5.71±0.02^{a}
Albumin (g/dl)	4.62±0.01^{b}	4.30±0.01^{d}	4.58±0.00^{c}	4.78±0.05^{a}
Globulin (g/dl)	1.01±0.04^{b}	1.12±0.01^{a}	0.96±0.02^{b}	0.93±0.01^{b}

Results are mean ±SE; a, b, c: means on the same column with different superscripts are significantly different ($P \leq 0.05$).

There was significant reduction in total protein level at the lowest inclusion T2 compared with the control, with Alkaline phosphatase (ALP) highest at T4 in Table 8 signifying that the activated charcoal supplemented diets enhanced the osmotic pressure in the vascular space through the stimulation of higher protein synthesis/metabolism. The albumin level was significantly ($P < 0.05$) increased in the sera of the noiler chickens in T4, while those fed lower inclusions recorded low ($P < 0.05$) sera levels of the albumin compared with the control.

The globulin levels were significantly elevated in the sera of chickens fed the least inclusion level (0.5kg/100kg feed), while the globulin levels of the groups T3 and T4 had the same (P > 0.05) sera level with the control. This result could mean that higher inclusion (T4) affected liver function, while lower inclusions (T2) tends to enhance liver function, suggesting that the least inclusion level could significantly improve the generation of antibodies. The result is in accord with Jiya *et al*. (2013) whose study indicated that 1.5% inclusion of activated charcoal in the diet of broiler chickens significantly increased serum albumin concentration.

2.5 Serum enzyme, metabolites and lipid profile:

The liver and kidney biomarkers are presented in Table 8 while the lipid profile is presented in Table 9.

Table 8: Liver and kidney biomarkers (mean ± SEM) of noiler fed with activated charcoal feed blend.

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
ALP (I/UL)	70.30 ± 0.34^{a}	51.30 ± 0.23^{c}	63.80 ± 1.50^{b}	69.10 ± 0.69^{a}
AST (I/UL)	62.30 ± 0.28^{c}	55.30 ± 0.46^{d}	67.90 ± 0.12^{b}	81.50 ± 0.11^{a}
ALT (I/UL)	29.60 ± 0.17^{b}	28.10 ± 0.34^{c}	29.70 ± 0.35^{b}	31.20 ± 0.23^{a}
Urea (mg/dl)	2.45 ± 0.04^{a}	2.34 ± 0.01^{b}	2.37 ± 0.01^{ab}	2.42 ± 0.03^{ab}
Creatinine (mg/dl)	0.28 ± 0.01^{ab}	0.24 ± 0.02^{b}	0.27 ± 0.05^{ab}	0.30 ± 0.01^{a}
Total bilirubin (mg/dl)	7.63 ± 0.13^{a}	5.82 ± 0.02^{c}	5.95 ± 0.04^{c}	6.20 ± 0.01^{b}

Results are mean ±SE; a, b, c: means on the same column with different superscripts are significantly different (P ≤ 0.05). ALP = Alkaline phosphatase; ALT = Alanine aminotransferase; AST = Aspartate aminotransferase.

The result of the liver and kidney biomarkers revealed significant alterations among the treated birds compared with the control group (Table 8). The mean serum level of ALP in T2 and T3 were significantly (P < 0.05) lower compared with the level in T4 and the control group. The serum levels of AST and ALT were significantly elevated in the highest inclusion group (T4) compared with the control, whereas, T2 recorded very low (P < 0.05) levels of these enzyme biomarkers.

The values of the liver enzymes (ALP, AST and ALT) in all the groups are within the normal physiological values of serum enzymes in broiler chickens as reported by Makama *et al.* (2021). The alterations in the value maybe due to differences in animals' body mechanisms. The result of the urea, creatinine and the total bilirubin biomarkers showed that the highest inclusion (T4) level did not increase their mean values. This result is in accord with the findings of Enyenihi *et al.* (2022) whose study showed that supplementing broiler feed with 8% activated charcoal derived from coconut shell significantly affected ($P < 0.05$) serum levels of AST and ALT.

Table 9 shows that cholesterol and triglyceride levels were significantly decreased in treated groups (T_2-T_4) compared to T_1 (control).

Table 9: Lipid profile (mean ± SEM) of noiler chicken fed with activated charcoal feed blend.

	Treatment group			
Parameters	**T_1**	**T_2**	**T_3**	**T_4**
Cholesterol (mg/dl)	154.50 ± 1.96^a	147.60 ± 0.46^b	125.40 ± 0.92^c	95.60 ± 0.23^d
Triglycerol (mg/dl)	142.60 ± 0.69^a	139.30 ± 0.69^b	112.30 ± 0.92^c	81.30 ± 0.23^d
HDL (mg/dl)	37.80 ± 1.67^b	39.60 ± 1.32^b	60.40 ± 0.40^a	62.10 ± 0.51^a

Results are mean ±SE; a, b, c: means on the same column with different superscripts are significantly different ($P \leq 0.05$). HDL: High-density lipoprotein.

The significant ($P < 0.05$) lowering of cholesterol and triglyceride levels in the sera of noiler chickens fed the activated charcoal supplemented diet compared with the control birds might suggest that activated charcoal was capable of inhibiting the activities of hepatic, lipogenic and cholesterogenic enzymes required for cholesterol synthesis (Vega *et al.,* 2003). The low levels ($P < 0.05$) of serum triglyceride in the supplemented groups may be associated with the role of activated charcoal in decreasing the availability and or the production of triglyceride precursors such Acetyl-CoA and glycerol phosphate (Campillo *et al.,* 2014). HDL-cholesterol otherwise called 'good cholesterol' was however, significantly increased in the sera of the noiler chickens fed with higher activated charcoal inclusions (T3 and T4) resulting in an improved lipid profile.

This result is in conformity with the report of Jiya *et al.* (2013) who reported that inclusion of 0.5%, 1%, 1.5% and 2% activated charcoal in broiler chickens showed significant difference ($P < 0.05$) in cholesterol and triglyceride compared to the control group and might be that activated charcoal absorbed fats soluble substances.

The observed dose-dependent reduction in serum cholesterol level in the experimental groups was in agreement with the results of previous researchers to the effect that serum cholesterol levels were reduced in birds whose diets were supplemented with AC (Shabani *et al*., 2010; Dim *et al*., 2018). These reductions in serum cholesterol resulting from activated charcoal supplementation indicate its possible use in the treatment of hypercholesterolemia (Neuvoneu *et al.,* 1989; Joseph *et al*., 2015; Roosdiana *et al.,* 2019). This is probably achieved by adsorption of cholesterol and cholesterol-containing bile acids in the gut by AC, thus preventing their absorption (Joseph *et al*., 2015). When bile acids are excreted, plasma cholesterol is converted to bile acids to normalize bile acids levels and this eventually lowers plasma and serum cholesterol levels (Neuvoneu *et al*., 1989; Roosdiana *et al.,* 2019). It should be recalled that approximately 2/3 of intestinal cholesterol is derived from bile while just about 1/3 comes from diet (Joseph *et al*., 2015, Roosdiana *et al*., 2019). Hence, serum cholesterol is determined by the balance between its synthesis, and intestinal absorption (Neuvoneu *et al*., 1989; Roosdiana *et al.,* 2019). Statin drugs which are the most common therapy for hypercholesterolemia act by inhibiting the enzyme, HMG-CoA reductase which is associated with some adverse side effects including joint pain and liver damage (Neuvoneu *et al*., 1989; Roosdiana *et al.,* 2019). By blocking cholesterol absorption and by being itself undigested, activated charcoal could be a better alternative for management of hypercholesterolemia.

CONCLUSION

It can be concluded that supplementing the diet of noiler chicken with activated charcoal could serve as an alternative feed supplement in ensuring growth /development of the birds. Its inclusion level of 0.5-1.5kg/100kg feed did not affect the blood and major organs, but enhanced the liver, kidney biomarkers and the lipid profile.

The hematological and biochemical parameters examined were within the range reported in poultry species indicating that AC is non-toxic and therefore safe for use in broiler feeds, respectively. There were also indications of its possible application in the management of high blood cholesterol levels. It becomes imperative to explore AC as an alternative medication for the treatment and management of hypercholesterolemia in both man and animals. The ready availability of biomass feedstock for AC production in addition to its high adsorption capacity and non-toxic nature makes it an affordable alternative for management of high cholesterol levels. The contribution of this work to science lies in the transformation of agricultural wastes to an environmental friendly and value added product that can be used as feed additives to improve performance of noiler chickens. In conclusion, the use of activated charcoal as feed additive has the potential to improve feed efficiency and productivity. With all these potentials derivable from agricultural waste-derived AC, the non-conversion of agricultural biomass to this great value-added product should be seen as a waste of economic resources when most of the activated charcoals used in industries for various adsorptive purposes in Nigeria are imported.

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