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Artificial Intelligence and Machine Learning in Precision Farming a Case Study of Nigeria: A Review

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Abstract

Precision farming leverages Artificial Intelligence (AI) and Machine Learning (ML) and has the potential to transform the agricultural landscape in Nigeria. This paper reviews the concepts, applications, benefits, and challenges of AI and ML in precision farming in Nigeria. Our case study highlights the use of AI-powered tools for crop monitoring, soil health analysis, and predictive analytics, demonstrating significant improvements in crop yields, water usage, and farmers' income. The paper also considers the future prospects and limitations of adopting AI and ML in Nigerian Agriculture including infrastructure, data quality and farmers awareness. Our findings suggest that AI and ML can play a vital role in enhancing agricultural productivity and sustainability in Nigeria, and we recommend increased investment in digital infrastructure, capacity building and policy support to unlock the full potential of precision farming in the country.

Key words: Precision farming; Artificial Intelligence (AI); Machine Learning (ML); Technologies; Yield.

Introduction

Precision farming is defined by its capacity to provide the right input (water, fertilizer, pesticide, etc.) at the right time, place, and quantity, tailored to the specific requirements of the individual plant or field zones (Mulla, 2018; Gebbers & Adamchuk, 2021). This farm-level crop management system depends on the application of multiple digital technologies—e.g., Geographic Information Systems (GIS), Global Positioning Systems (GPS), drone- and satellite-based remote sensing and smart sensor networks—providing real-time data for evidence-based decision-making (Pierpaoli et al., 2018; Zhang et al., 2023). Moreover, recent advancements in Artificial Intelligence (AI), machine learning, Internet of Things (IoT), blockchain, and robotics are dramatically transforming farm management and the processing, tracing, and transportation of agricultural goods through value chains (Wolfert et al., 2017; Jha et al., 2019; Rejeb et al., 2022). These technologies promise not just to maximize production and minimize resource waste , but also to maximize traceability, transparency, and efficiency throughout the entire agri-food system. AI refers to the simulation of human intelligence processes by machines, especially computer systems capable of learning, reasoning, and adapting over time. In agriculture, AI applications span a wide spectrum of uses, including predictive analytics for crop yield estimation, computer vision for pest and disease detection, machine learning algorithms for optimizing fertilizer and irrigation use, and natural language processing tools that facilitate personalized farmer communication (Kamilaris and Prenafeta-Boldú, 2017). Artificial Intelligence (AI) and Machine Learning (ML) are transforming precision agriculture by enabling smart, data-driven farming systems. Through predictive analytics, AI models can forecast crop yields, weather patterns, pest infestations, and disease outbreaks using both historical and real-time data (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2017). This integration supports informed decision-making, reduces input waste , and improves productivity. Yield forecasting, aided by satellite imagery and climatic data, helps in planning logistics and market strategies (Jha et al., 2019). Machine Learning (ML), a subset of AI, enhances adaptability by recognizing data patterns and improving decisions over time (Singh et al., 2020). Both supervised and unsupervised algorithms are used to detect plant diseases, monitor soil health, and manage irrigation. Convolutional Neural Networks (CNNs) achieve high accuracy in diagnosing plant diseases from images (Ferentinos, 2018), while reinforcement learning aids in resource optimization amid environmental uncertainty, making AI vital for resilient, market-responsive agriculture.

LITERATURE REVIEW

Concept of Precision Farming

The concept of precision farming is founded on the principle of site-specific management, which recognizes that soil characteristics, topography, climate, and other factors vary within a field (Kushwaha *et al*. 2024). By accurately mapping and analyzing these variations using technologies such as GPS, GIS, and remote sensing, farmers can make informed decisions about the allocation of resources such as fertilizers, pesticides, water, and seeds. This targeted application of inputs ensures that crops receive the right amount of nutrients and water precisely when and where they are needed, optimizing growth and yield potential (Kushwaha *et al*. 2024). This approach allows for better resource utilization, reduces the need for fertilizers, and improves water efficiency. By utilizing technology such as satellite positioning, internet-of-things, and data analytics, precision farming enables farmers to monitor and manage the quantity and quality of agricultural produce, while also maintaining the quality of the environment and improving the sustainability of the food supply (Zhang, *et al.,* 2019). Precision farming is a comprehensive approach that utilizes various technologies and scientific knowledge to optimize agricultural production by considering variability and uncertainties within agricultural systems. These technologies and knowledge are applied to adapt production inputs site-specifically within a field and individually for each crop and animal, allowing for better use of resources while maintaining. The Impact of AI and Smart Farming Techniques on Nigerian Agriculture are presented in Table 2.

Key components of precision farming include:

Data Collection: Precision farming relies on the collection of accurate and timely data about soil properties, crop health, weather conditions, and other relevant factors. This data can be obtained through various means, including satellite imagery, drones, ground-based sensors, and manual sampling (Kushwaha *et al*. 2024).

Data Analysis: Once collected, data is analyzed to identify patterns, trends, and spatial variability within the field. Advanced analytics techniques, such as spatial interpolation, statistical modeling, and machine learning, are often employed to derive actionable insights from the data (Kushwaha *et al*. 2024).

Decision Support Systems: Based on the analysis of data, decision support systems provide farmers with recommendations and guidance for optimizing farm management practices. These systems may include software tools, mobile applications, and online platforms that integrate data from multiple sources and provide real-time monitoring and decision-making support (Kushwaha *et al*. 2024).

Precision Application Technologies: Precision farming relies on technologies that enable the precise application of inputs, such as variable rate application equipment, GPS-guided machinery, and automated irrigation systems (Kushwaha *et al*. 2024). These technologies allow farmers to adjust input rates and application timing based on site-specific conditions, maximizing efficiency and minimizing waste. Precision farming is a comprehensive concept that incorporates various technologies and scientific knowledge, such as computer science, electronics, and geoprocessing. These technologies and knowledge are applied in agriculture to optimize production by accounting for variability and uncertainties within agricultural systems. Precision farming involves the use of sensors, information systems, enhanced machinery, and informed management to adapt production inputs site-specifically within a field and individually for each animal.

Precision farming offers a range of benefits that can revolutionize agricultural practices, but it also faces significant challenges that need to be addressed for widespread adoption.

Applications of Artificial Intelligence (AI) and Machine Learning (ML) in Precision Agriculture (PA)

Applications of AI and ML in precision agriculture are endless, with very innovative solutions to traditional farming challenges. Both have totally changed the way of looking by farmers at crop management, resource allocation, and risk mitigation. Through analysis of data from several sources like sensors, drones, satellites, and more, AI and ML algorithms provide insights that enable farmers to make proper decisions in a timely manner. It is a shift from conventional farming to data-informed farming practices that improve productivity by cutting costs and increasing sustainability. Probably the most important benefit that AI and ML bring into agriculture is processing a great amount of data, extracting necessary insights from the data that a human might miss. This can use AI to do environmental monitoring in real time, such as soil moisture, temperature, and humidity, to adjust the irrigation schedule or fertilization accordingly. Similarly, ML models are able to forecast the probabilities of pest infestations or disease outbreaks, considering historical data and current conditions, to develop proper preventive measures well in advance in order to avoid any damage. These technologies contribute not only to improved health of crops but also to better optimization of the use of resources, leading to improved economic returns to farmers (Akhter & Sofi, 2022). Moreover, AI and ML strengthen automation in the cumbersome tasks of planting, watering, and harvesting that reduces operational costs while increasing efficiency as well. Such automation releases farmers to divert their attention to other important aspects of farm management with a view toward ensuring the routine continues uninterrupted and with greater precision. The integration of AI and ML into precision agriculture can, therefore, turn out to be one of the causes for its paradigm shift toward intelligent and sustainable farming. Some Specific AI Tools and Platforms that have been in used from 2020 – 2025 are indicated in Table 1.

AI for Crop Yield Prediction

Precise forecasting of crop yield is one of the most critical features of farm management. It notifies farmers about the planning of resource allocation and the assessment of market demand necessary for food security. Traditional methods of yield prediction normally rely on historical data and personal experience, which are always uncertain due to shifting weather patterns, variable soils, and pest pressures. AI models that bestow more accurate and reliable output because of large and complex data they have analyzed, which capture a number of variables that affect crop yield (Adinarayana *et al.,* 2024), can further this. AI-based yield prediction models use some of the machine learning algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), and random forests, to analyze data emanating from many sources, including soil sensors, weather stations, and satellite imagery. These models look for complex interactions among variables that range from soil moisture and temperature to planting schedules, and even more precariously, to advance predictions related to crop yield. It will therefore give farmers the most needed opportunity to decide upon in crop management when to plant and when to harvest, apply necessary and correct inputs like fertilizers and water on time (Shaikh *et al.,* 2022). Besides inputs from terrestrial sensors, the applications of various remote-sensing technologies, including drones and satellites, also confer added strength on AI based yield prediction models. With multispectral and hyperspectral cameras, drones can even monitor critical growth stages in far greater detail, capturing images that detail plant health, nutrient deficiencies, and other stresses of the plants. These images, in turn, will be processed with AI algorithms to predict yields in real time and, thus, enable farmers to act proactively toward the mitigation of any potential risks and managing their farms in general (Senoo *et al.,* 2024). AI models can also integrate historical data on yield, soil quality, and weather to predict future prospects. Because of this, farming has been much easier in areas getting extreme variability in environmental parameters as farmers can make easy decisions based on the situation. Application of AI for the forecasting of crop yield allows farmers to handle resources optimally, keep wastage low, and enhance profitability.

Machine Learning for Disease Detection and Prevention

Crop diseases are among the most threatening factors to agricultural productivity on the global scale and, therefore, have the potential to cause widespread economic losses and food scarcities. Early detection of and preventive measures against disease in plants can bring crop losses to a minimum, with the benefit of making production more viable and sustainable. Traditionally, a farmer or agricultural expert through observation has detected plant disease, which is many times cumbersome and sometimes prone to human error. ML models have given a better handle on this and thus have emerged as a successful alternative, as through recognition of images and analysis of patterns, they automate the detection of diseases (Sharma *et al.,* 2020). Convolutional neural networks (CNNs) have been one of the most adopted ML algorithms in precision agriculture for disease detection. Their models are usually trained on substantial datasets comprising images of diseased and non-diseased plants. Analyzing minute visual appearances like leaf color, texture, and shape changes, a CNN can identify early symptoms of various plant diseases, sometimes way in advance before they might be observable by the human naked eye. This helps farmers practice precision in intervention, reducing the frequency and extensiveness of application of broad-spectrum pesticides and the detrimental impact on the ecosystem (Waseem *et al.,* 2024). For example, ML models have very successfully been in service at vineyards to recognize fungal infections such as powdery mildew and downy mildew. They detect early signs of infection from high-resolution images taken by drones or sensors, after which treatment can be conducted just where needed. Similar work on wheat, rice, and maize has also been performed where diseases identified by ML models included rust, blight, and leaf spot. Therefore, in disease prediction, ML models have the potential to consider environmental data other than mere image-based detection, such as soil moisture, temperature, and humidity. Such predictive models will use historical data in combination with active monitoring so as to afford farmers corrective action by adjustment in irrigation schedules or protective treatments against diseases before actual disease outbreaks occur (Sharma *et al.,* 2020). An active approach towards disease control is effective in reducing crop loss but also acts towards increasing the efficiency of general farming operations.

AI in Optimizing Water Usage and Irrigation

Water scarcity is one of the most limiting conditions in agriculture, particularly in arid and semi-arid regions. Efficient water management makes for healthy conditions for crops and conserves this precious resource. Traditional irrigation systems, for a long time, have resulted in water waste through over-irrigation or poor distribution. AI-powered irrigation systems will thus involve determining the level of water usage based on the specific needs of every crop in real time, guided by soil moisture sensors and weather forecasts (Lakhiar *et al.,* 2024). AI can process data about soil moisture, the water requirements for crops, and climatic conditions to assess how much water is required at any one given time. Such sensors, buried in the field for example, can monitor soil water continuously and send signals to AI powered irrigation systems to adjust delivery accordingly. In this way, optimal water delivery to crops is assured with reduced waste, and under or over-irrigation will be avoided (Shaikh *et al.,* 2022). One of the strong benefits of AI-powered irrigation systems is their ability to predict water requirements in the future. These systems study weather forecasts and historical data and can estimate any period of drought or excessive rain well in advance to plan irrigation schemes. In cases where the system predicts a period of drought, it may reduce water use much earlier to avoid unnecessary wasting of water while still retaining adequate crop health (Adinarayana *et al.,* 2024). Furthermore, AIdriven irrigation systems can be integrated with other technologies in precision agriculture, such as drones and satellites, to carry out large-scale monitoring of crop health and soil conditions. This integrated approach allows for finer-scale water management-particularly for fields containing variable soils or topographies. This can be achieved by optimizing water usage, which will reduce the bill for water usage; besides, natural resources can be conserved to increase crop yields, and thus contribute to economic and environmental sustainability (Lakhiar *et al.,* 2024).

Machine learning, a subset of artificial intelligence, is dedicated to establishing models and methods that enable computers to learn from data and improve without requiring explicit programming (Janiesch *et al.,* 2021). Machine learning involves developing mathematical models to analyse data patterns for making predictions or decisions. By iteratively examining historical data, these models identify patterns and enhance their precision as time progresses (Sarker, 2021). The typical process involves training the model on a dataset to uncover correlations between input features and output values. Unsupervised learning utilizes unlabeled data to identify concealed patterns, whereas supervised learning relies on labelled data (Chawla and Karakoulas, 2005; Bekker and Davis, 2020). Reinforcement learning utilizes interactions with the environment to learn how to attain specific goals. Neural networks, decision trees, support vector machines, and clustering algorithms are machine-learning methods utilized for data processing, pattern recognition, and autonomous prediction or decision-making (Shaikh *et al.*, 2022).

Applications and benefits in farm automation

Sowing

Machine learning technology used in precision planting with automated all-terrain vehicles (ATVs) has improved farming methods by allowing for accurate and flexible planting techniques. These applications utilize machine learning algorithms to examine soil variability, historical yield data, and environmental conditions in order to enhance seed location and density (Sarker, 2021). Machine learning algorithms can optimize planting depths, spacing, and seed kinds for maximum crop output by analysing real-time data from sensors on automated ATVs. The use of machine learning in precision planting using automated ATVs demonstrates how technology improves precision agriculture by refining planting procedures to promote efficiency and productivity. Artificial intelligence (AI) and machine learning (ML) improve the process of determining the optimal positioning of seeds, resulting in consistent growth of crops and increased productivity.

Harvesting

Machine learning algorithms incorporated into automated ATV systems assess various data sources, such as crop maturity indicators, weather patterns, and field conditions, to enhance harvesting operations. The algorithms provide predictive modelling to identify the optimal timing for harvesting, ensuring that crops are harvested when they are at their highest level of maturity, thereby maximizing both yield and quality (Xu *et al.,* 2019). ATVs equipped with sophisticated sensors and vision systems can use machine learning to selectively detect, categorize, and harvest crops based on certain criteria helps minimize field loss and increase productivity (Benos *et al*., 2020). Integrating machine learning with automated ATV systems for harvesting optimization demonstrates the potential to transform farming practices by ensuring timely and effective harvesting operations while maintaining crop quality and quantity.

Spraying

Machine learning algorithms are crucial for enabling accurate spraying and fertilizing operations in ATV automation, ushering in a new era of precise and efficient agricultural techniques. These algorithms are incorporated into automated ATV systems to utilize data from several sources, like soil composition, crop health indicators, and environmental conditions, for the efficient use of pesticides and fertilizers. By utilizing machine learning methods like predictive modelling and pattern recognition, these systems can identify the most effective spraying and fertilizing approaches customized for specific sections of a field, reducing excess usage and guaranteeing precise application (Thorat *et al.*, 2023). AI-driven vision systems on ATVs are used for real-time crop monitoring, indicating regions needing treatment, and enabling precise, automated distribution of agrochemicals based on detected needs. The incorporation of machine learning algorithms in ATV automation for spraying and fertilizing activities demonstrates its ability to enhance better farm input management and reduce environmental harm in agriculture.

Weeding

Machine learning plays a crucial role in transforming weeding and pest control methods in agriculture during ATV operations. Incorporating machine learning techniques into ATV systems allows for the creation of advanced weed identification and classification models. The models utilize data from sensors and camera systems to precisely distinguish between crops and weeds in real-time (Mathews, 2014). Machine learning-based pest detection systems integrated into automated ATV operations use environmental data to forecast and detect possible pest outbreaks, allowing for preventive actions in targeted pest management. Machine learning in ATV operations enables automated decision-making for accurate weed management and insect control, which can reduce pesticide usage, improve crop health, optimize agricultural techniques, and minimize environmental impact (Mathews, 2014).

Crop monitoring

Incorporating machine learning with all-terrain vehicle (ATV) automation has redefined crop monitoring and health evaluation, providing unparalleled understanding of field conditions and plant health. ATV-mounted sensors and imaging systems use machine learning algorithms to gather and analyse extensive data for evaluating crop health indicators like leaf colour, biomass, and disease symptoms. These algorithms facilitate the development of prediction models for early disease detection, stress identification, and yield forecasting (Singh, 2018). AI-powered image analysis systems on ATVs offer immediate evaluations of plant health and development, enabling prompt actions and specific management strategies (Mathews, 2014). Machine learning in ATV automation improves farmers' capacity to optimize yields and implement precision agricultural practices by enabling proactive decision-making through real-time crop health assessments.

Benefits:

Increased Productivity and Resource Efficiency: Precision farming optimizes resource use by applying inputs, such as water, fertilizers, and pesticides, precisely where and when they are needed. By tailoring management practices to match specific field conditions, precision farming maximizes crop yields while minimizing input wastage (Benos *et al*., 2020)..

Reduced Environmental Impact: Precision farming practices help mitigate environmental degradation by minimizing nutrient runoff, soil erosion, and chemical leaching. By promoting sustainable agricultural practices, precision farming contributes to soil health, water quality, and biodiversity conservation (Singh, 2018).

Enhanced Profitability and Sustainability: Precision farming improves farm profitability by reducing input costs, increasing yields, and optimizing operational efficiency (Singh, 2018).

By adopting precision farming practices, farmers can achieve higher returns on investment while promoting long-term sustainability and resilience in agriculture (Singh, 2018).

Table 1 shows specific AI tools and planforms that has been used from the year 2020 -2025

Table 2 reveals the impact of AI and Smart Farming Techniques on Nigerian Agriculture.

Roles of AI in Nigerian Precision Agriculture

Personalized Agronomic Advice

Platforms uses AI to analyze soil and crop data from remote sensing, providing farmers with customized recommendations for inputs such as fertilizer and water as seen in the Kitovu platform (Ahmed *et al.*, 2024).

Pest and disease detection

AI – powered systems uses computers vision and machine learning to analyzed images of crops to identify pests and diseases, allowing for targeted and precise treatment rather than broad application of chemicals (Ahmed *et al.*, 2024).

Smart Irrigation and Fertilization

By analyzing soil moisture, weather patterns and crop needs, AI helps manage irrigation to minimize water waste and ensure precision application of fertilizers to reduce over use and environmental impacts (Ahmed *et al.*, 2024).

Yield forecasting and market linkage

AI models uses data to forecasts crop yields and can connect farmers to markets, helping them with planning and logistics (Ahmed *et al.*, 2024).

Enhanced decision-making

AI – powered mobile apps and advisory services provides farmers with real-time data and insights to help them make better – informed decisions from farming to harvesting (Ahmed *et al.*, 2024).

The Future Prospects of Precision Farming

The future prospects of precision farming are promising, driven by advancements in technology, data analytics, and the potential to address global food security challenges. Here are some key areas of development and opportunities for precision farming:

Advancements in Technology and Data Analytics: Continued advancements in sensor technology, remote sensing, and data analytics will enable more precise and efficient monitoring and management of agricultural systems. Emerging technologies such as Internet of Things (IoT), unmanned aerial vehicles (UAVs), and blockchain will further enhance data collection, connectivity, and traceability in precision farming. Integration of advanced sensors, robotics, and automation will enable autonomous farm operations and real-time decision-making, improving productivity and sustainability (Gebbers, and Adamchuk, 2010).

Integration of Artificial Intelligence and Machine Learning: Artificial intelligence (AI) and machine learning (ML) algorithms offer new opportunities for predictive modeling, pattern recognition, and decision support in precision farming. AI-driven systems can analyze large datasets, identify trends, and generate actionable insights for optimizing agronomic practices, input applications, and resource allocation (Kushwaha *et al.*, 2024). ML algorithms can learn from historical data, adapt to changing conditions, and optimize management strategies, leading to more efficient and adaptive precision farming systems (Gebbers, and Adamchuk, 2010)

Potential for Addressing Global Food Security Challenges: Precision farming has the potential to contribute significantly to global food security by increasing agricultural productivity, improving resource use efficiency, and reducing food losses (Zhang, *et al.,* 2019). By optimizing crop yields and minimizing input wastage, precision farming practices can help meet the growing demand for food in a sustainable and environmentally responsible manner (Zhang, *et al.,* 2019). Precision farming technologies can also enhance resilience to climate change, mitigate the impacts of extreme weather events, and improve the adaptive capacity of agricultural systems (Kushwaha *et al.,* 2024)

Sustainable Intensification and Resilience: Precision farming enables sustainable intensification of agricultural production, allowing farmers to produce more food on existing land while minimizing environmental impacts (Kushwaha *et al*. 2024). By adopting precision farming practices, farmers can enhance the resilience of agricultural systems to climate variability, water scarcity, and other challenges, ensuring food security for future generations (Zhang, *et al.,* 2019).

Adoption of Digital Agriculture Platforms: Digital agriculture platforms, powered by cloud computing, big data analytics, and mobile technologies, will facilitate the adoption and scaling of precision farming practices (Zhang, *et al.,* 2019). These platforms provide farmers with access to real-time data, decision support tools, and agronomic services, empowering them to make informed decisions and optimize farm operations. Digital agriculture platforms also foster collaboration, knowledge sharing, and innovation across the agricultural value chain, driving continuous improvement and transformation in agriculture.

Challenges

Initial Investment Costs: The adoption of precision farming technologies often requires significant upfront investments in equipment, sensors, software, and training. High initial costs may pose barriers to adoption, particularly for small and medium-sized farmers with limited financial resources (Zhang, *et al.,* 2019).

Data Privacy and Security Concerns: Precision farming involves the collection, storage, and analysis of sensitive data related to farm operations and management. Data privacy and security concerns, including unauthorized access, data breaches, and misuse of information, need to be addressed to maintain trust and confidence in precision farming technologies (Kushwaha *et al.*, 2024).

Accessibility and Adoption Barriers in Developing Regions: Limited access to technology, infrastructure, and technical support services may hinder the adoption of precision farming practices in developing regions. Challenges such as inadequate internet connectivity, lack of skilled labor, and insufficient funding for technology investments need to be overcome to promote inclusive adoption of precision farming (Srinivasan *et al.,* 2018).

Conclusion and Recommendations

The use of AI – powered tools and machine learning as come to stay, as the world agricultural paradigm is changing likewise the approach of Nigerian agricultural farming systems must equally shift and align with global realities. If Nigeria must be food secure and sufficient the nation must imbibe the use of AI – powered technology and machine learning models in her agricultural practices. The role of AI and ML in precision agriculture cannot be overemphasized. Therefore, we call on the federal government and other relevant bodies to come in addressing the challenges befallen Nigerian precision farming. Hence, we recommend increase investment in digital infrastructure, capacity building and policy support to unlock the full potentials of precision farming in Nigeria.

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Apendix

Table 1: Specific AI Tools and Platforms from 2020 - 2025

AI Tools	Platforms
Zenvus	Uses satellite imagery and sensor data to provide farmers with insights on soil conditions, rainfall forecasts and pest incidence.
Hello Tractor	Leverages on AI – powered platform for mechanization scheduling, connecting small holder farmers with tractors owners which optimizes resources use and improves efficiency
Kitovu	Offers personalized soil and crop health analysis, inputs recommendations (fertilizer/pesticides) and yield optimization insights using remote sensing
AirSmart	Utilizes drones and sensors for aerial survey, helping farmers monitor crop health across large areas and optimize the use of water and fertilizer.
iSDA Virtual Agronomist	Advisory tool, used by Nigeria farmers, draws on machine learning, remote sensing and weather services to provide tailored agricultural advice and prediction
AI – Powered Mobile Application	Other mobile apps such as Crop2Crop, Pantix, Riceadvice, Akilimo and Darli are increasingly used by farmers to get tailored advice detect crop disease and analyzed soil conditions using AI
Nigerian Agricultural Intelligence Platform (NAIP)	Lauched by the Federal Government in collaboration with Pixel solution Limited, this platform uses AI to connect farmers, researchers, and Markets, offering AI – Powered advisory services and digital extension tools

Source: (Lakhiar *et al.,* 2024)

Table 2: Impact of AI and Smart Farming Techniques on Nigerian Agriculture

Agricultural Aspects	Traditional Methods	AI and Smart Farming Techniques	Estimated Improvement
Crop yield monitoring	Manual field inspection, estimate based on experience	Satellite imagery, AI-Powered yield prediction models	20 – 30% increase in accuracy
Irrigation managements	Field schedules, manual observation	IoT sensors, AI – driven irrigation scheduling	30 – 50% water saving
Soil health Analysis	Periodic Lab. Testing visual inspection	Real – time soil sensors, AI-Based nutrient recommendation	40 -60% reduction in fertilizer use.

Weather prediction	Reliance on general forecasts, traditional knowledge	Hyperlocal AI weather models, satellite data integration	70 -80% improvement in accuracy
Pest Control	Routine spray, manual pest scouting	AI powered pest detection, precision application of pesticides	50 -70% reduction pesticides uses
Greenhouse management	Manual climate control, periodic adjustments	Automated systems, AI – optimized environmental control	15 – 25% increase in crop yield and quality.

Sources: (Rhoads, 2023; Ahmed *et al.*, 2024; Javaid *et al.*, 2023)

