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Systematic Review of Current Trends in Precision Agricultural Model to Address Food Insecurity Challenges

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ABSTRACT: Agriculture contributes significantly to socio-economic development, food security, and employment opportunities for a large number of people globally. Hence, the objective of this paper was to explore a systematic review of current trends in precision agricultural model to address food insecurity challenges using appropriate standard techniques. The results revealed the potential of precision agriculture in solving food insecurity challenges, minimizing agricultural input wastage, and promoting lucrative farming. This agricultural model builds on innovative technology collect data, analyze, and make critical predictions thereby providing lasting solutions to complex agricultural challenges. According to the United Nations, about 2/3rd of the world's population will be living in urban areas by 2050. This report indicated the need to incorporate emerging technological innovation into agriculture to increase food production and ensure food availability. Robotics and drones are innovative technologies with the potential to change the agricultural landscape, especially in developing nations. Consequently, the application of automaton, AI, and predictive tools to tackle real-time agricultural challenges is at the nascent stage in the developing areas of the world. Financial constraints, lack of technical knowledge, and lack of government support remains major challenges influencing precision agriculture in developing countries. Finally, adopting a precision agricultural model by farmers will help in pest detection, and predicting crops with favourable output, to cope with the current food insecurity challenges, especially in developing countries.

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The development of a precision agricultural model assisted technological innovation poised to change the pre-existing paradigm in the agricultural landscape (Cui *et al.*, 2022; Gokool *et al.*, 2023; Gorai *et al.*, 2017). Precision agriculture is also known as Site-Specific Agriculture (SSA), Satellite Farming (SF), Precision Farming (PF), and Smart Farming (SmF) (Gokool *et al.*, 2023). This agricultural model harnesses the power of digital technology such as Information Technology (IT), Global Positioning System (GPS), Remote Sensing (RS), Data Analytics (DA), and machine learning to improve farm productivity, food security, and environmental sustainability (Gokool *et al.*, 2023; Gorai *et al.*, 2017). Precision farming ensures the proper application of farm inputs such as water, target seedlings, pesticides, herbicides, and fertilizers to plots or sections to improve crop yield and ensure ecosystem sustainability (Cesco *et al.*, 2023; Whelan and Taylor, 2013). This agricultural model with highly transformative potential offers lasting solutions to the impending food insecurity challenges and environmental degradation in developing countries of the world (Ncube *et al.*, 2018; Ritchie *et al.*, 2023; Dell'Angelo *et al.*, 2023; Ghalazman *et al.*, 2022).

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The precision agriculture model also includes precision irrigation mainly differential irrigation which treats different fields and/or farmlands according to the soil texture, crop variety, and nutrient requirement (Ncube *et al.,* 2018). This approach saves costs and minimizes wastage when compared to traditional irrigation (Smith and Baillie 2009; Ncube *et al.,* 2018). Ncube *et al.,* (2018) report that about 60% of agrochemical and 30% of mineral fertilizers have been saved by precision agriculture in West African farmers. However, adoption of this farming model is extremely low due to several challenges ranging from financial challenges to technical skills deficiencies. With an estimated 10 billion global population by 2050, digital transformation in the agricultural sector or precision agriculture remains inevitable to cope with the looming food crises, particularly in developing countries (Abu *et al.,* 2022).

Many developing countries including sub-Saharan African countries rely on agriculture for economic development. One-third of the gross domestic production in many sub-Saharan countries is contributed by the agricultural sector. Providing employment opportunities to two-thirds of the terming youth in the region (FAO, 2017). Despite the significant contribution of agriculture to economic development in developing countries including sub-Sahara Africa, agricultural development in the region remains a chronic challenge (FAO, 2017; Fuglie 2013). In 2017, an estimated 30 million people were ravaged by food insecurity in West African countries. Regrettably, 4.7 million children were intensely malnourished (FAO, 2017). This data revealed chronic food insecurity scenario in developing countries. By 2050, an estimated 40% decrease in cereal production is expected in West Africa below 80% production in 2015 from yield trend extrapolation (van Ittersum *et al.,* 2016).

Universally, studies relating to precision agricultural farming have been reported. Wall and King, (2004) critically analyzed the application of soil sensing technology in farming systems to improve crop productivity. Hemalatha and Sujatha (2015) reported that examining farmland temperature and moisture using remote sensors and vehicle predictions provides information on soil water content. However, in West Africa, studies about precision agriculture practices are relatively few (Schlecht *et al.,* 2006; Aune and Bationo, 2008). Their studies revealed improved crop varieties, seed priming techniques, fertilizers micro-dosing, manure and mulch targeted application, and cultivating food crops together with trees and fodder as the main precision agricultural technologies. On the other hand, Pierre *et al.,* (2017) reported the role of fertilizer micro-dosing in enhancing maize yields but may exacerbate nutrient mining in maize cropping systems in northern Benin. Louise *et al.,* (2019) reported the application of remote sensing in Maize yield estimation in West Africa. Also, the efficient semi-parametric estimation of multi-valued treatment effects under triviality was reported by (Matias 2010). These reports revealed relatively low adoption of precision agriculture technology in developing regions to improve food production, boost farmer's profits, and ensure environmental sustainability. With the increasing human population, food insecurity, and global climate change effect, precision agriculture aims to provide solutions to emerging challenges in the agricultural sector. Hence, the objective of this paper was carried out a systematic review of current trend in precision agricultural model to address food insecurity challenges.

MATERIALS AND METHODS

The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) model was adopted from Onyeneke *et al.,* (2019) and used for this study. This framework (PRISMA) provides useful criteria for collecting academic resources such as systematic reviews and research involving secondary data analysis. Inclusion and exclusion criteria, stepwise review process, data abstraction, and analysis were also adopted from the method (Shaffril *et al.,* 2018; Escarcha *et al.,* 2019; Onyeneke *et al.,* 2019).

An online literature search for relevant open-access English language-published, peer-reviewed, and gray literature was conducted using databases such as Google Scholar (GS), African Journals Online (AJOL), Web of Science (WoS), Data Citation Index, MEDLINE®, Science4Life; Science Direct; and SpringerLink JSTOR, Nigerian Higher Education-based Journals, Professional Association-based journals, and Government-owned Non-Governmental Organization-owned Repositories.

Search Coverage, Search Terms, and Data collection: The search criteria cover publications from 2000 to 2024 (Fig. 1). The research report on farmers' adaptations to the precision farming model to maximize limited available resources and achieve optimum agricultural output was given serious consideration. The following keywords string were used for the search "robotics + agricultural", "artificial intelligence + agriculture", "Machine learning model in agriculture", "Data science and agriculture", "Precision agriculture + sustainable food production", "precision agriculture + food security", "precision farming", "Site-specific farming", "soil sensor" and "crop sensor". A total of 2,356 resources were identified from the search databases.

Inclusion/exclusion criteria: (i) Studies that have used precision agriculture/site-specific farming/ smart farming concepts fully or partially were adopted
(ii) Studies that have used precision agriculture/climate smart/site-specific farming/ smart farming concepts/conservation agriculture elsewhere, fully or partially. These were considered relevant and included (Justine *et al.*, 2021)

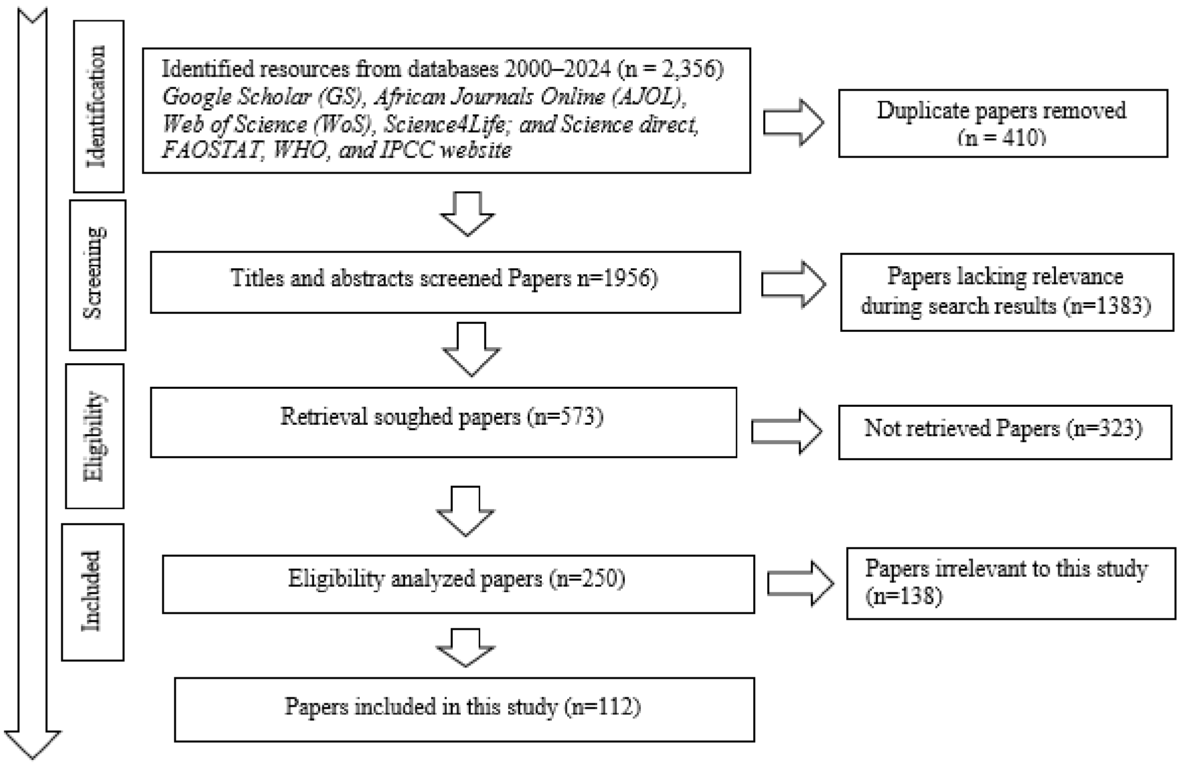

Fig. 1 Flow diagramme for literature search and inclusion criteria

Articles Screening Technique: Initial title screening of relevant articles for inclusion and exclusion was carried out on studies focusing on precision agricultural models/approaches for sustainable food production. The technique excluded topics that were not specifically on agriculture and environmental sustainability.

The second stage focuses majorly on the abstract for screening of retrieved resources. Studies lacking accessible abstracts, summaries, or non-English language abstracts were removed. Abstracts that were not focused on the potential of precision agriculture for ensuring food security in developing countries were excluded. Consideration was given to abstracts related to agriculture, and environmental sustainability. Abstracts that mention precision agriculture without information on specific focus in developing countries were also excluded.

Two independent reviewers screened the resources for inclusion and exclusion criteria for all studies at title and abstract levels. A third reviewer was consulted when there was no clear idea for inclusion or exclusion of any study. Consistent understanding among the reviewers was achieved through proper discussion of the procedure and criteria for screening at both levels according to the final database analysis and classification. The classified articles and studies based on precision agriculture were screened according to the scope of study and the purpose viz:

a) The application of precision farming practices in the study aimed at addressing: land, and crop improvement/intervention measures, soil mapping, crop mapping, growth monitoring, precision irrigation, nutrient and pest monitoring and management, and yield predictions.

b) Productivity: outcome of precision agriculture model used in the field of agronomy, environmental sustainability, and economic output
c) Study model: The precision agriculture study model was seriously considered. Specific terminology such as precision farming, site-specific farming, and climate-smart agriculture are closely related to precision agriculture concepts. Only primary research studies were incorporated into the final selected document for this study.

RESULT AND DISCUSSION

Impact of digital technology on the agricultural sector: Precision agriculture adopts and applies innovative improvements in science and technology to solve food insecurity challenges, minimize waste of resources, and ensure lucrative farming (Gebbers and Adamchuk, 2010). This farming approach, supported by advancements in technologies detects variations in patterns of different agricultural practices and suggests solutions based on those patterns (Yao and Wu, 2011; Robert, 2002). Global positioning systems (GPS) and timely spatial data remain the critical driver of precision agriculture. Farm planning, field mapping, soil sampling, tractor guidance, crop scouting, variable rate applications, and yield mapping are enhanced by GPS-based applications in precision farming (Yao and Wu, 2011). During low visible field conditions such as rain, dust, fog, and darkness GPS-based systems allow farmers to work with minimal risk of wasting farm input. This AI-assisted technology makes precision agriculture a solution to the impending food insecurity in developing countries (Zarco-Tejada, 2014).

The different precision agricultural practices, their output, and the corresponding impacts in the agricultural sector are presented in (Fig 2). AI-based technology contributed substantially to the development of the agricultural sector globally. This technology changes various fields of agriculture such as irrigation, soil content sensing and analysis, crop monitoring, weeding, and crop establishment (Kim *et al.*, 2008). High-value applications of AI in the agricultural sectors are built on robots to achieve maximum results.

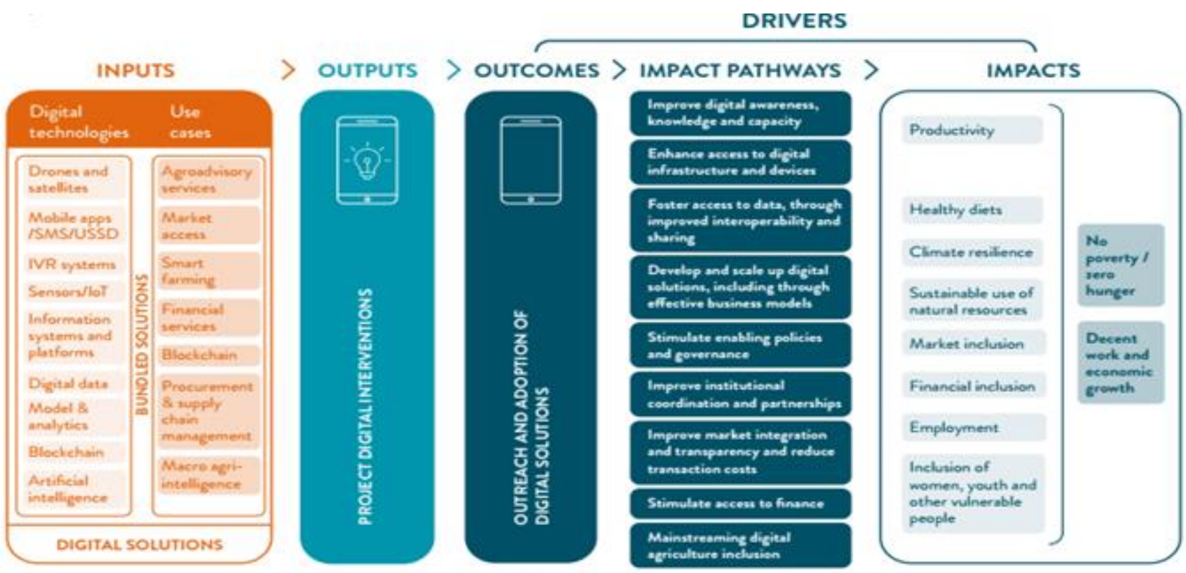

Fig 2: Digital technology in the agricultural sector
Source: (Adopted from IFAD Rural Development Report 2021; Ceccarelli *et al.*, 2022)

The application of AI in the agricultural sector has facilitated improved agricultural output with less input and less effort. An estimated 75 million technology-associated connected devices were expected to be used by farmers in 2020. However, an average of 4.1 million points of data is estimated to be generated in 2050 by farmers in developed and developing countries. These indicated the potential contributions of AI to agricultural development and curbing food insecurity in developing countries. The application of an AI-based model in agriculture allowed for the easy gathering of large amounts of data from relevant government and public websites analyzed and offered farmers solutions to complex problems, provided smart irrigation techniques, and increased farm productivity (Panpatte, 2018). Technical combination of AI model and biotechnology can potentially reduce the agricultural workforce, improve productivity, and reduce food insecurity (Panpatte, 2018). The United Nations report revealed that about 2/3rd of the world's population will be living in urban areas by 2050. This will lead to inevitable food insecurity and severe pressure on farmers and food security in developing regions of the world (Tanha *et al.*, 2020). Application of AI-base technology and machine learning models can help agriculture reduce threats, reduce the cost of production, and provide affordable and efficient farming systems, provide employment opportunities for women, youth, and children in the West African region.

Chatbots for farmers: Chatbots also known as conversational virtual assistants are automated to interact with humans efficiently. Chatbots powered by artificial intelligence and machine learning algorithms provide critical insight into natural language and communicate in a personalized way with humans (Tanha *et al.*, 2020). They are enhanced by mechanical and computer commands for various functions such as retail, travel, and media. This advantage has been harnessed to facilitate increasing agricultural productivity for farmers by receiving and answering challenging agricultural-related questions and providing advice and recommendations to farmers (Tanha *et al.*, 2020). The recent advancement in information technology facilitated by mobile connectivity chat-bots has great potential to help in agricultural development in developing countries (Chen and Liu, 2020). However, farmers in rural areas still witness glitches in communication due to the reliance on crude and/or handy peer knowledge to solve pressing agricultural challenges (Darapanemi *et al.*, 2022),

Mobile chat-bots for crop production: Fig. 3 shows a deep learning-based mobile chat-bots model designed for crop-based production farmers in Akwa Ibom State, Nigeria (Patience *et al.*, 2022). This model consists of the following significant components to facilitate its smooth operation viz Deep machine learning algorithms, natural language processing (NLP), intent recognition algorithm (query), knowledge base (dataset), response generator, and user interface (Patience *et al.*, 2022). The targeted population for this AI chat-bots was cassava farmers in the Uyo Metropolitans area. Their interaction occurs through the user interface of their mobile devices to send queries and observed responses generated.

“However, data obtained from identified sources were stored in the knowledge base and typically used to help the ML algorithms define rules for generating outcomes after processing user queries. Word shuffling and Jacquard Similarity algorithms were also deployed to develop classifiers for the users' intents. The NLP pre-processing techniques were used to interpret human natural language input to ease understanding of the users' input by the machine (chat-bots) (Patience *et al.*, 2022).

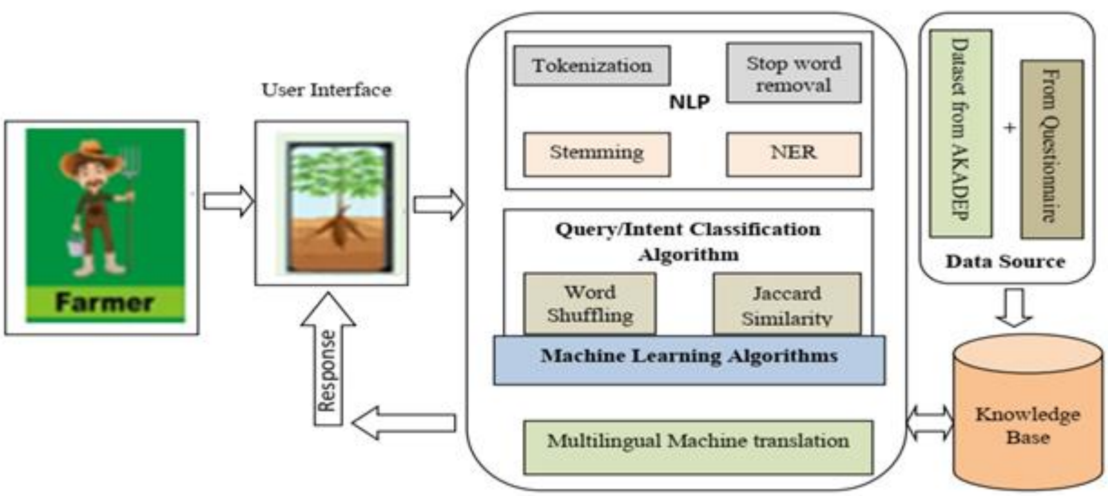

Fig 3: Mobile chatbots Proposed for crop production
Sources: (Patience *et al.*, 2022).

Robots in agriculture: According to Tanha *et al.*, (2020), a large sector of the economy with relatively low productivity such as the Agri-food sector drives the introduction of Robotics and Autonomous Systems (RAS). This technology has played a substantial role in the agricultural sectors in developed countries. The UK-RAS White papers (2018) revealed that over £108bn p.a., were mainly generated from the retail of the UK agricultural food chain, employing about 3.7 million persons and yielding £20bn of exports in 2016 from international. This significant milestone achievement has been enhanced by robots. This makes researchers advocate for the design of autonomous robotic systems to aid agricultural productivity and replace the lack of and/or efficient conventional farming machinery in developing countries globally (Dursun and Ozden, 2011).

Human labour replacement benefits in both small and large-scale agricultural farms drive the introduction of robotic technology in the agricultural sector (Manivannan and Priyadharshini, 2016; Pedersen *et al.,* 2008). Weeding, irrigation, farm guarding for delivering effective reports, adverse environmental conditions mitigation, increased precision, and individual plant management, are the major operations in the agriculture sector handled by autonomously robotic systems (Tanha *et al.,* 2020).

Artificial Intelligence for optimizing Irrigation in agriculture: Globally, 80% of the freshwater resources are consumed by the agriculture sector (Tanha *et al.,* 2020). Unfortunately, rapid population growth poses immense pressure on water resources due to the increasing demand for domestic and industrial use. Hence, the need for efficient technology innovation aims to reduce water wastage in the agricultural sector and replace manual irrigation practices (Tanha *et al.,* 2020). Implementing autonomous irrigation machines requires knowledge, of atmospheric parameters such as humidity, wind speed, solar radiations, and crop factors such as the stage of growth, plant density, soil properties, pest, and plant evapotranspiration.

Different irrigation models aimed at limiting resource usage and ensuring resource efficacy have been discussed (Kumar, 2014). To determine soil fertility and primary ingredient percentages such as potassium, phosphorous, and nitrogen conveniently, a fertility meter and pH meter are set up on the field to improve efficiency and agricultural output. To ensure improved agricultural productivity and reduce the number of manpower by detecting water level, soil temperature, nutrient content, and weather forecasting, AI-based technology is applied for irrigation including wireless technology for drip irrigation which is planted in the agricultural field to enhance automatic plant irrigators (Kumar, 2014).

In this model, turning ON/OFF the irrigation pump activates the micro-controller. Machine-to-machine (M2M) is used to share communication and data among the different components of the machine and the server (Shekhar *et al.,* 2017). In 2017, an automated robotic model (Arduino and Raspberry pi3) to detect the moisture content and temperature of agricultural land was developed (Savitha and UmaMaheshwari 2018). In this model, data sensing occurs regularly and is sent to the Arduino microcontroller which converts the analog input to digital, the data are sent to the Raspberry pi3 (embedded with the KNN algorithm). Finally, the signal is sent to the Arduino to start the water source for irrigation. Water supply from the store will be according to the requirement updated and stored in the sensor values. A similar automated irrigation system to reduce water consumption using remote sensing and Arduino technology to reduce water consumption in agricultural land to about 40% was developed according to (Jha *et al.,* 2019). Another automated model used in agricultural irrigation for optimum out is presented in Table 1.

The first technology innovation in the irrigation of agricultural land started from drip irrigation. This technique ensures a limited amount of water loss due to evapotranspiration, by directing water beneath the crop and ensures efficiency (Dukes *et al.,* 2009). Subsequent development and advancement saw the application of sensors to detect soil moisture content, raindrops, and wireless broadband networks, powered by solar panels (Dukes *et al.,* 2009). Water-on-demand irrigation is the major technique for moisture sensors. In this technique, thresholds are set based on the soil capacity. However, the sensor provides permission to the controller when water is needed on the farm. The moisture content level of a particular zone is read by the sensor at a specified time. If the moisture content in that zone is below the threshold, water will be allowed in that zone (Yong *et al.,* 2018).

Drones in Agriculture: Drones are Unmanned aeronautical vehicles (UAVs) or unmanned ethereal frameworks (UAS), mostly called automatons (Fig. 4a - f), which are remote control devices for different purposes (Mogli and Deepak, 2018). The application and utilization of drones in agricultural operations are aided by GPS and other sensors mounted on the drone. Data collection about soil quality, livestock well-being, nutrient levels, crop health and yield monitoring, weather and rainfall patterns, irrigation equipment monitoring, weed identification, herd and wildlife monitoring, and disaster management have been handled by drones recently in technologically advanced nations in the agricultural sector (Veroustraete, 2015; Ahirwar *et al.,* 2019; Natu and Kulkarni, 2016; Udit, 2021). Similarly, image capturing, processing, and analysis which are making a huge impact on agriculture are done by drone and remote sensing (Abdullahi *et al.,* 2015; Spoorthi *et al.,* 2017).

The different types of drones and their specification for agriculture are presented in Table 2. In the area of crop spraying, drones played a substantial role in the agricultural sector. They have been considered effective in clouded weather conditions to spray inaccessible fields with tall crops, for example, maize (Sugiura *et al.,* 2005; Simelli and Tsagaris, 2015). Their solid favorable position and satellite airborne sensors of high picture resolution make the drone favourable equipment in the agricultural sector (Jannoura *et al.,* 2015; Simelli and Tsagaris, 2015).

Table 1: Summary of Irrigation Automation Using Various Artificial Intelligence Technologies.

Reference	Algorithm	Evapotranspiration method	Result/Advantage	Other technology
Choudhary *et al.,* (2019	PLSR and other regression Algorithms	Evapotranspiration model	Improve efficiency and maximum economic productivity	Sensors for data collection, IoT Hardware Implementation
Umair and Usman (2010)	Artificial neural Network-based control system	Evapotranspiration model	Automation	Sensors for measurement of soil, temperature, wind speed, etc
Kia *et al.,* (2009)	Fuzzy Logic	FAO Penman-Monteith method	Optimization	N/A
Karasekreter *et al.,* (2013)	ANN (multilayer neural model), Levenberg Marquardt, Backpropagation	Penman–Monteith method	Decreased evaporation induced by signal from schedule and savings observed in water and electrical energy	N/A
Al-Ali *et al.,* (2015)	Fuzzy Logic	N/A	Verified experimental results can be applied used for home grass	WSN, Zigbee
Dela Cruz *et al.,* (2017)	ANN	N/A	Optimization of water resources in a smart farm.	N/A
Anand *et al.,* (2015)	Fuzzy Logic Controller	Penman–Monteith method	Drip irrigation prevents wastage of water and evaporation	Wireless sensor
Arvind *et al.,* (2017)	Machine Learning algorithm	N/a	Prediction and tackle drought situations	Sensors, Zigbee, Arduino microcontroller

Source: adapted from Tanha et al., (2020)

Table 2. Agro-based Classification of Drones

UAV	Rotary Wings	Fixed Wings
Flight duration	Fly ~20 min	Fly up to an hour
Wind pressure	Can be flown from in winds gusting from 20 - 50 mph	Obtained satisfactory images by in and out flight
Direction changing flexibility	Allow new direction during flight for re-direction	Allow new direction upload during flight for re-direction
Price range	\$500 - \$100,000	\$500 - \$100,000
Deployable option	Highly deployable	Highly deployable

Source: adapted from Tanha et al., (2020).

For spraying synthetic substances in the agricultural field, drone plays an important role in achieving accurate results with no harm to non-targeted crops or areas (Kale *et al.* 2015). These has been were enhanced with sensors conveyed on the crops in the field known as remote sensor networks (WSN) which controlled the way toward applying the synthetic compounds. From the data recovered by the drone, only data on synthetic substances only spread into the assigned region were recovered (Kale *et al.* 2015). Similarly, a low-volume sprayer for an unmanned helicopter to investigate principal rotor distance across about 3 m and a most extreme payload of 22.7 kg which utilizes one gallon of gas for 45 min was designed by (Huang and Reddy 2015). This model provides a framework that serves as a precursor for creating UAV flying applications to obtain higher yields with higher target rates and bigger VMD droplet sizes. Nørremark *et al.,* (2008) noted that the working principle for the sprayer involves crumbling the sprayed liquid such as suspension, emulsion, or tiny drops. These liquids are launched with negligible power to ensure adequate circulation. Additionally, the sprayer measures the pesticide to maintain a strategic distance from extreme application. Ineffective or inappropriate use of pesticides may result in severe harm to the crop yield. The residue definitions of pesticides are disseminated with the assistance of dusters. Different categories of drones used for several agricultural purposes have been categorized based on the required vitality to atomize and throw out the shower liquid, sensitivity, and performance.

Fig 4a: planting drone

Fig 4b: Soil analysis drone

Fig 4c: Crop spraying drone

Problem and Future Perspective: Precision agricultural technique has enormous potential to transform the agricultural sector using AI technology. In the areas of land quality, groundwater level, crop cycle, and pest attack, AI technology can provide critical insight to farmers to curb emerging challenges. Patterns and important data related to agricultural activities over a period can be extracted with AI-driven sensors. Installing AI-empowered sensors in robotic harvesting equipment will help in data collection.

Fig. 4d: crop health assessment drone

Fig 4e: irrigation drone

Fig. 4f: crop monitoring drone;
Source: (Unpaprom *et al.,* 2018).

Crop damage due to pest attacks and natural disasters remains the biggest challenge in crop farming which occurs mostly due to a lack of adequate information relating to their activities and life cycle. Adopting a precision agricultural model (AI) by farmers will help in pest detection, and predicting crops with favorable output, to cope with the current food insecurity challenges. With the growing devastating impacts of climate change on agriculture such as disruption of growing seasons, altered arable land, and floods disaster that brings seawater to fertile agricultural areas, adequate application of AI in agriculture is critical to support farmers and enhance the cultivation process, create an ambiance for sustainable food production and marketing strategies. Irrigation system challenges, variable temperature, low groundwater density, food scarcity, environmental pollutant from legacy contaminants/contaminants of emerging concerned, and substance wastage are the major challenges damaging the agricultural lands and agricultural sector in developing countries (Jacob *et al.*, 2024a; Jacob *et al.*, 2024b; Akangbe *et al.*, 2024). Recognized AI-driven solutions however are needed for these challenges to improve agricultural productivity. While the current research trend and solutions to agricultural challenges are promising, the agricultural sector still requires innovative technology and massive adoption to increase agricultural productivity (Shobila and Mood, 2014). The application of automation, AI, and predictive tools to tackle real-time agricultural challenges remains at the nascent stage in many parts of the world. Slaughter *et al.*, (2008) observed that strong technical application is needed to utilize the enormous scope of innovative technology (AI, machine learning, and robotics) in the agricultural sector to detect changes in external conditions, facilitate real-time decision-making and apply appropriate framework/platform for efficient contextual data collection. This innovative technology is promising, however, the financial implication associated with their procurement makes it difficult for smallholder farmers to adopt this solution in their day-to-day farming activities. The rapid adoption of these technologies can be achieved through open source platform technique, easy affordability, and increased penetration among farmers to help improve yield and reduce over-dependence on traditional knowledge and methods for livestock and crop production.

Conclusion: The agricultural sector has faced enormous challenges such as variable rainfall patterns, unpredictable weather, climate conditions, and low-density groundwater leading to food insecurity challenges in developing countries. Human cognitive intelligence and prediction have been used by farmers to predict seasons and changes in the farmlands for years. However, this method has been filled with a high degree of uncertainty. Existing technologies and large field research have provide lasting solutions to challenges facing the agricultural sector which is critical to improve food production in developing nations. Factors such as poverty, illiteracy, communication gap between smallholder farmers and agricultural extension officers, power shortages facility, connectivity, and techno phobia among others remain the major challenges toward precision agriculture.

Declaration of Conflict of Interest: The author declare no conflict of interest.

Data Availability Statement: Data are available upon request from corresponding author

REFERENCES

Abdullahi, HS; Mahieddine, F; Sheriff, RE (2015). Technology Impact on Agricultural Productivity: A Review of Precision Agriculture Using Unmanned Aerial Vehicles. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, pp. 388–400.

Abu, NS. Bukhari, WM; Ong, CH; Kassim, AM; Izzuddin, TA; Sukhaimie, MN; Norasikin, MA; Rasid, AFA (2022). Internet of Things Applications in Precision Agriculture: A Review. *J. Robot. Cont. 3*, 338–347.

Ahirwar, S; Swarnkar, R; Bhukya, S; Namwade, G (2019). Application of drones in agriculture. *Int. J. Curr. Microbiol. App. Sci.* 8 (1), 2500–2505.

Akangbe, OA; Chukwuka, AV; Imiuwa, ME; Adeogun, AO (2024). Gonad pathology, sex hormone modulation and vitellogenin expression in Chrysichthys nigrodigitatus from Lagos and Epe lagoons within the southern lagoon system, Nigeria. *Front. Toxicol*. 6:1336916. doi: 10.3389/ftox.2024.1336916.

Al-Ali, AR; Qasaimeh, M; Al-Mardini, M; Radder, S; Zualkernan, IA (2015). ZigBee-based irrigation system for home gardens. 2015 International Conference on Communications, Signal Processing, and Their Applications (ICCSPA'15). https://doi.org/ 10.1109/iccspa.2015.7081305.

Anand, K; Jayakumar, C; Muthu, M; Amirneni, S (2015). Automatic drip irrigation system using fuzzy logic and mobile technology. 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR). https://doi.org/10.1109/ tiar.2015.7358531.

Arvind, G; Athira, VG; Haripriya, H; Rani, RA; Aravind, S (2017). Automated irrigation with advanced seed germination and pest control. 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR). https://doi.org/10.1109/ tiar.2017.8273687.

Aune, JB; Bationo, A (2008). Agricultural intensification in the Sahel—the ladder approach. *Agri. Sys. 2*(98), 119–125.

Canton, H (2021). International Fund for Agricultural Development—IFAD. In The Europa Directory of International Organizations. (pp. 330-332). Routledge.

Ceccarelli, T; Chauhan, A; Rambaldi, G; Kumar, I; Cappello, C; Janssen, S; McCampbell, M (2022). Leveraging automation and digitalization for precision agriculture: Evidence from the case studies.https://doi.org/10.1126/SCIENCE.ADF9351/SUPPL_FILE/SCIENCE_ADF9351_DATA_S1.XLSX.ZIP.

Cesco, S; Sambo, P; Borin, M; Basso, B; Orzes, G; Mazzetto, F (2023). Smart agriculture and digital twins: Applications and challenges in a vision of sustainability. *Europ. Journ. of Agrono*. *146*, 126809. https://doi.org/10.1016/J.EJA.2023.126809.

Chen, APS; Liu, CW (2020). Intelligent commerce facilitates education technology: the platform and chatbots for the Taiwan agricultural service. *Int. Journ. of e-Edu. e-Bus. e-Manag. and e-Learn.* 11(1), 1 – 10 https://doi.org/10.17706/ijeeee.2021.11.1.110.

Choudhary, S; Gaurav, V; Singh, A; Agarwal, S (2019). Autonomous crop irrigation system using artificial intelligence. *Intl. J. of Eng. and Adv. Tech.* 8 (5S), 46–51.

Cui, M; Qian, J; Cui, L (2022). Developing precision agriculture through creating information processing capability in rural China. *Journ. of Rur. Stud. 92*, 237–252. https://doi.org/10.1016/J.JRURSTUD.2022.04.002.

Darapaneni, N; Raj, S; Sivaraman, V; Mohan, S; Paduri, AR (2022). LSTM-RASA Based Agri Farm Assistant for Farmers. *arXiv preprint arXiv:*2204.09717.

Dell'Angelo, J; Rulli, MC; D'Odorico, P (2023). Will war in Ukraine escalate the global land rush? *Sci*. 379 (6634), 752–755.

Dukes, MD; Shedd, M; Cardenas-Lailhacar, B (2009). Smart Irrigation Controllers: How Do Soil Moisture Sensor (SMS) Irrigation Controllers Work? AE437/AE437, rev. 3/2009. *EDIS*, P. 2.

Dursun, M; Ozden, S (2011). A wireless application of drip irrigation automation supported by soil moisture sensors. *Sci. Res. Ess.* 6 (7), 1573–1582.

Escarcha, JF; Lassa, JA; Zander, KK (2018). Livestock under climate change: a systematic review of impacts and adaptation. *Climate*, 6(3), 54.

FAO. Food and Agriculture Organization of the United Nations, 2017. THE STATE OF FOOD AND AGRICULTURE LEVERAGING FOOD SYSTEMS FOR INCLUSIVE RURAL TRANSFORMATION. 978-92-5-109873-8pp. 1–181.

Fuglie, K; Rada, N (2013). Resources, policies, and agricultural productivity in sub-Saharan Africa. *USDA-ERS Economic Research Report*, (145).

Gebbers, R; Adamchuk, VI (2010). Precision agriculture and food security. *Sci.* 327(5967), 828– 831. https://doi.org/10.1126/science.1183899.

Ghalazman EA; Das, GP; Gould, I; Zarafshan, P; Rajendran SV; Heselden, J; Badiee, A; Wright, I.; Pearson, S (2022). Applications of robotic and solar energy in precision agriculture and smart farming. *In Sol. Ener. Advan. in Agri. and Food Prod. Sys.* 351–390. Academic Press. https://doi.org/10.1016/B978-0-323-89866-9.00011-0.

Gokool, S; Mahomed, M; Kunz, R; Clulow, A; Sibanda, M; Naiken, V; Chetty, K; Mabhaudhi, T (2023). Crop Monitoring in Smallholder Farms Using Unmanned Aerial Vehicles to Facilitate Precision Agriculture Practices: A Scoping Review and Bibliometric Analysis. *Sust.* 15, 3557, 15(4), 3557. https://doi.org/10.3390/SU15043557

Gorai, T; Ahmed, N; Patra, AK; Sahoo, RN; Sarangi, A; Meena, MC; Sharma, RK (2017). Site Specific Nutrient Management of an Intensively Cultivated Farm Using Geostatistical Approach. *Proceed. of the Nat. Acad. of Sci. India Sec. B – Bio. Sci*. 87(2), 477–488. https://doi.org/10.1007/S40011-015-0590-1/METRICS.

Hemalatha, T; Sujatha, B (2015). Sensor-based autonomous field monitoring agriculture robot providing data acquisition & wireless transmission. *Intern. J. of Inno. Res. in Comp. and Comm. Engi.* 3 (8), 7651–7657.

Jacob, US; Isangedighi, IA; Akangbe OA; and Jonah, UE (2024a). Environmental Occurrence, Toxicity and Mitigation Strategies of Micro-Plastics in the Aquatic Ecosystem *Bim. J. of Sci. and Tech. 8*(1B), 385-405. DOI: https://doi.org/10.56892/bima.v8i1B.649

Jacob, US; Obot, OI; Umoh, EM; Akangbe, OA (2024b). Paraquat-Induced Acute Toxicity Response in Juvenile African Catfish *Clarias gariepinus* (Burchell, 1822). *J. Appl. Sci. Environ. Manage.* 28 (6) 1757-1763 DOI: https://dx.doi.org/10.4314/jasem.v28i6.14

Jannoura, R; Brinkmann, K; Uteau, D; Bruns, C; Joergensen, RG (2015). Monitoring of crop biomass using true color aerial photographs taken from a remote-controlled hexacopter. *Biosyst. Eng*. 129, 341–351.

Jha, K; Doshi, A; Patel, P; Shah, M (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artific. Intell. in Agric.* 2, 1–12.

Kale, SD; Khandagale, SV; Gaikwad, SS; Narve, SS; Gangal, PV (2015). Agriculture drone for spraying fertilizer and pesticides. *Inter. Journ. of Adv. Res. in Comp. Sci. and Softw. Eng.* 5 (12), 804–807.

Karasekreter, N; Başçiftçi, F; Fidan, U (2013). A new suggestion for an irrigation schedule with an artificial neural network. *J. of Exp. and Theo. Arti. Intell.* 25 (1), 93–104.

Kia, PJ; Far, AT; Omid, M; Alimardani, R; Naderloo, L (2009). Intelligent control-based fuzzy logic for automation of greenhouse irrigation system and evaluation in relation to conventional systems. *W. Appl. Sci. J.* 6 (1), 16–23.

Kumar, G (2014). Research paper on water irrigation by using wireless sensor network. International Journal of Scientific Engineering and Technology, IEERT conference Paper, Pp. 123–125.

Louise, L; Mathieu, C; Christian, B; Maria-Jose, E; Agnès, B; Danny, LS (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. *Europ. Journ. of Agro*. 108: 11–26.

Manivannan, L; Priyadharshini, MS (2016). Agricultural robot. *Intern. Journ. of Advan. Res. in Elect. Electro. and Instruct. Eng.* 153–156.

Matias, DC (2010). Efficient semi-parametric estimation of multi-valued treatment effects under ignorability *Journ. of Eco.* 155: 138–154.

Mogili, UMR; Deepak, BBVL (2018). Review on application of drone systems in precision agriculture. International Conference on Robotics and Smart Manufacturing. Procedia Computer Science 133, Pp. 502–509.

Natu, AS; Kulkarni, SC (2016). Adoption and utilization of drones for advanced precision farming: a review. *Inter. Journ. on Rec. and Innova. on Trends in Comp. and Comm.* 4 (5), 563–565.

Ncube, B; Mupangwa, W; French, A (2018). Precision agriculture and food security in Africa. *Sys. Anal. Approach for Comp. Global Chall.* 159–178. https://doi.org/10.1007/978-3-319-71486-8_9/COVER.

Nørremark, M; Griepentrog, HW; Nielsen, J; Søgaard, HT (2008). The development and assessment of the accuracy of an autonomous GPS-based system for intra-row mechanical weed control in row crops. *Biosyst. Eng.* 101 (4), 396–410.

Nyaga, JM; Onyango, CM; Wetterlind, J; Söderström, M (2021). Precision agriculture research in sub-Saharan Africa countries: A systematic map. *Prec. Agri. 22*, 1217-1236.

Onyeneke, RU; Nwajiuba, CA; Emenekwe, CC; Nwajiuba, A; Onyeneke, CJ; Ohalete, P; Uwazie, UI (2019). Climate change adaptation in Nigerian agricultural sector: A systematic review and resilience check of adaptation measures. *Agric. and Food*. *4*(4), 967-1006.

Panpatte, DG (2018). Artificial intelligence in agriculture: An emerging era of research. *Anand. Agri. Uni.* 1-8.

Patience. UU; Udo, EN; Asuquo, DE; James, OR (2022). A machine learning-based mobile Chatbot for crop farmers in Uyo metropolis. In International Conference on Electronic Governance with Emerging Technologies (pp. 192-211). Cham: Springer Nature Switzerland.

Pedersen, SM; Fountas, S; Blackmore, S (2008). Agricultural robots – applications and economic perspectives. *Serv. Rob. Appli.* 369–382.

Pierre GT; Irenikatché APB; Euloge, KA; Pierre, B; Charles, LB (2017). Fertilizer microdosing enhances maize yields but may exacerbate nutrient mining in maize cropping systems in northern Benin. *Field Crops Research.* 213; 130–142.

Ritchie, H; Rosado, P; Roser, M (2023). Agricultural Production. *Our World in Data*. https://ourworldindata.org/agricultural-production.

Robert, PC (2002). Precision agriculture: A challenge for crop nutrition management. *Plant and Soil. 247,* 143–149.

Savitha, M; UmaMaheshwari, OP (2018). Smart crop field irrigation in IOT architecture using sensors. *Int. Journ. Adv. Res. Comp. Sci.* 9 (1), 302–306.

Schlecht, E; Buerkert, A; Tielkes, E; Bationo, A (2006). A critical analysis of challenges and opportunities for soil fertility restoration in Sudano-Sahelian West Africa. *Nutr. Cyc. Agroecosys.* 76:109–136. doi:10. 1007/s10705-005-1670-z.

Shaffril, HA; Krauss SE; Samsuddin SF (2018). A systematic review on Asian's farmers' adaptation practices towards climate change. *Sci. Tot. Environ.* 644: 683–695.

Shekhar, Y; Dagur, E; Mishra, S; Tom, RJ; Veeramanikandan, M; Sankaranarayanan, S; (2017). Intelligent IoT based automated irrigation system. *Int. J. Appl. Eng. Res.* 12 (18), 7306–7320.

Shobila, P; Mood, V (2014). Automated irrigation system using robotics and sensors. *Int. J. Sci. Eng. Res.* 3 (8), 9–13.

Simelli, I; Tsagaris, A (2015). The use of unmanned aerial systems (UAS) in agriculture. 7th International Conference on Information and Communication Technologies. *In Agric.* 730-736.

Slaughter, D.C., Giles, D.K., Downey, D. 2008. Autonomous robotic weed control systems: a review. Comput. *Elect. Agric.* 61 (1), 63–78.

Smith, R; Baillie, J (2009, January). Defining precision irrigation: A new approach to irrigation management. In *Irrigation Australia 2009: Irrigation Australia Irrigation and Drainage Conference: Proceedings*. University of Southern Queensland.

Spoorthi, S; Shadaksharappa, B; Suraj, S; Manasa, VK (2017). Freyr drone: pesticide/fertilizers spraying drone - an agricultural approach. 2017 2nd International Conference on Computing and Communications Technologies (ICCCT). https://doi.org/10.1109/ iccct2.2017.7972289.

Sugiura, R; Noguchi, N; Ishii, K (2005). Remote-sensing technology for vegetation monitoring using an unmanned helicopter. *Biosyst. Eng.* 90 (4), 369–379.

Talaviya, T; Shah, D; Patel, N; Yagnik, H; Shah, M (2020). Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides. *Artif. Intell. in Agri. 4*, 58-73.

Udit, D (2021). Drones Applications in Agriculture. *Chronic. of Biores. Manag*. 5(3):115-120.

UK-RAS White papers, (2018). Agricultural Robotics: The Future of Robotic Agriculture. *Agri. Rob.* 1–36.

Umair, SM; Usman, R (2010). Automation of irrigation system using ANN-based controller. *Intern. J. Elec. Comp. Sci.* 10 (2), 45–51.

Unpaprom, Y; Dussadeeb, N; Ramaraj, R (2018). Modern Agriculture Drones The Development of Smart *Farm.* p. 2018.

Van Ittersum, MK; Van Bussel, LG; Wolf, J; Grassini, P; Van Wart, J; Guilpart, N; Cassman, KG (2016). Can sub-Saharan Africa feed itself? *Proceed. of the Nat. Acad. of Sci. 113*(52), 14964-14969.

Veroustraete, F (2015). The rise of drones in agriculture. *Ecron.* 2 (2), 1–3.

Wall, RW; King, BA (2004). Incorporating plug-and-play technology into measurement and control systems for irrigation. Management, 2004, Ottawa, Canada August 1–4.

Whelan, B; Taylor, J (2013). Precision Agriculture for Grain Production Systems. *In Prec. Agri. for Grain Prod. Sys.* CSIRO Publishing. https://doi.org/10.1071/9780643107489.

Yao, H; Wu, Y (2011). A Research about the Application of Information Technology in Precision Agriculture: Taking the Operating System of Shanghai Agriculture Economy as an Example. Springer.

Yong, W; Shuaishuai, L; Li, L; Minzan, L; Arvanitis, KG; Georgieva, C; Sigrimis, N (2018). Smart sensors from ground to cloud and web intelligence. IFAC-Papers Online 51 (17), 31–38.

Zarco-Tejada, P. J. (2014). Precision agriculture: An opportunity for EU farmers—Potential support with the CAP *2014-2020*. Joint Research Centre (JRC) of the European Commission. Retrieved from https://publications.jrc.ec.europa.eu/repository/handle/JRC91993