



A Review of Transformative Technologies in Digital Agriculture: Integrating IoT, Remote Sensing, and AI for Smart Crop Management

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ABSTRACT

This study reviews the potential of smart crop management through the use of technologies like digital agriculture, which takes into account the latest technological tools used in agriculture, including artificial intelligence (AI), remote sensing, and the Internet of Things (IoT), to increase crop production sustainability and efficiency. This is crucial given that different climates have an impact on the resources available for agriculture. Data-based decision-making to optimize irrigation, fertilization, and pest control can ultimately result from the integration of tools like the Internet of Things and sensor networks, which can give farmers access to real-time data on their crops and assess important health factors like soil conditions, plant water status, pest presence, and environmental factors, among others. Additionally, this can be improved by utilizing technologies like unmanned aerial vehicles (UAVs) and drones, which can improve monitoring capabilities by accurately tracking crop growth and conducting extensive field surveys. However, in order to find patterns and trends in large datasets and offer insightful information for bettering agricultural operations, big data analytics and artificial intelligence are essential. In addition to addressing issues and obstacles to the widespread adoption of both new and existing technologies, this paper highlights the major technological developments and applications in smart crop management. It also recommends the necessity of continued research and cooperation in order to achieve efficient and sustainable crop production.

Keywords: Digital agriculture; sensor networks; smart crop management; remote sensing; internet of things.

1. INTRODUCTION

The use of digital innovations and technologies in food systems, value chains, and agricultural production systems is referred to as "digital agriculture" (Bwambale et al., 2022). It includes many ideas, including precision agriculture (Ayushi et al., 2018a) and smart farming (Nazirul et al., 2019). These ideas relate to the collection and analysis of data on location, weather, behavior, phytosanitary status, consumption, energy use, prices, and economic information using data, sensors, machines, drones, and satellites (Bwambale et al., 2022). The information is utilized to improve monitoring of disputes in agricultural chains and sectors, optimize agricultural production systems, address social concerns, boost knowledge exchange and learning, and make more accurate

and well-informed decisions (Ayushi et al., 2018b). Specifically, the terms "precision farming" (PF) and "precision agriculture" (PA) describe a novel method that began in the 1990s (Ayushi et al., 2017a) and collects crop data using a variety of sensors, drones, and monitoring equipment. Crop productivity is maximized and resources like water, fertilizer, and pesticides are used less frequently thanks to this knowledge. A more effective and sustainable method of crop cultivation is offered by PF, which is essential given the world's expanding population and rising food need (Chergui et al., 2020). Growing awareness of crop and soil variability, together with the advent of advanced technologies such as microcomputers, geographic information systems (GISs), and global navigation satellite systems (GNSSs), are responsible for the creation of PF.

Given the significance of these technologies for agricultural production, the major objective of this study is to thoroughly investigate the synergistic use of IoT, remote sensing, and artificial intelligence (AI) in smart crop management. Doing so will involve examining how IoT sensors and remote sensing technologies are used in various agricultural settings to collect data on important parameters, using tools like drones, and using AI and big data analytics to create decision support systems and predictive models that help farmers optimize their practices. Furthermore, this article will offer useful perspectives and suggestions to help farmers and agribusinesses successfully apply smart agricultural practices. A thorough examination of how digital technology might be used into farming methods to solve contemporary issues like water scarcity and environmental sustainability will be provided by this material. It will also give farmers and agribusinesses wishing to use intelligent crop management strategies useful advice and insights. Finally, the study will emphasize the significance of current and upcoming research as well as cooperation between farmers and academics in order to completely understand the potential of digital agriculture.

2. INTEGRATION OF IOT AND AI IN SMART FARMING

Smart farming is the integration of the Internet of Things (IoT) and Artificial Intelligence (AI) into cyber-physical systems for all-encompassing agricultural management. Numerous fields, including soil management, crop health monitoring, disease detection, and weed control, are covered by AI applications. Notable examples include computer vision systems, ANN-GIS, fuzzy logic-based Soil Risk Characterization Decision Support Systems (SRCDDS), Management-Oriented Modeling (MOM), Artificial Neural Networks (ANNs), CALEX, PROLOG, Invasive Weed Optimization (IWO), and Support Vector Machines (SVMs) (Ayushi, 2019b). Mobile expert systems are an important use of AI that allow farmers to use smartphones for activities like species identification, disease diagnosis, and soil health analysis using mobile applications. 5G, LoRaWAN, NB-IoT, Sigfox, ZigBee, and Wi-Fi are examples of wireless network and communication technology advancements that have greatly expanded the use of IoT in a variety of industries. These technologies allow for advances in coverage, bandwidth, connection

density, and end-to-end latency, as well as high-capacity phenotyping and real-time remote management. IoT and cloud computing enable smart farming applications in agriculture, including weather tracking, fishery management, smart greenhouses, and livestock monitoring. Typical IoT communication technologies include Bluetooth, Zigbee, LoRa, 5G, and Wi-Fi (Ayushi et al., 2020b). Low power consumption, cost-effectiveness, and quick reaction times are qualities that are necessary for agricultural equipment communication.

The operation of robotics and autonomous systems (RAS) depends on artificial intelligence (AI). Continuous data stream creation is made easier by its interaction with IoT. For agricultural data to be transformed into useful insights for decision-making, data mining techniques are essential (Ayushi et al., 2018b). In agricultural decision support systems, artificial intelligence (AI) discovers hidden patterns that are essential for identifying pests, diagnosing illnesses, forecasting yields, and optimizing fertilizer regimens by analyzing a variety of environmental data and previous farming records kept in vast data banks. These realizations are crucial for increasing agricultural practices' accuracy and efficiency since they allow for well-informed judgments based on thorough data analysis.

3. AGRICULTURAL IOT CONTROLLER

There are several different types of IoT controllers used in agricultural applications. These controllers are essential to farm IoT systems because they facilitate communication, data collection, and automated procedures (Nolack et al., 2020). Let us examine some of the common controllers and their characteristics in brief. The Arduino is a popular gadget in the agricultural IoT space (Ayushi et al., 2020a). Because it is simple and easy to understand, the Arduino is an entry-level gadget. But because it doesn't have built-in Wi-Fi, it could not be as useful for some IoT applications that need direct connectivity. The ESP8266 Node MCU, on the other hand, is frequently preferred by farmers and IoT enthusiasts with an interest in agriculture since it has built-in Wi-Fi connectivity and is better suited for applications that need direct communication (Malay et al., 2020). A wireless link allows the Microcontroller Unit (MCU) to communicate, which makes it easier to integrate into Internet of Things systems. Particularly well-known for being inexpensive and simple to use, the ESP8266 Node MCU is a preferred option for

farmers. This makes it possible to create efficient and reasonably priced IoT systems for agricultural operations (Ayushi et al., 2019a).

Larger farms with more intricate control systems are frequently best served by Raspberry Pi boards (Ayushi, 2019b). As for the Raspberry Pi, it's important to note that it runs faster than the Arduino Uno. More I/O ports and a variety of ways to connect and interact with different storage systems are further included. Among the Raspberry Pi's specialties are its ability to analyze large volumes of data and enable live feeds from farm cameras (Ayushi and Manoj, 2021). Despite its computational prowess, the Raspberry Pi's limited memory might cause issues when managing big data sets (Ayushi et al., 2020b). Large farms, however, continue to favor the Raspberry Pi because of its powerful processing capabilities (Deepak et al., 2021). New boards have recently received a lot of attention from specialists and farm IoT manufacturers. The Giant Board, Particle Photon, and Discovery STM32MP157C Crypto Board are a few of these boards. These boards provide improved capabilities that further boost the utilization of IoT-based services for agriculture while satisfying specific needs. Fishing, horticulture, and aquaponics growth factors can all be measured using the Intel Edison (Amiri et al., 2022).

4. AGRICULTURAL REVOLUTIONIZED WITH IOT-BASED SMART MACHINERY

Concerns including low worker efficiency and labor shortages have caused agriculture to undergo major changes, moving toward automation and technology-driven solutions (Brook et al., 2020). Thanks to automated technology, the Internet of Things has completely changed agriculture (Delgado et al., 2019). Applications include drones or UAVs, smart tractors, and harvesters. Efficiency and productivity have increased thanks to autonomous tools that require less human involvement (Al-Khasawneh et al., 2023). With the use of sensor data, smarter and self-determining tractors, cultivators, and ploughers have become essential components of contemporary farming (Craglia and Nativi, 2018). These vehicles can drive at safe speeds because they use lidar and radar technologies to identify obstructions. But it's still hard to see the difference between barriers and grass. Although the Global Navigation Satellite System (GNSS) is usually used for autonomous location, its

performance is restricted in congested areas such as fields (Ehlers et al., 2021). By enhancing object recognition and tracking, depth cameras and artificial neural networks (ANNs) are being used more and more to improve autonomous farming (Ayushi et al., 2020). Autonomous tractors and harvesters are now on the market because to the development and commercialization of companies like John Deere.

Field surveys and pesticide spraying are just two of the operations that have been transformed by the use of drones in agriculture (Ayushi and Avinash, 2019). Drones that are outfitted with sensors like lasers, accelerometers, cameras, gyroscopes, compasses, and GPS units are able to sense their environment and follow predetermined flight routes (Bhanu et al., 2021). Base station operators keep an eye on the motions of the drones, which are guided toward preset target sites. Hyperspectral drones and other advanced drones are able to take pictures with several bands, which makes it easier to calculate metrics like the normalized difference vegetation index (NDVI). The NDVI gives farmers important information and is a vital measure of crop health and growth (Ayushi and Manoj, 2020). Usually, drone spraying is used when insecticides are reasonably priced and require little manpower. The spraying mechanism is controlled by a mapped spray tip that is affixed to the UAV (Abbasi et al., 2022, Kumar et al., 2017).

5. REMOTE SENSING AND SATELLITES IMAGES

With the use of remote sensing and geographic information from satellite photos, farmers may now monitor and assess far dispersed areas for farming. Smart farming has been totally transformed by this (Cravero et al., 2022). Using sophisticated technology, such as drones and satellites, this entails taking incredibly clear images of agricultural areas. Details regarding crop health, disease outbreaks in the region, and field conditions are shown in these photos (Javaid et al., 2023). The ability to monitor enormous areas quickly and effectively is one of the best features of satellite imagery and remote sensing. They may view all of the crop's hidden information at once rather than having to search the entire farm for crop secrets (Ayushi and Avinash, 2017b). This enables them to make adjustments nearly instantly by identifying stressed crops, pest infestations, and any other problems they may be experiencing. Farmers

may reduce crop loss and guarantee that their plants are not negatively impacted by these issues by identifying them early. Additionally, satellite imagery or remote sensing can help identify the ideal locations for planting as well as which fields are suitable (Avinash et al., 2017, Sahu et al., 2017). Farmers can identify areas with varying soil richness, moisture content, or other factors that may impact crop growth by examining the photos. This information enables accurate site-specific management, such as adjusting fertilizer or water dosages in various fields to suit their requirements (Ben and Hanana, 2021, Sahu et al., 2015).

6. REMOTE SENSING: MONITORING CROP GROWTH, SOIL MOISTURE CONTENT, AND OTHER IMPORTANT VARIABLES THAT AFFECT CROP HEALTH THROUGH THE USE OF SATELLITE AND AERIAL IMAGERY

These days, satellite and aerial photography are effective instruments for tracking soil moisture content, crop growth, and other important aspects that affect crop health. These technologies have revolutionized the way agribusinesses and farmers approach agriculture by enabling better decision-making and offering insightful information about the health and growth of crops (Cravero et al., 2022). There are several different spatial resolutions that satellite data can provide, including kilometers, hundreds, or tens of meters. The majority of these lower-resolution goods are widely available, but they are not appropriate for small-scale agriculture. The accompanying costs still need to be reduced in order for modern satellite systems with exceptionally high spatial resolutions of a few meters or less to be widely used in agriculture and other fields. Accessible satellite platforms such as Sentinel and Landsat, particularly the most recent Sentinel-2 mission from ESA and the Landsat 9 mission from NASA, have recently made data primarily aimed at vegetation research available. Effective large-scale crop monitoring benefits greatly from high-resolution measurements, quick revisit times, and extensive coverage (Javaid et al., 2023, Ayushi and Avinash, 2017b). The multi-spectral nature of satellite photos also means that they record data from a variety of wavelengths or spectra, including thermal, infrared, and visible. However, the distance between the satellite and the ground limits satellite systems,

and signal attenuation from many sources, including aerosols, water vapor, and atmospheric gases, affects data quality (Avinash et al., 2017, Ayushi and Avinash, 2019).

To help differentiate between areas that are used for crops and those that are not, a number of academics have proposed several imaging indices or mathematical formulas (Ben and Hanana, 2021, Liu, 2020). It takes a great deal of skill and understanding to use these indices, though. Comprehending the distinct characteristics of various crops, their developmental phases, and the environmental elements that impact their visibility in satellite imagery is necessary. The performance of these indices in precisely detecting crop patches may also be impacted by hostile conditions, such as changes in lighting, atmospheric disturbances, or the presence of obstructing objects like clouds or shadows. The sluggish delivery of information to users, intermittent coverage, and coarse pixel resolutions are further problems that restrict the usage of satellite platforms. Because of these expert knowledge requirements, these indices and technology may be difficult for non-experts or those without specialized training to use (Khattak et al., 2019, Polymeni et al., 2023, Nandeha et al., 2017).

Nonetheless, satellite imagery is now being utilized for agriculture water management to offer useful data on crop water needs, irrigation effectiveness, and plant water stress detection. They assist in monitoring water availability, streamlining irrigation scheduling, and enhancing agricultural water resource management.

A UAV's design is frequently determined by the particular requirements of agriculture, including precision spraying, field mapping, and crop monitoring. The following are a few UAV types used in agriculture (Vikas et al., 2024, Nandeha et al., 2016b):

- For takeoff and landing, fixed-wing UAVs typically need runways. They are able to transport larger payloads and cover vast distances.
- Considering the height and speed of flight, rotary-wing UAVs offer a greater resolution. Their coverage area is smaller than that of fixed-wing UAVs.

In order to overcome both of its drawbacks, hybrid UAVs integrate the best

features of both types. They combine fixed-wing UAVs' cruise flight capabilities with rotary-wing UAVs' vertical take-off and landing (VTOL) capability. As previously said, agricultural management employs a variety of UAV kinds. The degree of detail needed for data gathering, the size of the agricultural area, the existence of impediments, and the particular operations being carried out all influence the type of UAV that is selected. Farmers may increase agricultural productivity, optimize techniques, and utilize less resources with the use of this technology.

7. DATA ANALYTICS AND MACHINE LEARNING

Analyzing the massive volumes of data produced by IoT devices in agriculture requires the use of machine learning and data analytics. Making well-informed judgments, streamlining procedures, and increasing general productivity are all made easier by this study. It's critical to recognize that these technical tools are not intrinsically IoT-based, but rather are a component of the larger process of using IoT data (Farooq et al., 2020 Nandeha et al., 2016a). This makes it possible to develop prediction models for calculating crop yields, evaluating pest damage, and maximizing the use of available resources. The capacity to use both historical and real-time data for decision-making is one of the main benefits of machine learning and data analytics in smart agriculture (Vinay et al., 2020). Farmers can use historical data to better understand the conditions that support plant growth, which helps them make decisions about when to sow and harvest, how much fertilizer and irrigation to use, and how to control pests (Surbhi et al., 2020). Moreover, machine learning techniques can be used to create prediction algorithms that foretell future food production and insect outbreaks. By predicting possible outcomes based on variables that can be controlled, such as climate, soil moisture, nutrient levels, and insect population dynamics, these models can help farmers (Ayushi et al., 2022a). Farmers are empowered by this proactive strategy to take preventative measures, make wise decisions, and reduce possible hazards. The flowchart of machine learning and data analytics techniques used in smart farming illustrates the difficulties that come with integrating these technologies into smart agriculture.

8. BIG DATA AND ARTIFICIAL INTELLIGENCE (AI): USING AI AND BIG DATA TO ANALYZE MASSIVE DATA AND OFFER UNDERSTANDING OF FOOD PRODUCTION PROCESSES

Big data is the term used to describe the vast amount of data generated by tracking various variables linked to crop management optimization. Since digital agriculture depends on the use of big data tools and practices to achieve sustainable agricultural development, it is closely related to big data [38]. This is because digital agriculture integrates various technologies, including computer science, machine learning, software engineering, environmental science, and more, with core agricultural disciplines to analyze large volumes of historical datasets and extract new and useful knowledge [39]. For example, big data on the cloud, smart sensing and monitoring, smart analysis and planning, and smart control are all ways that big data can support smart farming (Nirjharnee et al., 2023). This term has been used in a number of agricultural studies, such as the case of (Nirjharnee et al., 2024), which used high-resolution imagery to determine the relationship between soil water availability and water flow and use efficiency in a commercial vineyard (cv. Aglianico). This finding suggests that the ultra-high spatial resolution capabilities of UAVs and UASs are currently producing big data that requires prompt analysis. A research by Deepika et al., (2023) provides another example, stating that in the event of a severe climate change scenario, agriculture must transition to a "Sustainable Precision Agriculture and Environment" based on automation that integrates artificial intelligence (AI), the Internet of Things (IoT), drones, robotics, and big data. A novel image encryption system that integrates chaotic maps with the MapReduce architecture to improve the security and effectiveness of encrypting big batches of satellite photos was created and assessed in a study by Vinay et al., (2023).

9. MANAGING WATER USE IN AGRICULTURE WITH DIGITAL TOOLS AND SENSORS TO REDUCE WASTE AND INCREASE EFFICIENCY: SMART IRRIGATION SYSTEMS

The problem of effective water management in agriculture has a technological solution in the form of smart irrigation systems (SISs). In order to monitor and control water use, SISs employ

sensors and digital tools, which makes this valuable resource more sustainable and effective (Ayushi et al., 2023, Deepika et al., 2023). As a result of climate change and water shortage, water use efficiency (WUE), which is defined as agricultural yield per volume of water utilized (Nirjharnee et al., 2024), has drawn attention from researchers and policymakers globally (Ashwini et al., 2024, Smita et al., 2024). Farmers have always estimated the water requirements of their crops by hand and by making educated guesses. But since the introduction of the SIS, farmers have been able to track plant needs in real time and modify their irrigation systems as necessary. In addition to ensuring that crops receive the ideal amount of water for maximum growth, this helps to prevent water waste. Smart irrigation can be monitored using plant-, weather-, or soil-based techniques. Using direct (gravimetric sampling) and indirect (electromagnetic properties, heat conductivity, neutron count, water potential, or electrical resistance) methods, soil moisture monitoring takes into account measuring either soil water potential or soil water content in order to understand moisture dynamics within the plant root zone and its relationship to irrigation and plant water uptake (Ashwini et al., 2024, Vikas et al., 2024).

Weather-based approaches take into account tracking a number of meteorological factors in order to determine the reference evapotranspiration (ET_o), as plant water loss is influenced by temperature, wind, solar radiation, and relative humidity. The FAO-56 Penman-Monteith equation is used to calculate the ET in the majority of agricultural applications, and an automated weather station (AWS) is typically used to monitor these variables (Ashwini et al., 2024). For irrigation management, however, plant-based monitoring or plant stress sensing is the ideal approach since the plant combines the impacts of the soil and the atmosphere. Plant water status can be evaluated using a variety of techniques, such as stomatal conductance, sap flow, tissue water content (RWC), leaf or stem water potential, thermal sensing, and stem diameter (dendrometry) (Prabha et al., 2024).

10. THE INTEGRATION OF AGRO-BOTS FOR PRECISION AGRICULTURE: PROGRESS AND OBSTACLES

Agro-Bots are made to perform precise agricultural activities like transportation, weeding, spraying, and harvesting. They use cutting-edge

technologies to maximize efficiency. These developments guarantee precise chemical application while lowering the negative effects on the environment by using fewer harsh chemicals and conserving water. By 2026, the global agricultural robot (Agro-Bot) market is projected to have grown from its 2020 valuation of \$4.9 billion to \$11.9 billion, demonstrating the growing use and development of robotic solutions in agriculture (Cravero et al., 2022). By achieving accurate, real-time targeting at the plant level, Agro-Bots aim to reduce labor costs dramatically, reduce the hazards associated with dangerous operations, and give farmers the critical data they need to make well-informed decisions (Craglia and Nativi, 2018). Agro-Bot integration, however, is fraught with difficulties, especially in developed countries. These difficulties include a lack of workers and growing production expenses. While crops vary greatly in colour, size, form, and sensitivity all of which are frequently hidden by foliage agricultural fields present unpredictable situations due to changes in light, weather, and topography.

Several controlled contexts, including greenhouses, simulated plantations, and various outdoor agricultural settings, have seen the effective deployment of Agro-Bots. Automated fruit picking and intelligent gear for crop weed removal have been made possible by recent developments in robot technology (Javaid et al., 2023). These robots combine a variety of interdisciplinary technologies, including mechanical engineering, electronics, and machine vision. Robots formerly struggled to perform a variety of jobs needed in fields and warehouses and to adapt to changing conditions (Delgado et al., 2019). These days, complex image processing algorithms, inexpensive but strong sensors, and hardware enable flexible task control that takes into account naturally occurring objects with different sizes and shapes, which frequently manifest as "unknown" or only partially understood entities.

11. ONGOING AND FUTURE WORK

Crop production with digital agriculture is a sector that is always changing. The combination of artificial intelligence (AI) and machine learning (ML) is one area of current and future research that has a lot of promise for further development. Data analytics and decision-making processes can be improved in digital agriculture by incorporating AI and ML algorithms. Additionally,

farmers may optimize resource allocation, forecast crop yields, identify anomalies or diseases in real-time, and gain deeper insights from the data they collect by incorporating AI and ML techniques (Ayushi et al., 2024, Nandeha and Kewat, 2018).

12. CONCLUSION

A revolutionary method of producing crops, digital agriculture uses cutting-edge technologies to improve sustainability and optimize farming methods in a variety of cultivation systems, such as soilless culture, open-field, greenhouse, and vertical farming. It has been investigated how crucial it is to make decisions based on data and incorporate big data analytics into precision agriculture. Artificial intelligence (AI), drones, sensors, and other digital tools have completely changed the agriculture sector by providing chances to increase productivity, efficiency, and resource management. To fully realize the potential of digital agriculture, these gaps in technical development and acceptance must be addressed. To spur innovation, overcome obstacles, and guarantee that the advantages of digital agriculture are available to all parties involved in the agricultural industry, scholars, farmers, technology providers, and legislators must continue their research, investment, and cooperation. By enhancing decision-making, boosting output, and encouraging sustainable farming methods, digital agriculture has the potential to completely transform agricultural production. A bright future for the sector is presented by integrating IoT, AI, and big data technologies in a variety of agricultural sectors, including supply chain management, irrigation, and crop monitoring. Digital agriculture has the potential to create a more resilient and sustainable agricultural system in the ensuing decades, guaranteeing food security and tackling environmental issues by tackling the obstacles and encouraging cooperation. Crop production could be revolutionized by digital agriculture, which is also essential to creating a more resilient and sustainable food supply for coming generations.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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