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Review

Seeding a Sustainable Future: Navigating the Digital Horizon of Smart Agriculture

Sakshi Balyan [1], Harsita Jangir [1], Shakti Nath Tripathi [2], Arpita Tripathi [3], Tripta Jhang [1] and Praveen Pandey [1,*]

[1] Division of Plant Breeding and Genetic Resource Conservation, CSIR-Central Institute of Medicinal and Aromatic Plants, Lucknow 226015, India; sakshibalyan620@gmail.com (S.B.); hjangir2000@gmail.com (H.J.); jhangt@gmail.com (T.J.)
[2] Department of Botany, Nehru Gram Bharati Deemed to Be University, Prayagraj 221505, India; tripathishaktinath@gmail.com
[3] Microbial Technology Department, CSIR-Central Institute of Medicinal and Aromatic Plants, Lucknow 226015, India; arpitatripathi0391@gmail.com
* Correspondence: pandeypraveen1986@yahoo.com

Abstract: Agriculture is essential to the existence of the human race, as well as the foundation of our civilization, because it provides food, fuel, fiber, and other resources necessary for survival; however, it is facing critical challenges due to anthropogenic climate change, which hampers food and nutritional security. Consequently, the agriculture industry must adjust to farming issues, such as the shift in global temperatures and environmental degradation, the scarcity of farm workers, population growth, and dietary changes. Several measures have been implemented to enhance agricultural productivity, including plant breeding, genetic engineering, and precision agriculture. In recent years, the world has witnessed the burgeoning development of novel scientific innovations and technological advancements enabled by drones, smart sensors, robotics, and remote sensing, resulting in a plethora of revolutionary methods that can be applied to real-time crop modeling, high-throughput phenotyping, weather forecasting, yield prediction, fertilizer application, disease detection, market trading, farming practices, and other environmental practices vital to crop growth, yield, and quality. Furthermore, the rise in big data, advanced analytics, falling technology costs, faster internet connections, increased connectivity, and increases in computational power are all part of the current digitalization wave that has the potential to support commercial agriculture in achieving its goals of smart farming, resilience, productivity, and sustainability. These technologies enable efficient monitoring of crops, soil, and environmental conditions over large areas, providing farmers with data to support precise management that optimizes productivity and minimizes environmental impacts. Though smart farming has significant potential, challenges like high implementation costs, data security concerns, and inadequate digital literacy among farmers remain. In summary, agriculture is rapidly transforming from conventional to digital farming, offering global solutions, efficient resource utilization, and minimized input costs while fostering farmer livelihoods and economic growth. Delivering a comprehensive view of how technology could help in tackling critical issues like environmental degradation and threatened world biodiversity, this perspective emphasizes the perks of digitalization. Future advancements may involve data encryption, digital literacy, and particular economic policies.

Keywords: smart farming; digitalization; drones; sensors; IoT; precision agriculture; sustainable farming; robotics

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1. Introduction

Digitalization is the most significant technological advancement of our time, and it profoundly affects agriculture and other industries. Digitalization is the adoption of information communication technologies, such as the internet, mobile technologies, and devices.

It also includes data analytics to enhance the creation, gathering, sharing, aggregation, combination, analysis, access, searchability, and presentation of digital content, including for the creation of services and applications. Beyond particular equipment, methods, and techniques, digitalization has the potential to drastically change the way agriculture functions. It may benefit new organizational structures for manufacturing and supply chains and innovation [1]. Greater focuses on precision agriculture, artificial intelligence (AI), the Internet of Things (IoT), and the use of big data to promote production and business efficiency are just a few of the dramatic changes digitalization is bringing about in the agricultural sector [2]. For public and private players involved in agro-food value chains and the more extensive agricultural innovation system (AIS), the digital transformation of agriculture can produce several benefits. By leveraging digital technologies and the insights gained from agrarian data, farmers may be better able to ignite innovation and increase agricultural productivity, sustainability, and resilience. Digital technologies may offer opportunities for new sources of efficiency and value creation both upstream and downstream of farms, in addition to supporting research and innovation, new services for the industry, improved traceability, and more efficient value chain transactions [3]. Furthermore, policymakers have the potential to create novel and enhanced policies for the agriculture sector and leverage digital technology to improve the process of formulating, executing, and supervising policies. For example, digitalization may provide real-time data on various parameters like weather conditions, crop yields, and market trends. Additionally, it may help in optimizing resource allocation, making effective decisions, and monitoring and evaluating sustainable agricultural practices. Thus, the integration of technology enhances transparency, efficiency, and overall effectiveness in shaping agricultural policies.

Digitalization is a game changer that has transformed peoples' perspectives and shaped the planet as well as rapidly advanced trends in agriculture, and it is also referred to as "smart agriculture", which is the application of data-driven and precise technology to assist farmers in making decisions at the right time and location [4–6]. Farming processes are optimized by using technology such as drones, sensors, artificial intelligence (AI), robotics, cloud computing, blockchain, and decision support software. Agricultural systems, governance systems, and international trade focuses on value chains [7–10]. There is broad agreement that sustainable digital agriculture can significantly contribute to feeding the world's growing population [11,12]. Digitalization may increase agricultural output while benefiting society and the environment in several ways. According to Walter et al. [9], digital agriculture can improve food safety through enhanced traceability, lessen the burden on finite resources, and address climate change [11]. The expansion of international agricultural markets [10], the establishment of new, highly skilled employment possibilities [12], and improvements to animal welfare [13] are some further possible advantages of agricultural digitalization.

Revolutionary scientific and technological developments, especially in remote sensing, have greatly influenced agriculture in the 21st century. Crop monitoring using UAV (unmanned aerial vehicle)-enabled remote sensing technologies is crucial for identifying and mapping large-scale agricultural fields. Extensive crop observations can yield valuable knowledge in agricultural policy formulation. They are also a prerequisite for estimating crop productivity. Using this approach, the farmer can improve their farm's productivity, reduce farm input costs, and minimize environmental impacts. Crop health assessment at early crop growth stages ensures crop productivity. UAVs (or drones) equipped with cameras and sensors are remote sensing technologies that bridge the gap between tedious ground-based measurements and satellite imagery [14]. Compared to conventional ground-based crop monitoring, drones facilitate rapid and non-destructive measurements and provide much faster turnaround times than satellites at competitive costs [15]. In spatial resolution, UAVs permit the acquisition of appropriate images whose pixels are considerably smaller than objects, thus diminishing the bias effect due to background intensity [16]. Furthermore, they can safely fly at low altitudes in the proximity of vegetation, permitting high resolutions at low costs [17]. Considering the above facts, UAVs will likely open new possibilities in crop mapping and monitoring in precision agriculture.

Throughout agriculture's history, a series of revolutions have increased productivity, yield, and profitability to levels never before achieved. Forecasts from the market indicate that in the next ten years, there will be a "Digital Agricultural Revolution", which may be the most recent advancement to ensure that agriculture will continue to meet the global population's needs. It has been acknowledged that agriculture needs to be digitalized, and efforts have been undertaken to digitize the current value chain. In summary, by analyzing the current state of smart agriculture, its key technologies, and its applications, this analysis has mapped out the ongoing revolution in digital farming. Sophisticated sensors, data analytics, smart algorithms, and networking infrastructure have come together to enable the creation of a data-driven, precision-based paradigm for agricultural management.

2. Methodology

This review utilized a rigorous systematic approach to select publications, using search tactics like PubMed, Google Scholar, Scopus, and pertinent databases. This method involved searching for research papers based on manuscript names, keywords, institution affiliation, and published article citations. Numerous research publications relevant to digital agriculture, smart agriculture, and precision agriculture are available in these gigantic scholarly libraries; hence, a strong criterion was devised and used to choose the most influential research findings and reject unsuitable search results. The papers were chosen based on relevance, publication in prestigious journals, research published in the English language, publications with proper citations and accessible via the internet, publications providing vital information for subsequent calculations related to various scientific aspects, and the importance of their conclusions. Citation tracking and significant references were also used to locate other relevant studies. This comprehensive approach ensured a thorough examination of the topic, minimizing potential bias and providing a comprehensive overview of the existing literature.

3. Digital Technologies and Their Contribution in Agriculture

Over the past few decades, agriculture and food production have rapidly changed due to the increasing prevalence and mobility of digital technology [18]. The proliferation of mobile technology, remote sensing services, and distributed computing in food and agriculture is already enhancing smallholders' access to markets, information, and inputs. It also boosts productivity and production, optimizes supply chains, and cuts operational costs. However, there are obstacles to overcome in the "digitalization" of agriculture and the food value chain. These include high initial implementation costs, especially for small farmers, limited digital literacy among farmers, reliable access to high speed internet in rural areas, and data security concerns. To guarantee that everyone gains from the developing digital society, the FAO is dedicated to supporting partners and governments in bridging such transdisciplinary digital gaps [19]. A schematic representation of the benefits and challenges of digitization in agriculture is illustrated in Figure 1.

Using digital technology to link agricultural production from the paddock to the customer is known as "digital agriculture". Digital technologies can help emerging nations more quickly combat hunger and global poverty in rural areas [20]. Prominent technical developments include precision agriculture, artificial intelligence, blockchain, automation, robotics, livestock technology, indoor vertical farming, and contemporary greenhouse techniques. Farm equipment is linked to software systems that collect data from the farm and allows for studies of the soil and climate in particular areas. This will enable farmers to receive recommendations on seed selection and more accurate application of fertilizer and pesticides. Mobile phones have one of the greatest adoption rates among all the technologies invented in the last century. Digitalization will bring farmers and customers closer [21]. Customers can see more transparency in farming thanks to the accessible information on plants and animals. Agricultural productivity will be impacted by smart farming in the long run [22].

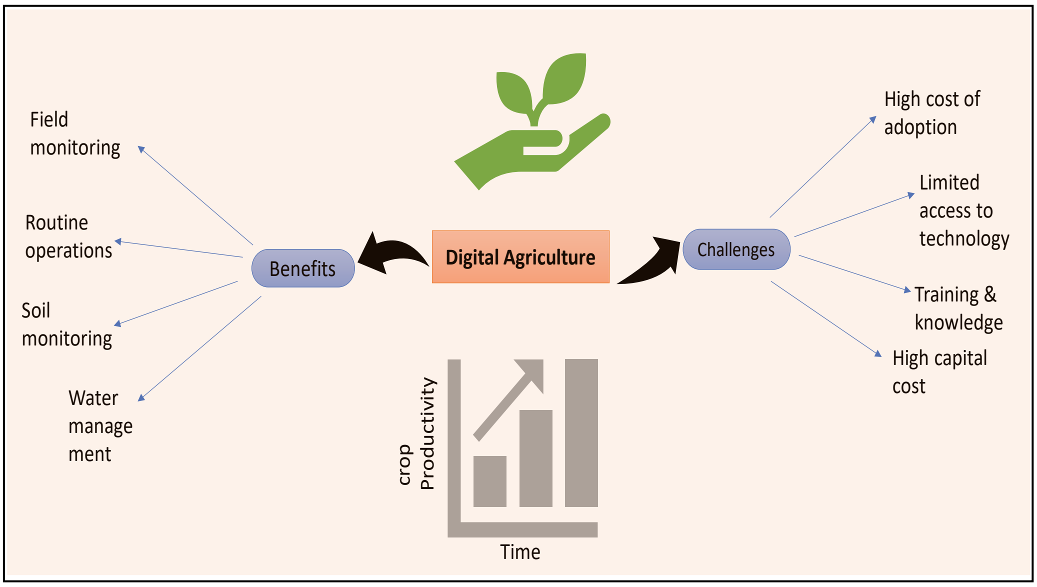

Figure 1. A schematic representation of the benefits and challenges of digitization in agriculture.

4. Mobile Applications and Farm Management Software (FMS)

Global connectedness has increased since the introduction of digital technologies. There is a smaller, faster, cheaper, and more efficient way to use mobile devices. Many farmers and businesses are receiving assistance so they may make better decisions. Assistance is being provided to farmers so they may operate more efficiently and apply fertilizer and water in more precise amounts. Digital technologies facilitate a multitude of operations, such as planning farming activities, budgeting, reporting, and keeping track of chores and performance. Agronomy, farm equipment, livestock handling facilities, communication, and other fields all make use of digital technologies. A new agricultural revolution will begin, and connectivity and data will be crucial. Advanced technologies such as artificial intelligence, analytics, and linked sensors can improve yields and boost the efficiency of water and other inputs. These can support the development of resilience and sustainability in both crop and animal husbandry. Robotics, automation, and sensor applications are examples of digital agricultural technologies used in production systems [23,24]. These days, farmers have access to a variety of applications. While most are accessible in Hindi and English, several offer additional regional languages to improve communication with farmers and cover all parts of the nation [25]. Figure 2 depicts the implications of mobile applications in agriculture.

The main focus of crop advising apps is how to manage the crop beforehand for a higher yield at a reduced cost. This makes the information easy and clear for farmers to understand [26]. Applications for soil testing are also accessible to farmers to test the soil and determine which crops will do well in a specific soil type [27]. Specific applications also provide market prices and the most recent information on the farming techniques used by farmers across the nation [28]. It will be possible for farmers to ascertain which crops yield a profit in a given season. Various mobile apps in Indian agriculture, like FarmersEdge, AgriApp, and AgriBus-NAVI, offer farmers tools for data-driven decisions, weather updates, crop disease diagnosis, and navigation support. Apps such as Plantix assist with crop diseases and nutritional deficits. FarmLogs provides comprehensive farm management tools, including crop health monitoring and financial insights. Krish-e offers a customized crop calendar and agricultural consulting, while Kheti Badi focuses on organic farming information in multiple languages. The Crop Insurance app helps farmers calculate insurance rates, and Krishify serves as a social farming app. Pusa Krishi, Shetkari, and Kisan Suvidha introduce technologies, market prices, and government initiatives, enhancing farming productivity. MenthaMitra, developed by CSIR-CIMAP, provides precise information for menthol mint growers, fostering collaboration among stakeholders and scientists [29,30].

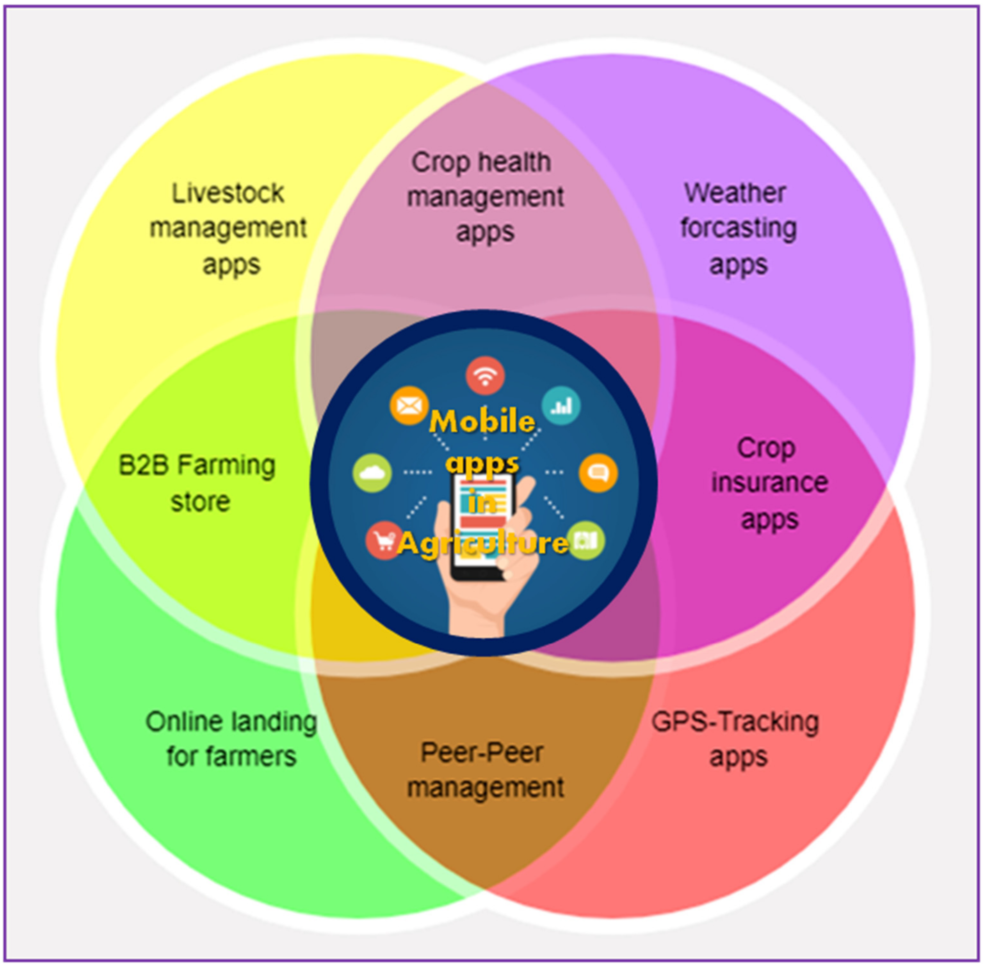

Figure 2. Implications and importance of mobile application in agriculture.

Mobile apps have completely changed how stakeholders worldwide participate and disseminate information thanks to their enhanced user-friendliness, dependability, and connectivity [30]. By ensuring that farming communities implement the good agricultural practices that researchers have devised and by making them aware of these practices—which can be readily accomplished through a mobile application—the socio-economic situations of these communities can be improved (Figure 3).

AI and IoT coordination is a part of the integrated strategy that is farm management software. It provides an improved tracking mechanism for analyzing many types of biological, chemical, and physical production [31]. With real-time data processing capabilities, it requires fewer workers. Thus, with less work and time, FMSs can support the sustainability and quality of agricultural produce. Modern farmers do not use traditional farming methods; to assist them in managing their farms, the majority of farm management software is available as open source [32]. An application or collection of programs known as farm management software aids in automating, enhancing, and supporting farm businesses' operational procedures. These management tools help with error correction, task completion, reporting, and general efficiency and effectiveness enhancement. All things considered, farm management software is made to best satisfy the requirements of company procedures.

Deciding on an effective FMS is not usually simple because different FMS characteristics are employed for various objectives [33].

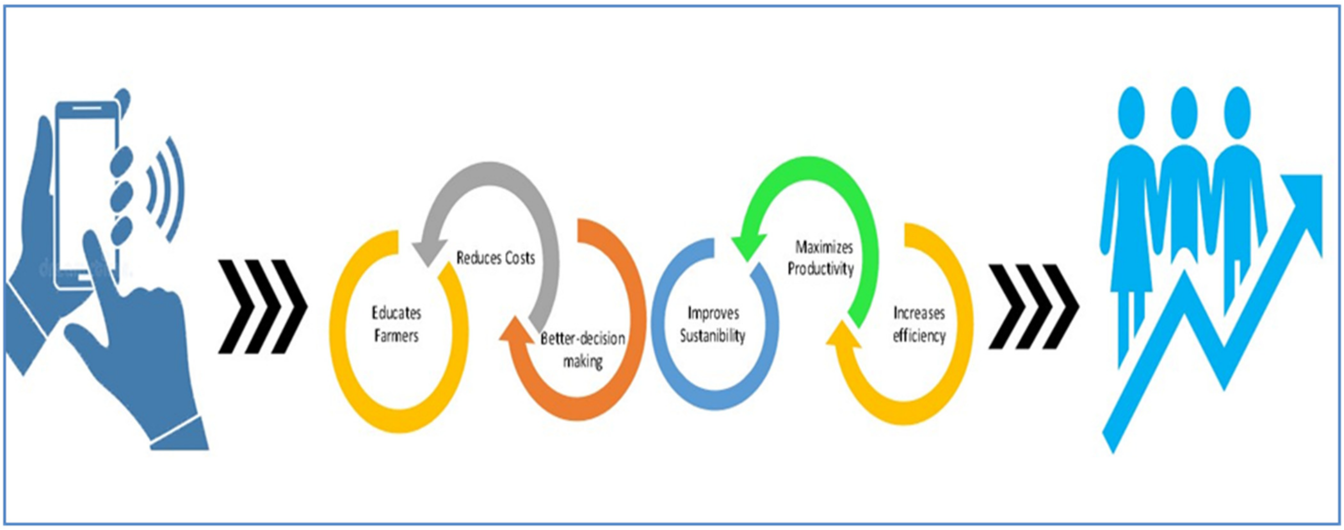

Figure 3. A schematic illustration of socio-economic transformation through mobile applications.

5. Crop Monitoring and Phenotyping Using Artificial Intelligence

AI in agriculture refers to using AI to enhance agricultural productivity and real-time monitoring, harvesting, processing, and selling. It is fundamentally playing a significant role in changing the agriculture industry. AI protects the agriculture industry from various threats, including population increases, climate change, job shortages, and food safety. AI has elevated the agricultural system of today to a new level. Crop productivity and real-time monitoring, harvesting, processing, and selling have increased thanks to artificial intelligence. Numerous advanced computer-based technologies are intended to identify multiple crucial criteria, including crop quality, yield detection, weed identification, and many more. AI can actually help the farmers move towards demand-driven agriculture. The world is now rapidly changing its attitude towards acceptance of AI. For instance, recently, the US government introduced a bill called the Farm Tech Act 2023, for regulations in AI technology in the agriculture sector.

In recent years, there have been significant advancements in understanding plant phenomics, making precision farming more possible. This process is due to new technologies that allow detailed study of complex plant features. Deep learning, machine learning, and computer vision, which are measure features of AI, have become increasingly popular in various scientific areas. These AI features are now integrated into non-invasive imaging methods, improving the efficiency of data collection and analysis. This integration helps in creating tools and software for gathering information about plant phenomics in the field. Some open-source systems and tools allow researchers to work collaboratively and share data, providing the large amounts of information needed for reliable plant phenomics analyses. Moreover, they utilize three critical aspects of managing phenomic data: developing models to comprehend the relationships between genotype and phenotype and the interactions in the environment, managing databases to exchange information and resources, and developing algorithms and programs to transform sensory data into phenotypic information.

Repeated experiments under various conditions must be conducted to screen plants for desired traits, considering the statistical requirement for an unbiased evaluation. Phenotyping, a method of assessing plant development in controlled environments, has been extensively debated, but it often fails to accurately represent the development of plants in open-field situations [34,35]. There is an apparent disparity in plant performance between the lab and the field. Compared to other imaging techniques, AI integration in tomography and thermography is advancing towards smarter, faster, and lower-cost solutions, particularly in phenotyping image data analysis. Sustainable crop production depends on field phenotyping, yet the throughput in the field lags behind indoor facilities, requiring more development to investigate useful applications of phenomics.

According to recent investigations, AI-assisted crop phenotyping and yield predictions have improved crop phenotyping [36–42]. Furthermore, the following applications of AI-assisted high-throughput phenotyping platforms have been proven as successful: identifying the plant growth stage in wheat and maize [37] and segmenting plant images [38]; semantic segmentation of crops and weeds for oilseed crops [39]; phenotyping crop disease resistance [40]; and boosting the productivity of crops [41,42]. The importance of AI technologies in various fields is shown in Figure 4.

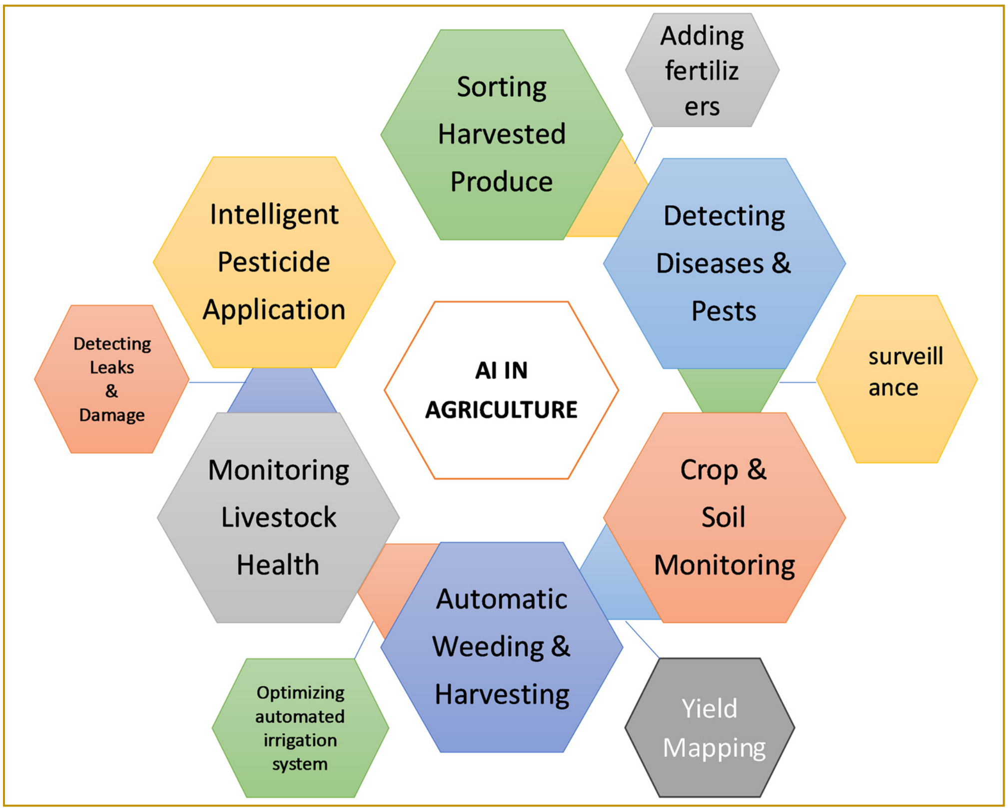

Figure 4. Artificial intelligence is transforming the modern agricultural system.

6. Precision Agriculture and Remote Sensing Technologies in Crop Production and Breeding

Precision farming is the most important and sustainable approach to maximizing crop production and improving farmers' socio-economic and livelihood conditions. A collection of methods known as precision agriculture (PA) can be used in various agricultural research fields, and variable rate technology, site-specific crop management, and prescription farming are among its additional names. It is a novel management method that uses georeferenced data to govern agricultural systems, applies monitoring procedures, and integrates soil, plant, and climate factors to detail georeferenced data employing computers, satellites, positioning systems, and remote sensing equipment to offer information on the better decisions that can be made. Furthermore, after carefully examining all the variables that influence crop growth in a given farm field, it promotes tillage and the accurate application of agricultural inputs, such as herbicides, fertilizers, and irrigation. To put it more clearly, Gomiero [43] describes it as an information-technology-based agricultural management system used to detect, assess, and control soil variability in terms of space and time within fields to increase profitability, preserve the environment, and promote sustainability. The science of PA uses advanced technology, sensors, and analysis tools to help with management, decision making, and crop production improvements. The world has embraced PA, a novel idea that promises to boost output, cut down on labor costs, and guarantee efficient management of irrigation and fertilizer systems. It uses a lot of data and information to enhance crop quality, yields, and the utilization of agricultural resources [44]. Farmers have adopted this novel and sophisticated technique in recent years to improve productivity, quality, and yield to deliver optimum inputs like water and fertilizer [45]. It needs an enormous amount of high spatial resolution data regarding the health or status of the crop during the growth season.

Connecting the GPS and the GIS (geographic information system) has enabled the advancement and implementation of site-explicit cultivation owing to a large amount of geospatial information that can now be effectively controlled and analyzed. The GPS and GIS enhance precision agriculture by providing accurate location data and spatial analysis capabilities. The GPS enables precise navigation for optimized field operations, while the GIS facilitates variable rate technology (VRT) implementations, adjusting input application based on field variability. GPS-based applications are being used for agriculture planning, field planning, soil examination, crop exploration, variable rate application, and yield mapping. Furthermore, GPS systems are essential for the majority of PA application technologies since customers utilize them to schedule production activities in real time at specific locations. They are most frequently used in agriculture for a wide range of tasks, including crop soil mapping and monitoring, contouring of fields, and production tracking. An information retrieval unit, mapping and visualization software, a GPS receiver, and a differential global positioning system (DGPS) mounted on a field-traveling vehicle make up a conventional GPS. The farmer contours the field with identical equipment and collects data with both GPS units. They can also traverse the area and record data on regions affected by pests and diseases during the plant season. Farm trucks are driven in designated field regions during crop surveying using GPS devices. Depending on each zone's soil conditions and production system characteristics, a farm vehicle can help perform duties at different rates.

Regardless of the data sources, PA's primary goal is to assist farmers in running their businesses. This assistance can take many forms, but ultimately results in a reduction in the resources required. Automatons, sometimes referred to as UAVs or unmanned ethereal frameworks (UASs), are crewless aircraft that can be remotely operated in a mechanical setting [46]. They work together because they have additional sensors and a GPS installed. Drones are utilized in agriculture for various purposes, including weed identification, crop health monitoring, herd and animal monitoring, irrigation equipment monitoring, and disaster management [47–49]. Remote sensing, which collects, processes, and analyzes images using UAVs, has significantly impacted agriculture [50]. UAVs are primarily utilized in precision agriculture for applications such as crop monitoring [51], soil and field analysis [52], pesticide spraying [53–55], and crop height estimations [56–59]. Growing populations and changing climate patterns are expected only to increase the need for efficient agriculture.

To summarize, a diagrammatic illustration of precision agriculture using remote sensing combined with sensors, machine learning algorithms, and artificial intelligence is presented in Figure 5.

Drones or UAVs rely mostly on sensor and microcontroller developments designed to make up for pilot absences, allowing autonomous behavior and crewless vehicle flight [57]. Farmers have been employing these drones to spray chemicals for years since they are believed to be highly practical and efficient in overcast conditions. The problem of being limited access to a field of tall crops, such as maize, has also been resolved with their assistance [58,59]. A microcomputer-based sprayer control framework was used in [60] to retrofit an air carrier plantation sprayer. They are also recognized to have a major advantage over satellite aerial sensors in their high picture resolution [61,62]. Kale et al. [63] employed drones to establish a control circle for horticultural reasons by spraying artificial materials on produce in places where the drones were connected. These drones were fitted with remote sensing network (RSN) sensors, which were positioned atop the crops and controlled the synthetic material application procedure. Based on the information from these remote sensors, drones could only spray synthetic materials in approved regions. Huang and Reddy [64] built a low-volume sprayer that was mounted to an autonomous helicopter. With larger droplet sizes and greater target rates, this technology and its systematic results are a foundation that may be applied to the creation of UAV flying application frameworks for higher yields.

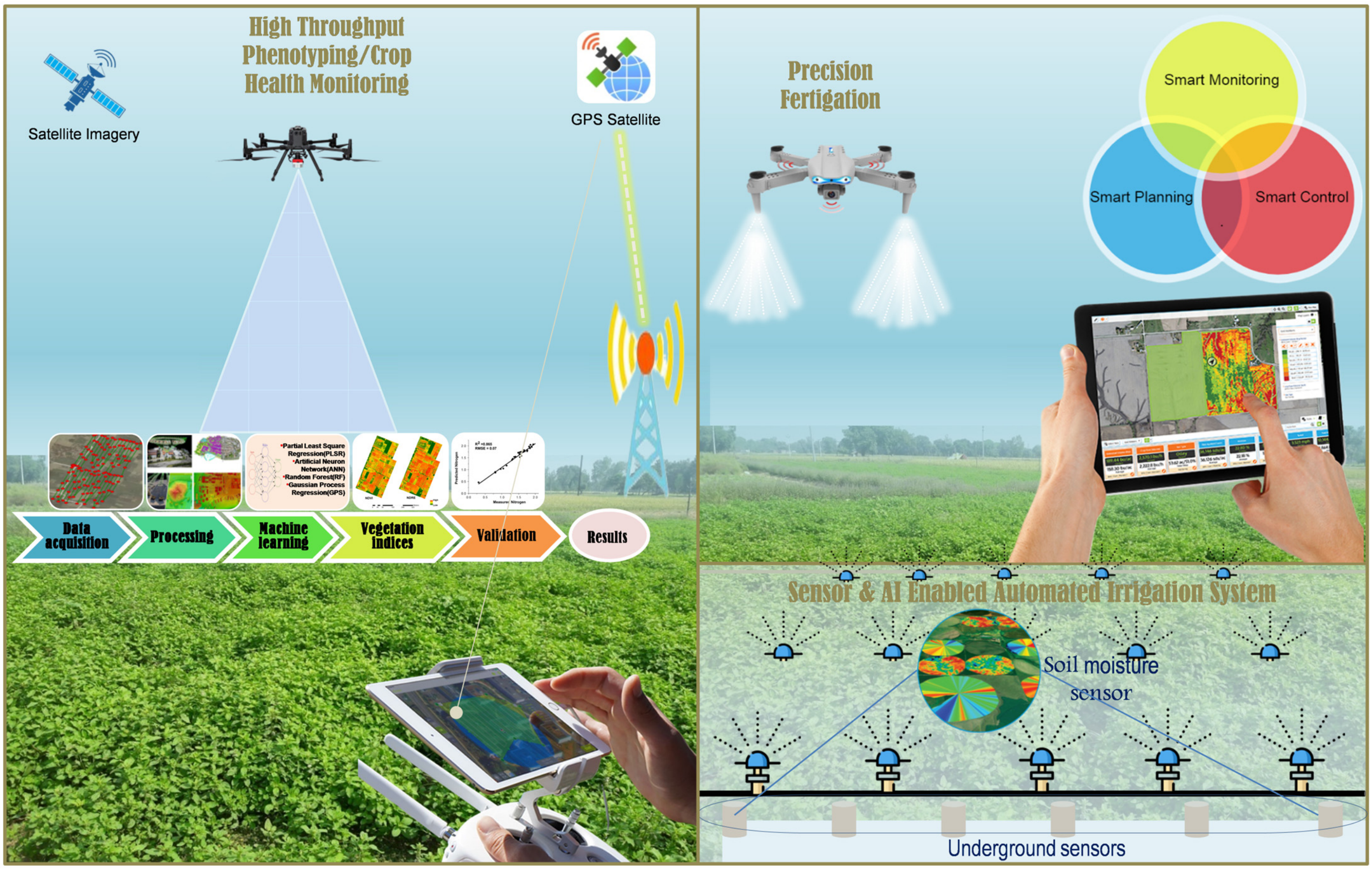

Figure 5. Precision farming systems combined with drones, sensors, and artificial intelligence.

Farmers now have a plethora of new options to boost yields and minimize crop damage owing to the development of sophisticated sensors and imaging capabilities. In recent years, UAVs that are utilized for practical reasons have not performed optimally. Novel sensors are affixed to unmanned aerial vehicles (UAVs), and modern cameras serve as the client's eyes on the ground. Optimal data collection, analysis, and surveying protocols are continuously being devised and tested [65,66]. In the field of agriculture, performing aerial surveys is nothing new. For the past ten years, large croplands and forests have been inspected by satellites, but the deployment of UAVs has brought the precision and flexibility to a new level. Since UAV photos are acquired 400–500 feet above the ground, they yield a higher quality and accuracy. Digital photographs from a model aircraft were assessed [67] to remotely sense crops' biomass and nitrogen status. This study utilized a computerized camera and colored canvases, observing extreme disparities in the computerized numbers for a comparable reflectance due to variations in the introduced parameters selected by the sophisticated camera. Additionally, they made use of the Normalized Green–Red Difference Index (NGRDI) and established a direct correlation between it and the normalized contrast of the respective red and green reflectances. A low-cost multispectral imaging system was created for use in crop monitoring [68]. It is composed of two cameras that are integrated into a drone and a microprocessor. While one camera is a standard RGB camera, the first is sensitive to infrared radiation. This technology offers data and pictures that software can use to calculate the crop's health condition based on the NDVI. Reinecke and Prinsloo [69] investigated the advantages and drawbacks of drone use in agriculture, providing real-world examples of how drones are used on farms.

Based on their application in the agricultural industry, precision agriculture technologies (PATs) are classified into crop PATs and animal PATs. Crop PATs maximize crop output and ecological impacts by studying spatial and temporal deviations, whereas livestock PATs strengthen livestock product supply [24,70]. Farmers are progressively embracing fewer chemical agricultural practices, frequently linked to conservation agriculture concepts. This transition is mostly due to the reduced usage of fertilizers, pesticides, and herbicides, effective water use, and lower greenhouse gas emissions [71]. The utilization of cutting-edge sensors, decision-making systems, and technological innovations has led to greater adoption of revolutionary crop management technologies in major crops, lowering pesticide/herbicide inputs [72,73]. Micro-dosing and herbicide/pesticide patch spraying endeavor to minimize fertilizer, herbicide, and pesticide inputs by targeting specific weed species and plants. Farmers face problems in fertilizer and pesticide choices, rates, and application, necessitating rigorous decision making based on the yield of crops, weed flora, population dynamics, revenues, detrimental effects on the environment, and soil components [74,75].

In the realm of crop breeding, crop PATs have emerged as game-changing technologies that are transforming conventional agricultural techniques and promoting more sustainable and effective food production. The accuracy and productivity of crop breeding procedures have been dramatically improved by this combination of cutting-edge technologies, boosting agricultural yields, resource efficiency, and environmental sustainability [76]. Utilizing GPS-guided tractors, drones, sensors, and satellite imaging, one can gain valuable insights and data to optimize farm management by understanding crop health, soil conditions, and environmental factors. Furthermore, they help to collect vast amounts of data about fields, enabling informed decision making regarding crop breeding [40,41,45,58,61,64,69]. This data-driven approach helps assess crop health, detect diseases, and identify nutrient deficiencies, leading to superior varieties. Moreover, these technologies enable early detection of stress, diseases, and pest infestations in crops, enabling breeders to take proactive measures, reduce chemical inputs, and minimize yield losses [56]. Additionally, they optimize resource use by accurately assessing crop needs through remote sensing data and fostering environmental resilience and sustainable practices through more resilient crop varieties. By integrating these technologies, breeders can develop crop varieties suited to diverse ecological conditions, enhancing crop performance [76]. As a result, the breeding process is accelerated; breeders can assess crop varieties' performance under varied conditions faster when data are gathered swiftly and accurately. Therefore, these technologies constitute vital tools for modern crop breeding, delivering breeders helpful information for resource optimization and well-informed decision making. Especially in light of shifting climates, these technologies are critical to developing durable, high-yielding, and adaptive crop varieties.

7. The IoT and Sensor Technology

The IoT and smart sensors have enormous potential for gathering and analyzing real-time data to track crop quality and yield, soil health, and water content at a location [77]. The IoT and smart sensors work together to replace traditional farming practices with smart farming, which produces higher yields. In agriculture, IoT-enabled technological approaches aid in evaluating crop quality, soil health, soil erosion, fertilizer needs, and soil fertility [78]. Some examples in the real world are the following: John Deere's connected farm integrates IoT sensors in tractors for real-time field monitoring, aiding farmers in decision making about planting and harvesting. Sundrop Farms in Australia uses the IoT in smart greenhouses, monitoring climate conditions. Also, IBM's "The Weather Company" provides real-time weather data for agriculture, assisting farmers in planning activities like planting and irrigation. The role of the IoT in agricultural farming is illustrated in Figure 6.

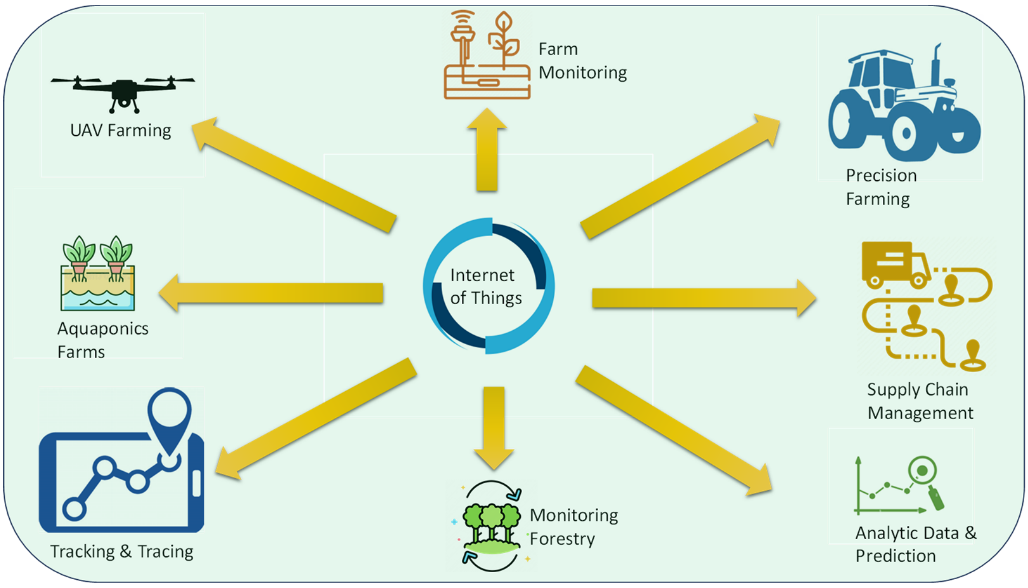

Figure 6. The role and significance of the IoT in smart agricultural farming.

Additionally, the IoT facilitates optical irrigation and seed quality and crop development monitoring in different phases [79]. IoT-enabled equipment, real-time data collectiion, and automation are critical requirements for advancing the smart agriculture market [80]. Real-time IoT and remote sensing data can be processed for PA and forestry [81–83]. Smart soil moisture sensors offer real-time data for precise irrigation, reducing water wastage by enabling farmers to determine the optimal timing of application and the quantity of water needed. Efficient water use and reduced energy consumption for irrigation lead to cost savings. Furthermore, smart soil moisture sensors and the IoT monitor pre- and post-harvest conditions in agricultural areas. For accurate temperature, moisture, soil condition, and crop measurements in particular locations, the IoT, ZigBee, and Arduino sensors can be employed [84]. However, cognitive complexity, security concerns, privacy, and inadequate facilities have been noted as some of the limitations of using the IoT in smart agriculture.

8. Automation and Robotics in Agriculture

In agriculture, automation has significantly changed the landscape by enabling machines to perform jobs that previously required human labor [85]. Agriculture needs to include technology more as the world's population and food demands rise [86–88]. Using intelligent seeding robots that can recognize crop varieties and planting regions is one advantage of autonomous farming; it streamlines and increases efficiency [89]. Weeding robots enable precision herbicide application, minimizing pesticide use and environmental impacts [90]. Furthermore, with the use of robot arms, automated harvesting robots can determine when a crop is ready to be harvested, reducing labor expenses and time spent on the task while boosting output. In significant economic sectors like agri-food, which have a relatively low productivity, robotics and autonomous systems (RASs) are being implemented. A significant impact of robotics has been demonstrated on agriculture management and productivity. Due to the inefficiency of traditional farming machinery, researchers have recently begun focusing on technologies for designing autonomous agricultural equipment [91]. The development of this technology aims to supplant human labor and yield efficient outcomes for both small- and large-scale facilities [92]. The use of robotic technologies in this industry has greatly increased production. Moreover, robotics technologies improve agricultural practices by providing harvesting automation by differentiating the factors and characteristics of vegetation, monitoring, and data collection by providing soil health and environmental factors, sorting and packaging, labor assistance utilizing exoskeletons and wearables, robotics scouting for diseases and nutrient deficiency in crops, etc.

Sometimes, a trivial but significant change towards advancement of technology results in multifold benefits. For example, the invention of a device known as Eli Whitney's cotton gin gave rise to the idea of developing a technology that could dramatically speed up the process of separating the cotton fiber from seed, revolutionizing the cotton industry [93,94]. In a single day, it produced fifty pounds of cotton; autonomous agricultural robots are a result of this.

A simple automated model was developed to accurately determine seed placement [95]. Additionally, extremely accurate seed positioning was devised to guarantee a seed ground velocity of zero. This is crucial because it ensures that the seed will not bounce from its original place upon impact with the soil. Automated machinery recorded the plant's development or status. Numerous biosensors were developed to track plant development and identify plant illnesses [96,97]. The human weeding method was superseded by laser weeding technology, which uses a computer-controlled mobile concentrated infrared light beam to damage weed cells [98]. Additionally, automatic irrigation systems were developed to ensure efficient use of water. The agriculture industry uses 85% of the freshwater resources that are available worldwide. This percentage is rising quickly in tandem with population expansion and rising food prices. As a result, we must develop more effective systems to guarantee that water resources are used appropriately for irrigation. Automatic irrigation scheduling techniques have replaced manual irrigation based on soil water measurements. When using autonomous irrigation machines, consideration should be given to plant evapotranspiration, which depends on several atmospheric parameters like humidity, wind speed, and solar radiation, as well as crop factors like growth stage, plant density, soil characteristics, and pests.

Smart irrigation technology aims to enhance yields without requiring a lot of labor by using sensors to measure water levels, soil temperatures, fertilizer contents, and weather patterns. Machine-to-machine technology was created to facilitate data sharing and communication between agricultural field nodes as well as between them and the server or cloud via a main network [99]. An automated robotic model was created to identify the temperature and moisture content of Raspberry Pi 3 and Arduino boards. The Arduino microcontroller, which is connected to edge-level hardware, receives data at regular intervals and processes them by converting the analog input to digital. To save labor and time during watering, ref. [100] also created an automated irrigation system using Arduino technology. Savitha and Maheshwari [101] also devised the concept of an automated and effective watering system by creating remote sensors with Arduino technology, which can boost the output by as much as 40%. Zimdahl [102] conducted extensive research on the subject and concluded that weeds were the greatest rivals for water, with plants starting to compete for water and nutrients when their roots overlapped in the soil. The amount of water needed to generate one pound of dry matter is the amount required for the plant's above-ground parts.

Light constitutes an essential component required for plant growth. Tall weeds usually obstruct the plants' access to sunlight. Certain weeds, including redroot pigweed and green foxtail, are shade intolerant, but other weeds, like Arkansas rose, field bindweed, and common milkweed spotted spurge, are sometimes tolerant to shade. A vision-based weed detection technique in natural illumination was devised by [103]. It was developed using a genetic computation to identify a location in the Hue–Saturation–Intensity (HSI) shading space (GAHSI—Genetic Algorithm for Hue–Saturation–Intensity) for field weed detection. It makes use of unusual lighting situations, such as radiant and shady conditions, which are mosaicked to determine the probability of using the GAHSI to locate the location or zones in the field in the shading space where these two limits are surpassed simultaneously. A robotic weed management system was presented in [104]. The robot had many vision systems built into it. Two types of vision were employed: one was color-based and used to distinguish between individual weeds, and the other was gray-level vision, which was employed to create a row structure to guide the robot along the rows. An innovative algorithm was used to generate the row recognition system, which has an accuracy of ±2 cm [104]. This technique was first tested for weed management within a row of crops in a greenhouse. The robots were guided along the row structure using vision-based technology to eliminate weeds and distinguish a single crop from weed plants.

By integrating automation into fundamental activities, farmers can maintain their competitiveness in the market and considerably increase the economic value of their operations.

9. Climate-Smart Future Agriculture Crops for Sustainable Agriculture

Climate-smart agriculture requires a digital integration of climate and agriculture information. It plays a pivotal role in enhancing CSA, which aims to make agriculture more resilient to climate change while ensuring sustainable productivity. India is digitalizing rapidly, so its policies and practices to achieve climate-smart agriculture must also promote digital integration. The Sustainable Development Goals (SDGs) of the G20 and India include climate-smart agriculture (CSA) [105]. It is a hugely complex task. The digitalization roadmap for CSA in India clearly and concisely visualizes the challenges. The Agriculture Action Plan (2023–2030) of the World Bank, which intends to allocate USD 35 billion to climate-related agricultural initiatives, includes CSA as a major component. By adopting a comprehensive approach to landscape management that considers crops, livestock, forests, and fisheries, CSA transcends conventional farming and is more than just a development of traditional agricultural methods. Its main objective is to successfully handle the interrelated problems of climate change and food security. While CSA is applicable globally, regional differences may lead to different objectives and concerns, whether in a country from the Global South or the Global North. A concept ideotype of a climate-smart agriculture future crop is presented in Figure 7.

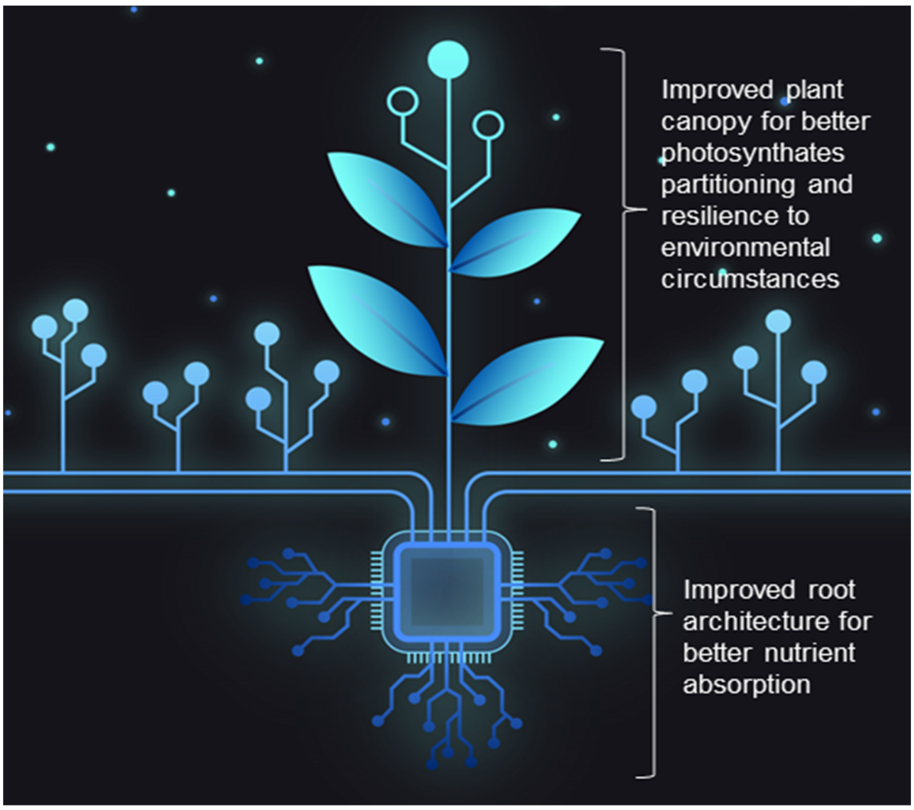

Figure 7. A concept ideotype of the climate-smart agriculture future crop.

In India, where agriculture is a vital livelihood amid a growing population, climate-smart agriculture (CSA) practices have demonstrated significant impacts. The system of rice intensification (SRI) in Bihar has enhanced rice productivity through improved planting, water management, and organic practices, leading to increased yields, a reduced water usage, and a heightened resilience to extreme weather events. Drought-resistant crop introduction in Maharastra, coupled with rainwater harvesting, has resulted in improved yields during water-scarce periods, enhancing food security. Agroforestry initiatives in Andra Pradesh, involving tree intercropping, have contributed to increased crop yields, improved soil health, and additional income sources. Integrated pest management (IPM) adoption in Gujrat, emphasizing natural predators and biological controls, has improved crop health, reduced environmental impacts, and heightened resilience to pests. In Odisha, research and adoption of climate-resilient crop varieties have led to improved yields, reduced vulnerability to climate stresses, and an increased overall agricultural productivity.

Climate-smart agriculture (CSA), also known as climate-resilient agriculture, is an integrated approach to land management that aims to ensure food security by taking into account the growing global population and helping to adapt agricultural practices, livestock, and crops to the effects of climate change. CSA will work to counteract these effects whenever possible by reducing greenhouse gas emissions from agriculture. Increasing agricultural productivity is just as important as practicing sustainable agriculture or carbon farming. The three pillars of the CSA are raising agricultural incomes and production, constructing and adjusting to climate change resilience, and lowering or eliminating greenhouse gas emissions from agriculture. Several steps have been proposed to address the issues that crops and plants may face. For instance, for CSA, cultivating heat-tolerant crop types, mulching, water management, shade houses, boundary trees, carbon sequestration, and suitable housing and spacing for cats are advised to combat rising temperatures and heat stress. Efforts are being made to integrate CSA into essential government spending, policy, and planning frameworks. Policies to combat poverty, promote sustainable development, and expand economic growth are necessary for CSA to succeed. They must also be incorporated into social safety net initiatives, disaster risk reduction plans, and activities.

Sustainable agriculture aims to preserve the planet's capacity to support future generations while producing the resources required for the world's human population. Sustainable agriculture focuses on growing various crops, such as heritage plants, which are frequently climate-adapted [105]. Instead of depending on a single crop, consider polyculture, which extends several crops alongside one another. A critical aspect of sustainable agriculture is water conservation. Improving water storage techniques to stop evaporation losses and seepage and planting climate-appropriate or drought-resistant crops are two ways to reduce wastewater. The poisoning of groundwater and surface waters is another issue that sustainable agriculture aims to solve. Pollutants from large-scale facilities, such as pathogen-filled animal excrement and pesticide runoff, frequently find their way into bodies of water, harming the ecosystem and hurting both people and wildlife [106]. In addition to lowering agricultural yields and the amount of area accessible for agriculture, soil erosion also deteriorates the quality of the water. Farmers can use no-till techniques or lower the frequency and intensity of tillage to reduce these effects. In order to minimize runoff, fertilizers and pesticides, whether synthetic or organic, should only be applied in modest quantities, especially in dry weather. Before using agrochemicals, extra precautions should be taken to prevent the airborne spread of contaminants. Buffer plants are a tool some farmers use to trap nutrient pollution before it enters water bodies. Digital technology enhances sustainable agriculture through precision farming, data-driven decision making, smart irrigation, crop monitoring, supply chain optimization, climate-resilient crop selection, efficient resources with smart machinery, educational platforms, and weather risk mitigation, ultimately promoting environmental sustainability and resilience.

10. E-Commerce and Direct-to-Consumer Sales

In agriculture, e-commerce utilizes digital platforms to facilitate the buying and selling of agricultural goods and services (Figure 8). E-commerce platforms in agriculture enhance clarity and consistency by removing intermediaries, providing transparent information, enabling real-time inventory management, supporting direct marketing, facilitating digital payments, leveraging data analytics, and ensuring visibility in the supply chain. This transformation benefits both farmers and consumers in the evolving landscape of agricultural sales.

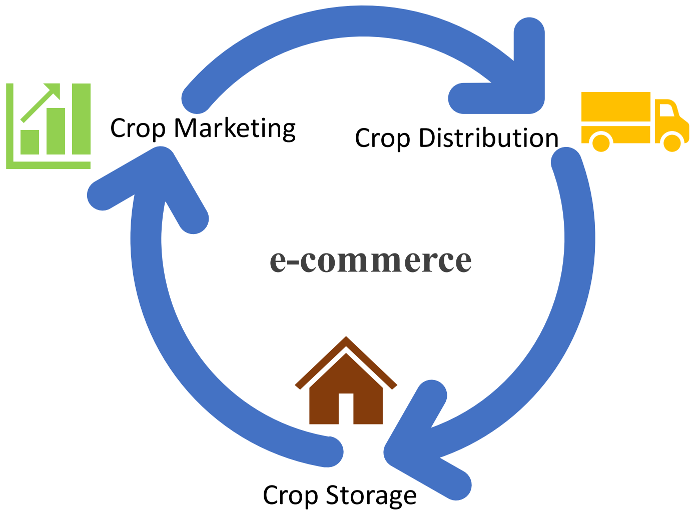

Figure 8. Role of e-commerce in the agriculture sector.

E-commerce encompasses a variety of tasks, including farmers selling their produce directly to customers or businesses through online marketplaces, as well as the digital delivery of suppliers, tools, and agricultural information [107]. With the help of this creative strategy, farmers will be able to reach a wider audience, enhance the effectiveness of the farm supply chain, and boost the availability of fresh, locally made products. Incorporating digital technology into traditional agriculture promises to yield novel prospects and benefits. In the agricultural sector, mobile and online commerce provides a direct communication channel between farmers and consumers. Digital technologies enable farmers to build trust in the agricultural supply chain, reach a broader audience, and provide transparent information about their produce's origin and quality.

Agri-businesses can boost farmers' incomes and enhance customer purchase convenience using digital technologies. Everyone benefits from this integration because it has so many advantages. Integrating digital technology with traditional farming methods is a critical first step in creating a more productive, transparent, and sustainable agricultural system [108,109].

11. Conclusions

With 10 billion people expected to live on Earth by 2050, there will be a lot of pressure on the agricultural sector to boost crop yields and productivity. Two possible strategies have emerged to address the impending food shortages: either embracing innovative practices and utilizing technological advancements to increase the productivity of existing farmland or expanding land use and adopting large-scale farming. The modern agricultural landscape is changing and branching out in various innovative directions due to numerous obstacles to achieving the desired farming productivity, including limited land, labor shortages, climate change, environmental issues, and declining soil fertility, to name a few. Farming has undoubtedly advanced from the days of manual ploughs and horse-drawn equipment. New technologies are being introduced every season to increase productivity and optimize yields. However, large agri-businesses and small farmers frequently lose out on the improvements to farming practices that artificial intelligence might bring to the agricultural industry. The agricultural sector must adjust to a plethora of growing issues, including shifting consumer preferences, environmental deterioration, the scarcity of farm workers, population growth, and nutritional changes. In conclusion, digitization in agriculture promises comprehensive solutions, efficient resource use, reduced costs, enhanced farmer livelihoods, economic growth, and environmental sustainability. Moreover, the upcoming era of nanotechnology, quantum computing, and machine learning with big data analysis, blockchain technology, etc., will present new possibilities and opportunities in this sector and will serve mankind to create better options for future generations.

12. Future Research Directions

Smart agriculture is dynamic, and ongoing research and technological advancements are expected to generate new results and insights. As a result of our findings, we propose specific fields and future perspectives for further strengthening research. These fields include investigating the application of smart agriculture in urban and controlled areas, vertical farming, hydroponics, and aquaponics, where PA can be employed to maximize resources such as water, nutrients, and energy, ensuring sustainable and productive farming practices in tight spaces. Smart agriculture is a promising solution to address the challenges of limited land availability in urban areas, and farmers can monitor their crops and detect early signs of pests or diseases, allowing them to target specific areas with pesticides instead of applying them broadly. This reduces pesticide use and minimizes the negative impact on beneficial insects and the environment. These innovative techniques can reduce the carbon footprint associated with traditional agricultural practices. Smart agriculture in urban areas can help address food security challenges by enabling local production and reducing dependence on long-distance transportation. Moreover, developments in drone technology and satellite-based remote sensing for more accurate and fast data collection can help with large-scale agricultural surveillance, crop health assessment, and resource optimization. Advancements in drone technology and satellite-based remote sensing can revolutionize disaster management by monitoring affected areas and enabling swift response efforts. Conservation efforts allow for more efficient tracking of wildlife populations and the identification of habitat degradation, allowing for the identification of pollution sources and the implementation of effective mitigation strategies. In addition, more targeted research is needed to investigate how intelligent agriculture technology can help sustainable farming goals, such as reducing pesticide use, effectively managing water, and improving soil health. Crop varieties can be selected that are more resilient to changing climate conditions, reducing the risk of crop failure. Takes smart post-harvest management technologies, including cold chain monitoring, quality control, and efficient shipping, as an example. These technologies can help preserve the freshness and quality of harvested crops, ensuring a longer shelf life and reducing waste. Implementing these solutions can also increase perishable items' shelf lives, allowing for extended storage and distribution periods. By expanding the IoT and sensor networks in agriculture, farmers can gain real-time insights into their crops and make data-driven decisions, which will lead to increased productivity, reduced resource waste, and improved overall sustainability in the agricultural sector. AI technology, such as machine learning algorithms, might improve agricultural decision-making processes such as crop monitoring, disease/pest identification, yield forecasting, and resource optimization. AI integration can also enable the development of autonomous farming systems that can automate tasks such as planting, harvesting, irrigation scheduling, crop disease detection, and precision farming techniques, resulting in an increased efficiency, time and resource savings for farmers, and an increased agricultural productivity. Additionally, future research will focus on building solid frameworks and methods to protect sensitive agricultural data, which could involve exploring encryption techniques and secure communication protocols to safeguard data transmission in smart agriculture systems. These frameworks and procedures should ensure data encryption and secure storage and address potential vulnerabilities in innovative agriculture systems. Exploring the potential of blockchain technology in securing and maintaining the integrity of agricultural data could be a promising avenue for future research. In addition, the interaction between farmers and smart agricultural technology emphasizes the necessity of user-friendly interfaces and farmer training programs to ensure optimal adoption and usage. By understanding these interactions, we can identify the challenges that arise from the complexity of these technologies.

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