DIGITAL AGRICULTURE: FUTURE TOWARDS SUSTAINABILITY

Abstract

Escalating global population and their demands for food, water and energy is exploiting the available resources. The intensive agricultural practices results into higher greenhouse gas emissions, deforestation and land degradation. This demand for reformation in traditional agricultural systems and "Digital Agriculture" could be a possible solution. Agriculture 4.0 has revolutionary potential of growing more food on lesser land, feed numerous people and improve farmers' livelihood. This not only meets the growing demand but also help mitigate the adversities of climate change. Artificial intelligence, Internet of Things, drones, robots, machine and deep learning algorithms, sensors, etc., generate a hyper connected network of farms, machines and factories that optimizes both food production and consumption. It ensures need based, precise application of inputs and aids in adoption of best management strategies, thereby, making agriculture environment friendly, profitable and sustainable in the long run. Thus, this chapter presents the potential of digital agriculture in enhancing crop health and productivity for a sustainable future.

Keywords: Algorithms, Drones, Internet of Things, Robots, Sensors

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I. INTRODUCTION

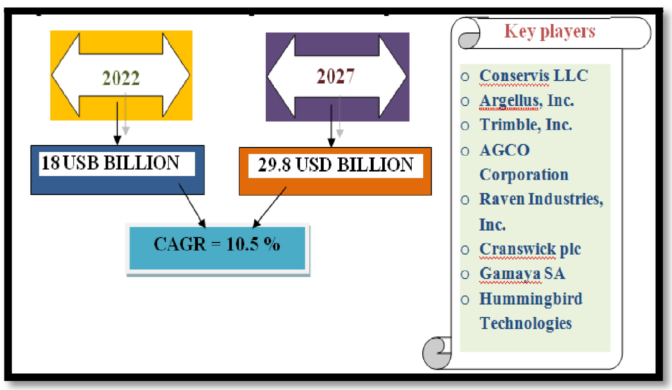
The burgeoning population along with its food and nutritional insecurities have become a key concern in agriculture. Global population is expected to reach nearly 10 billion by 2050 A.D (Anonymous, 2017), creating pressure on the limited natural resource base. Within the next 2–3 decades, the demand is expected to rise for food by 60% (Anonymous, 2018), for water by 55% (Anonymous, 2015b) and for energy by 50% (Anonymous, 2019b). Meeting the escalating demands with conventional farming practices may result into exploitation of natural resources, higher greenhouse gas (GHG) emissions along with deforestation and land degradation (Kanianska, 2016). Further, adding up the adversities are the shrinking average landholding sizes of farmers. Globally, nearly 85% farmers have agricultural landholding below 2 ha (Lowder et al., 2016), while, in India the average landholding size has reduced to 1.08 ha (2015–16) from 2.28 ha during 1970–71 (Anonymous, 2019a). Fertilizer scenario depicts a still worse situation. Despite escalating fertilizer dosages, the response of crop to the applied fertilizers has become stagnant. Biotic and abiotic stresses on crop are on the rise. Increased emissions of GHGs and agricultural practices are reported to contribute to nearly 19–29 % global anthropogenic GHG emissions (Vermeulan et al., 2012, Malhi et al., 2021). Further, unpredictable weather aberrations and extreme climate events cause huge loss to farmers (Raza et al., 2019). Lack of preparedness for climatic abnormalities denudes both quality and quantity of produce and lowers market value as well (Martinich and Crimmins, 2019). The miseries of farmers not only end up here. Regardless of the tremendous labour they put into the field, the resultant remuneration is extremely discouraging. Also, many a time, marketing linkages are unavailable, or even if available, middlemen takes away majority of the profits. Thus, conventional agricultural practices are facing severe setbacks (Sumberg and Giller, 2022). In order to overcome the challenges, agriculture calls for some revolutionary changes.

Agriculture in the modern era needs modern solutions. Technological interventions or digitalization have great capacity to shape agriculture (Rijswijk et al., 2021). Technological revolution in agriculture is termed as Agriculture 4.0 or Digital Agriculture (Zambon et al., 2019). According to Zhang (2011), digital agriculture, places the processes of providing, processing and interpreting digital data based on the agricultural production and management systems. This comprise the tools that collect, store, analyze and share digitized data in agriculture (Chandra and Collis, 2021). While Agriculture 4.0 brings ground-breaking changes in crop husbandry, it also aims to grow more food on lesser land, feed larger set of people and improve farmers' living standards (Anonymous, 2022b). It has the potential to address the current challenges by making the agricultural value chain more efficient, equitable and environmentally sustainable (Naik and Suresh, 2018, Schroeder et al., 2021). Agriculture 4.0 signifies the digital transformation of food and agricultural systems through the utilization of technologies such as artificial intelligence (Gallordo et al., 2020), the Internet of Things (IoTs) (Kakani et al., 2020), drones (Dayana et al., 2021), robots (Lottes et al., 2017), as well as machine and deep learning algorithms (Sonka, 2015; Kamath et al., 2019), along with sensors (Jia, 2020). These advancements work in tandem to establish an intricately connected network encompassing farms, machinery, and factories, ultimately leading to the optimization of both food production and consumption.

The potential of digital agriculture in enhancing crop health and productivity is acknowledged in this chapter. There are enough tools available to make digitalisation a success, however, the key problem lies in the fact that these innovation fails to reach the farmers, the main stakeholders. Elucidation of the constraints needs immediate attention, which will make agriculture a highly profitable and less laborious field.

II. STATUS OF DIGITALISATION IN AGRICULTURE

The present valuation of the worldwide digital farming market stands at approximately $18 billion (Figure 1). It is anticipated to expand significantly, reaching a projected value of $29.8 billion by the year 2027. The global digital agriculture sector is expected to experience a compound annual growth rate (CAGR) of roughly 10.5% throughout the forecast period spanning from 2022 to 2027 (Anonymous, 2022a). This substantial growth can be attributed to the heightened adoption of digital infrastructure, extending its influence even to the most rural regions.



In India, presently more than 1000 start ups are working in the field of agriculture as compared to only 43 start ups in 2013 (Figure 2). Among the different apps developed in India for digitization of agriculture and its allied sectors, 12% apps are working on farm management, 14% on agriculture, poultry and fisheries each, and 23% for animal husbandry and food traceability each. In agriculture, the Plantix app (also known as plant doctor app) is the most used app with over 50 lakh users (Balakrishna et al., 2020). Thus, India is also growing in the digital space and with continued researches and application of technology can become an IT giant and revolutionize farming.

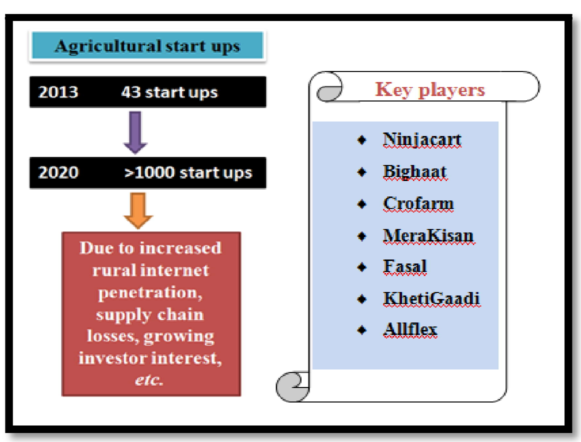


Figure 2: Status of digitalisation in India

III. COMPONENTS OF DIGITAL AGRICULTURE

The accessibility to sensors, mapping and tracking technologies, deep learning algorithms, artificial intelligence, etc., in agriculture, have transformed farming systems and its management. The analysis of extensive data holds a pivotal role within the context of the digital agricultural revolution. A plethora of technological advancements have opened up significant opportunities for leveraging big data (Sonka, 2015). Hashem et Al. (2015) states that big data comprises a collection of techniques that necessitates integrated approaches to discern unrecognized values from large scale, various and complex data sets. Stubbs (2016) proposes that the term "big data" is less concerned with the sheer size of the data and more focused on the amalgamation of technology and advanced analytics, thereby ushering in a novel approach to processing information in a manner that is more pragmatic and timely. Big data empowers farmers to view all real-time operations and enhance decision-making processes (Anonymous, 2015a). As described by Coble et al. (2016), data is characterized by its volume, velocity, variety, and veracity. Here, "volume" denotes the data size, "velocity" gauges the data flow rate, "variety" underscores the often unstructured or diverse nature of the data, and "veracity" encapsulates the accuracy and reliability of the data.
The components of digital agriculture include (Figure 3):

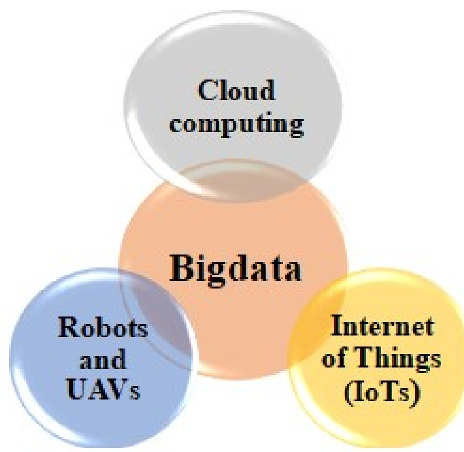


Figure 3: Components of digital agriculture

IV. APPLICATION OF DIGITAL TECHNOLOGIES TO ENHANCE CROP PRODUCTIVITY

1. **Cloud Computing:** Cloud computing refers to the practice of utilizing a network of remote servers hosted on the internet for the purpose of storing, managing, and processing data, as opposed to relying on a local server or a personal computer. The term "cloud computing" is coined because users are not required to have explicit knowledge of the entities providing these services; they perceive these services as being delivered by the cloud—an entity unknown to them (Nath and Chaudhuri, 2012). Cloud computing serves as the foundational infrastructure that facilitates the implementation of intelligent farming practices, encompassing aspects like scalable calculations, software deployment, and access to data and storage services (Kaloxylos et al., 2012; Lakshmisudha et al., 2016). Through the medium of cloud computing, vast amounts of data can be stored with

minimal investment costs, and the capability for instant data access whenever needed is realized (Chavali, 2014). A basic view of cloud computing is shown in figure 4.

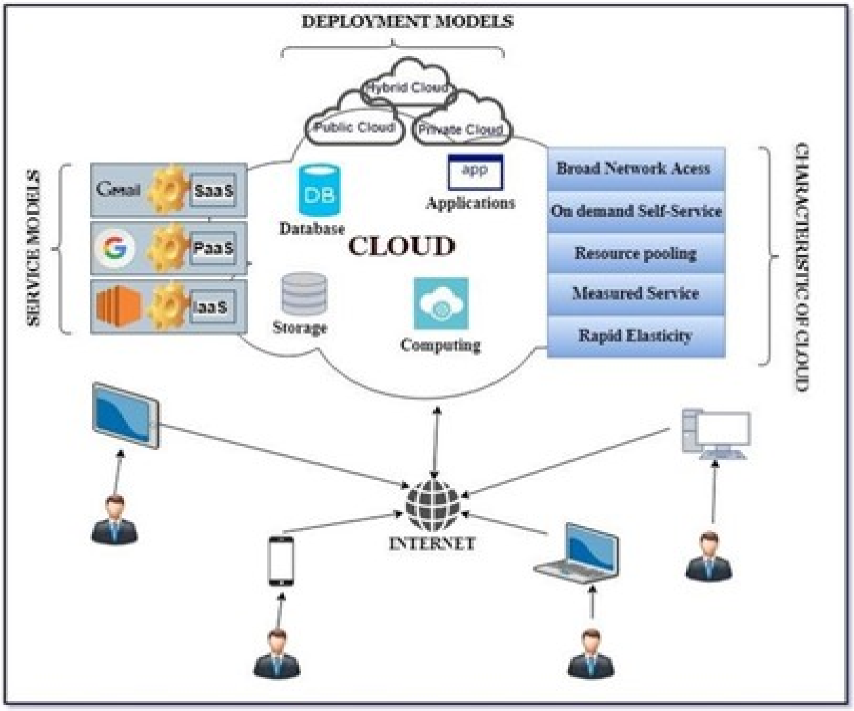


Figure 4: Overview of cloud computing (Haris and Khan, 2018)

Cloud computing has a wide range of application in agriculture and its allied components. Some of its applicabilities are mentioned below in figure 5.

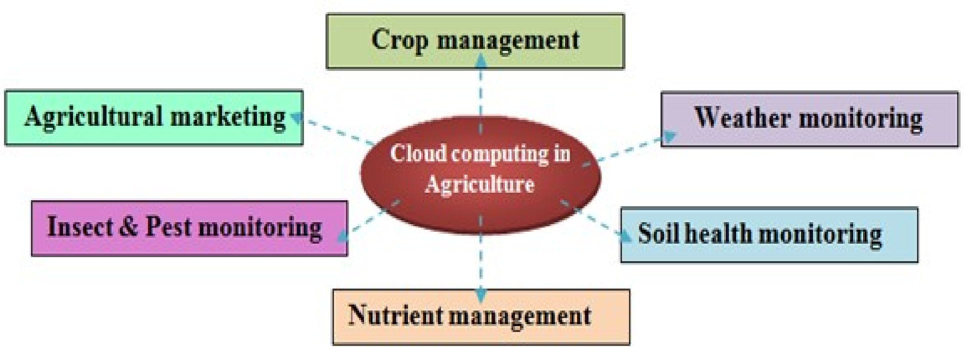


Figure 5: Various applications of cloud computing in agriculture

- **Agricultural marketing:** Cloud computing and big data have the potential to facilitate the attainment of global agricultural product integration (Zhang and Rao, 2020). By harnessing cloud computing technology, operators in the agricultural e-commerce sector can swiftly gather consumer information. This means that even if local sales for agricultural products are not feasible, farmers' goods can align with diverse market demands. This enhancement leads to increased efficiency in marketing endeavours and a reduction in associated costs (Choudhary et al., 2016). Some of the examples of use of cloud computing in better marketing of agricultural produce is give in table 1.

Table 1: Cloud computing in agricultural marketing

Sl. No.	Application	Characteristics
1.	Cloud Based Virtual Agricultural Marketing and Information System (CLOVAMINS)	The CLOVAMINS application let farmers enter their personal and product details and help them reach the customers. The customers also place order for the required items into the app itself (Sateesh et al., 2015).
2.	Agrobros market app	A digital platform employed in the marketing of agricultural products serves as a linkage between farms and markets, facilitating the promotion of local products on a global scale.
3.	AgriMarket	Its purpose includes obtaining the market prices of crops from markets situated within a 50-kilometer radius of the device's location.

- **Weather Forecasting:** Weather forecasting is the application of science and technology for predicting the atmospheric conditions of a given location in a given time. This helps in controlling pests and diseases in crops and obtain optimum yield. The cloud can store weather data for specific regions as well as forecast weather condition for specific time periods. Through the utilization of public Infrastructure as a Service (IaaS) systems, the capacity to perform regional weather predictions can be extended to distant geographical locations, ensuring timely execution of modeling capabilities developed by the meteorological community. This approach occurs within a balanced framework that considers the end-user's demands for cost-effectiveness and computational efficiency. Cloud computing data assist farmers in determining the day-to-day operations efficiently.

Table 2: Cloud computing in weather forecasting

Sl. No.	Application	Characteristics	Reference
1.	The Weather Research and Forecasting Model	This is world's most popular cloud based numerical weather prediction model. This system is built for both meteorological research and real-time forecasting.	Skamarock et al. (2019), Powers et al. (2017).
2.	SEG-001	A smart environment gauge used to monitor flood, weather, PM 2.5 and support additional monitoring devices such as rain gauges.	
3.	Arduino	The device collects, organizes and displays	Tiwari et al.

	board	information by monitoring and controlling the environmental condition using sensors. The data captured is transmitted to the cloud. A web page is created which has access to the cloud and it displays and organizes the required result.	(2020)

- **Nutrient Management:** Cloud based nutrient management ensures optimum need based application of fertilizers. Timely release of nutrient at specific growth stages help absorb and translocate adequate amount of photosynthates to the sink, resulting in elevated growth and yield.

Table 3: Cloud computing in nutrient management

Sl. No.	Application	Characteristics	Reference
1.	Azofert	Azofert is nutrient based decision support system (DSS) developed in France. It is used by advisory services to decide the rate of N fertilization for different yield objectives and timing of fertilization. Optimized and balanced application of nutrients improves agricultural productivity in a sustainable manner.	Parneaudeau et al. (2009), Machet et al. (2017), Gallordo et al. (2020).
2.	VegSyst-DSS	VegSyst model is developed from Spain which estimates irrigation on a daily basis, N requirements, nutrient solution and concentrations of nitrogen for vegetable crops cultivated in greenhouses.	Gallordo et al. (2014), Gallordo et al. (2016).

- **Crop Management:** Different sensors can be used based on the crop characteristics that can monitor vegetative health, soil moisture, and various other pivotal agricultural attributes occurring across the various stages of crop development. (Tsouros et al., 2019).

Table 4: Cloud computing in nutrient management

Sl. No.	Application	Characteristics	Reference
1.	Hydro-Tech	Hydro-Tech represents a cloud-based application designed for the automated and real-time scheduling of irrigation activities, relying on the water balance principle. This application seamlessly integrates the FAO56 methodology for estimating crop evapotranspiration (ETc) using either current or predicted weather data. This estimation approach is coupled with continuous monitoring of soil water content and the ability to remotely manage the water supply network. The practical application of the Hydro-Tech system	Todorovic et al. (2016), Gallordo et al. (2020).

		was evaluated on commercial farms, yielding reductions in water usage ranging from 5% to 20%.	
2.	Imaging for yield prediction	The Wide Dynamic Range Vegetation Index exhibited an improved correlation coefficient (R=0.949) in comparison to LAI ground truth data (R2=0.902). Likewise, the Modified Chlorophyll Absorption Ratio Index demonstrated a stronger correlation coefficient (R=0.975) when compared to SPAD chlorophyll ground truth data (R2=0.951). Notably, the yield prediction derived from the utilization of LAI and SPAD chlorophyll displayed a more pronounced positive correlation with the observed yield, achieving an R2 value of 0.822.	Shanmugapriya et al. (2022)

- **Soil Health Monitoring:** Cloud computing based soil health monitoring gives instant soil health report. Besides being non-destructive in nature, it largely avoids soil disturbance and the labour behind soil sampling as well. The accuracy and precision with which soil health is monitored is very high.

Table 5: Cloud computing in soil health monitoring

Sl. No.	Application	Characteristics	Reference
1.	LoRaWAN (long-range wide area network) based soil health monitoring	LoRaWAN uses low power processor to construct multi-sensor combination module for data acquisition. The wetland monitoring system with water temperature sensor, pH sensor, turbidity sensor, dissolved oxygen sensor and water level sensor, collects data from the sensors and transmitted to local monitoring stations. At the local monitoring station, the processed data can either be transmitted via a long-range communication technology or stored within a local database on-site. These data storage options facilitate subsequent retrieval by a user who visits the location in order to collect the recorded information.	Jia (2020) , Adu-Manu et al. (2017)
2.	Sensor based soil monitoring	The accuracy and precision of the sensor for measurement of soil moisture is 99.33% and 100%, respectively. The time taken in laboratory technique was approximately 10 days whereas sensing technique took nearly 2 m and data could be displayed on cloud within 30 seconds.	Patidar and Joshi (2019)
3.	Soil moisture nutrient salinity (SMNS) based cloud platform	The software is a collaborative effort between the Environmental Systems Research Institute (ESRI) in the USA and GeoScene Information Technology Co. Ltd. in China. It comprises a comprehensive database management system, complemented by a PC client, a web client, and a mobile application. This integrated platform, known as SMNS, effectively expedites the collection and analysis of regional soil quality information.	Zhang et al. (2023)

		To illustrate, when examining the spatial distribution of soil organic matter in the southwest Shandong province, the outcomes obtained through the cloud platform inversion closely aligned with the data from measured sample points and interpolation analyses. The SMNS platform has been successfully employed for analyzing soil indicators in various regions, yielding favorable operational outcomes and benefits. Ultimately, its deployment contributes to an enhancement in overall crop productivity.	

2. **Internet of Things (IoTs):** IoT means the ability to make everything around us i.e., machine, devices, mobile phone and cars and even cities and roads, connected to the Internet with an intelligent behaviour and taking into account the existence of the kind of autonomy and privacy (Ali et al., 2015).

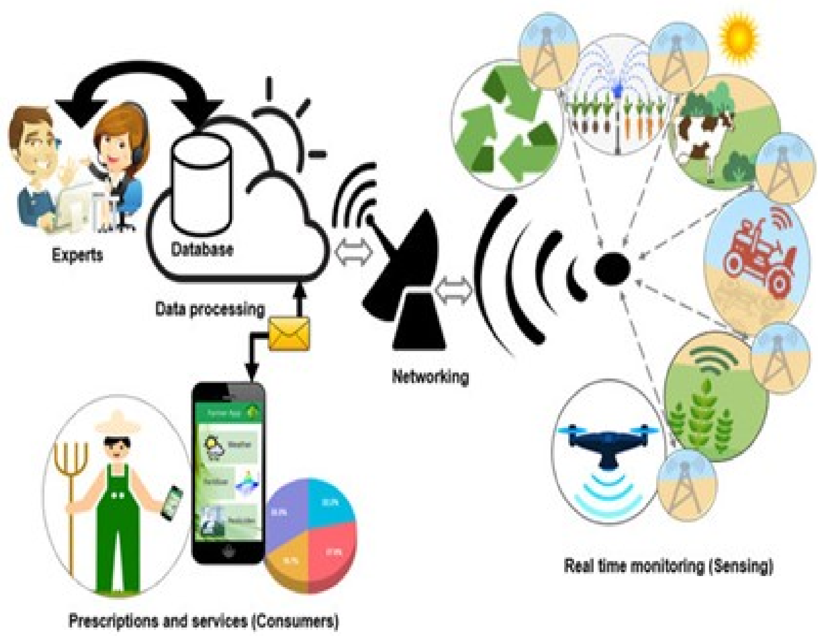


Figure 6: Procedures of the Internet of Things (IoT) in agriculture (Kim et al., 2020)

Incorporating the Internet of Things (IoT) into agriculture will not only enhance the capabilities of existing tools but also seamlessly integrate the physical world into an information system through advanced networked innovative systems (Ozdogan et al., 2017). The IoT technology empowers more effective resource utilization by providing producers with real-time and accurate data, enabling them to make timely and well-informed decisions (Savale et al., 2015). Agricultural enterprises can optimize production strategies to boost harvest yields by leveraging interconnected intelligent machines and cloud computing, facilitated by comprehensive analysis of big data (O'Halloran & Kvochko, 2015). An illustrative example of IoT's application is the work by Kamath et al. (2019), who evaluated the use of IoT-based Raspberry Pi technology to independently classify paddy crops and weeds based on their distinct shape features. The average accuracy obtained in this classification was around 73%. Some more applications of IoTs in agriculture are mentioned in Figure 7.

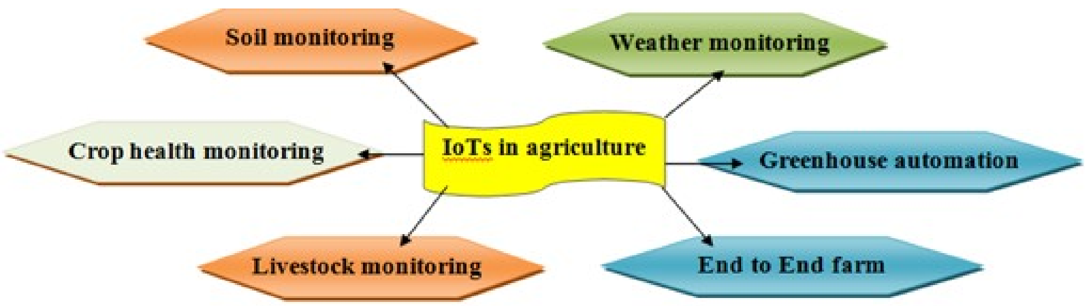


Figure 7: Application of IoTs is Agriculture

- **Soil Health Monitoring:** Soil health monitoring with IoT technologies maximise yield, reduce disease and optimise resources. IoT sensors can measure soil physical, chemical and biological properties and the data from the sensors are transmitted for analysis, visualisation and trend analysis. This optimises farming operations, identify trends and help make subtle adjustments to conditions to maximise crop yield and quality. Table 6 shows some application of IoT in soil health monitoring.

Table 6: IoT based soil health monitoring

Sl. No.	Application	Characteristics	Reference
1.	Soil Scout	Soil scout is a wireless, real-time monitoring application that validates soil properties and improves crop productivity. A validation measurements of soil scout indicated that the model is accurate for radio signal attenuation in sandy and loamy soil and predicts moisture influence correctly.	Tiusasen (2007)
2.	CropX Starter Kit	CropX Starter Kit is equipped with sensors for monitoring real time soil temperature. Monitoring soil quality helps enhance microbial population and thereby improve crop growth and productivity.	Farooq et al. (2019), Farooq et al. (2020)
3.	Temperature Sensor	An array of 3D crop sensors, incorporating photosynthetically active radiation (PAR) technology, can be strategically positioned within a field to monitor a range of environmental parameters, including temperature, CO2 levels, and humidity. Real time monitoring of soil properties maintains soil fertility and productivity hence, results in better quality produce.	Farooq et al. (2020)
4.	IoT based soil and weather	An Internet of Things (IoT) driven monitoring system designed for the analysis of crop environments employs a variety of sensors, including those for temperature,	Jagnam et al. (2018),

	monitoring system	humidity, soil electrical conductivity (EC), and soil pH. The outcomes of this system demonstrate the effectiveness of real	Lee et al. (2013)
5.	Trace Genomics	Trace Genomics specializes in addressing multiple pathogens simultaneously and derives valuable insights from the collected data. The primary input for Trace Genomics is derived from the micro	Kakani et al. (2020)

- **Climate Condition Monitoring:** IoT-based approach enhances the extraction of valuable insights from collected data. The entirety of available data can be conveniently viewed within specified date ranges, enabling the identification of historical trends in the data. With precise weather data collection, activities such as water management, planting, and maintenance become notably more accurate and resource-efficient. This not only conserves time, labor and financial resources, but also contributes to making agriculture more productive and financially rewarding.

Table 7: IoT based climate monitoring

Sl. No.	Application	Country	Characteristics	Reference
1.	allMETEO	USA	The system comprises a portal dedicated to the management of IoT based micro weather stations and the creation of weather maps. The data collected from these stations is employed to generate climatic condition maps. This system offers farmers direct access, enabling them to closely monitor weather predictions and consequently strategize their crop planning with precision.	Kaur and Bharti (2020), Divesh et al. (2022)
2.	Pycno	London	An integrated software and sensor solution enabling seamless and uninterrupted data collection, facilitating the smooth transmission of information from the farm directly to a smart phone.	Kaur and Bharti (2020)
3.	Raspberry Pi	United Kingdom	Raspberry pi is a machine connected to sensors. The smart farming sensors collect various data from the environment and send it to the machine. The average accuracy obtained is around 73%.	Shete and Agrawal (2016), Kamath et al. (2019)

- **Greenhouse Automation:** Greenhouse farming technique enhances the yield of crops, vegetables, fruits etc. A smart greenhouse through IoT embedded systems aids in intelligent monitoring and control. Various sensors, including a soil moisture sensor for gauging soil water content, a light sensor for measuring light intensity, and a humidity sensor for detecting atmospheric moisture levels, are employed. These sensors collectively contribute to remote monitoring systems that safeguard valuable plants from drastic temperature variations, thereby providing an optimal growth environment for plants. Table 8 represents some green house automating apps.

Table 8: IoT based Greenhouse automation

Sl. No.	Application	Country	Characteristics	Reference
1.	Farmapp	Australia	This integrated pest management app service operates on the foundation of combining data derived from geo-referenced scouting and spraying apps, soil sensors, and weather stations. The collected information undergoes processing and analysis, after which it is disseminated back to farmers via email, SMS, and the platform itself. This invaluable information serves a multitude of purposes, including planning for biological controls, strategically scheduling specific product sprays, monitoring pest and disease activity, and even enabling the automation of greenhouse operations.	Anonymous (2023).
2.	Growlink	USA	It integrates hardware and software products, enable wireless automation, data collection, optimization, monitoring and visualization. The app is used for controlling climatic condition (temp, humidity, CO_2 and light), fertigation, precision irrigation, diagnose pests and hence optimize crop performance.	Farooq et al. (2019)
3.	GreenIQ	Denmark	Controls irrigation and lighting from all locations and connect IoT devices to automation platform. Growers can save outdoor water bills up to 50%.	Farooq et al. (2019)

- **Crop Monitoring:** Crop monitoring facilitate detection of pests, diseases and weeds, check level of water, animal intrusion in to the field, crop growth and development, etc. IoT based crop monitoring tracks real-time environmental changes which makes it possible for farmers to respond instantly to sudden changes and take ready action, thereby improving overall quality and quantity of the produce. Some examples of such IoT based apps are mentioned below in table 9.

Table 9: IoT based crop health monitoring

Sl. No.	Application	Country	Characteristics	Reference
1.	Arable	USA	It offers continuous indicators of stress, pests and disease.	Kandula et al. (2019)
2.	Semios	Canada	It enables farmers to assess and respond to insects, diseases and crop health using real-time data. Semios platform is reported to reduce crop damage upto 50%, increasing profitability of the grower.	**Giesbrecht (2019)**, Kandula et al. (2019)

3.	Plantix (PEAT)	Germany in collaboration with ICRISAT and ANGRAU, India	It controls and manages the agriculture process, disease control, and the cultivation of high-quality crops. It is trained on detection of more than 250 plant damages with detection accuracy of over 90%.	Rupavatharam et al. (2018), Balakrishna et al. (2020)
4.	Yolo V3	USA	It is an object detection algorithm for disease, pest and weed detection in crops. The model trained with images could achieve disease and pest detection accuracy of 92.39% in 20.39 m.	Chen (2020), Wang and Liu (2021)

- **Livestock Monitoring and Management:** IoT based livestock management helps monitor the health and vitality of livestock in real-time. It enables farmer in early detection of illness or diseases, helping in quick recovery of the animals. This can also be used in tracking the grazing animals and identify grazing patterns. A few IoT based livestock monitoring applications are mentioned in table 10.

Table 10: IoT based livestock monitoring and management

Sl. No.	Application	Country	Characteristics	Reference
1.	Allflex	India	It delivers information regarding heat, health and nutrition insights of cattlles. Allflex visual ear tag has the tag retention of 96.1%.	Salina et al. (2016), Groot et al. (2016)
2.	Cowlar	Pakistan	Detects health disorders before the appearance of visual symptoms in animals.	Molina et al. (2019)
3.	Micro-Doppler phenomen on in IoT	-	The micro-Doppler phenomenon offers an opportunity for non-contact monitoring of animals, presenting a cost-effective solution that minimizes stress on the animals. By detecting the micro-Doppler phase associated with the motion of the chest cavity, which closely corresponds to the animal's respiration, this technology provides an effective means of observation.	Michie et al. (2020)

- **End-to-end Farm Management Systems:** An end-to-end farm management system seamlessly brings together various agricultural IoT devices and sensors into a unified platform. This system can be implemented on-site, offering a robust dashboard enriched with advanced analytics functionalities. Moreover, it incorporates integrated accounting and reporting features, providing farmers with a comprehensive toolkit to efficiently manage their operations. A system like this is critical for identifying areas for improvement in agriculture.

Table 11: IoT based end-to-end farm management systems

Sl. No.	Application	Country	Characteristics	Reference
1.	FarmLogs	Canada	Monitors field conditions, facilitates planning and management of crops and markets agricultural produce.	Schwering et al. (2022)
2.	Cropio	Cyprus	Optimizes fertilization and irrigation through real time data.	Kumar et al. (2019)
3.	Agro-Tech	India	Agro-Tech is designed to capture, store, and continually update data collected from diverse sensors deployed within specific crop areas. This system empowers farmers with the ability to access and closely monitor their crops by providing them with ready access to this valuable information.	Pandithurai et al. (2017), Gomez-Chabla et al. (2019)

3. **Robotics and Un-manned Aerial Vehicles (UAVs):** Robots are electro-mechanical machines that operate automatically through computer programs, often equipped with sensors, control systems, manipulators, power supplies, and software, working in tandem to perform tasks. Automation in agriculture introduces numerous advancements to the industry, offering farmers opportunities to save both time and money. A variety of robots find exclusive application in agriculture, such as weeding robots, flying robots, forester robots, and Demeter, among others (Naresh et al., 2021).

   Demeter stands as a computer-controlled, speed-rowing machine equipped with video cameras and global positioning sensors. It excels at orchestrating harvesting operations for entire fields by cutting crop rows, sequentially turning to cut successive rows, repositioning within the field, and detecting unexpected obstacles (Pilarski et al., 2002). Similarly, automatic weeding robots bolster weeding efficiency, economize resources, minimize environmental pollution, and enhance agricultural product yield and quality. The BoniRob weeding robot showcases the ability to execute mechanical weed control in carrot and sugarbeet cultivation, achieving an impressive weed control rate of 93.86% (Lottes et al., 2017).

   Kiwifruit harvesting robots, relying on stereo-vision technology, exhibit a visual recognition success rate ranging from 76.3% to 89.6% (Williams et al., 2019). In assessing the overall performance of harvesting robots, Bac et al. (2014) reviewed 50 systems and reported location finding efficiency of 85%, fruit detachment efficiency of 75%, harvesting efficiency of 66%, and fruit damage rate of only 5%.

   Unmanned Aerial Vehicles (UAVs), also known as Agricultural drones, play a significant role in precision agriculture—a modern farming approach that harnesses Big Data, aerial imagery, and other tools to optimize efficiency. In agriculture, UAVs are primarily employed for tasks like harvesting, spraying, sensing, and mapping. Tevel Aerobotics Technologies of Israel developed a fruit harvesting drone that can pick over 90% of fruit from trees, helping growers increase tree heights by 20% and subsequently boosting yield (Anonymous, 2020). Application of 2% TNAU pulse wonder with 50 L ha-1 of drone spray fluid demonstrated superior outcomes in grain yield, haulm yield, grain protein, and carbohydrate content compared to manual spray with 500 L water ha-1 and control in green gram (Dayana et al., 2021). Cai et al. (2019) showcased the potential of UAV and CubeSat based multispectral sensing for monitoring nitrogen stress.

Figure 8: UAVs and robots used in farming

V. ROBOTS IN AGRICULTURE

Robots have been successfully used in many industrial applications. Agriculture is also in need of mechanization in the form of automated equipments and robots for its successful development. Robotics can be used for various agricultural activities like seeding, harvesting, weed control, chemical application, etc. Some successful application of robots in agriculture is mentioned in Table 12.

Table 12: Application of different robots in agriculture

Sl. No.	Application	Characteristics	Reference
1.	**Micro spraying**	The effective eradication of weeds in close proximity to crop plants can be achieved through the technique of micro-spraying. Utilizing machine vision technology, the precise position of each individual weed plant is identified. A configuration of closely spaced nozzles can then deliver targeted herbicide application directly onto the weed.	Pedersen et al. (2008), Reddy et al. (2016)
		Robots play a crucial role in accurately detecting and efficiently spraying 85% to 100% of the diseased area, resulting in a notable reduction of up to 20% in pesticide usage.	Oberti et al. (2013), Oberti et al. (2016).
		By integrating plant recognition, micro-dosing, and autonomous robotics into a machine vision system, the application of spray liquid can attain sub-centimetre accuracy. This innovation allows for a substantial reduction in application rate,	Sogaard and Lund (2007)

		by up to two orders of magnitude when compared to conventional broadcast spraying methods.	
2.	**Seed mapping**	Seed mapping is the passive recording of geospatial position of each seed while sowing, using kinematic models. The seed coordinates are used to target subsequent plant based operations.	Reddy et al. (2016)
		A Real Time Kinematic Global Positioning System, optical seed detectors and a data logging system were retrofitted on to a precision seeder for mapping. The average error between the seed map and the actual plant map was about 16–43 mm.	Griepentrog et al. (2005
		PhenoSeeder is a system consisting of a pick-and-place robot along with a modular setup of sensors. It enables the handling and phenotyping of individual seeds of very different sizes. It can be used for seed germination studies as well.	Demilly et al. (2016), Jahnke et al. (2016)
3.	**Weeding**	Bosch's Bonirob weed control robot was incorporated with conditional Generative Adversarial Networks to distinguish multi-spectral images of crop and weed. The images helped in accurate weed detection and obtained a weed control rate of 93.86%.	Lottes et al. (2017), Fawakherji et al. (2020)
		AgBot II was used in cotton for multimode weed management. The robot could control weed with an accuracy of 92.3%.	Bawden et al. (2017), Hall et al. (2017).
		Digo robot was used for precision herbicide spraying in carrot. The Drop-On-Demand system on Digo can reduce herbicides used by more than 90%.	Utstumo et al. (2018)
4.	**Harvesting**	Machine vision based harvesting robots have the ability to sense and adapt to different crop types or environmental changes collect information, detect targets and learn autonomously.	Zhao et al. (2016), Silwal et al. (2017)
		Indoor and outdoor picking experiments were conducted for litchi and citrus using the picking manipulator based on binocular vision. The picking success rates were over 84% and 78% in indoor and outdoor tests, respectively. The recognition accuracy was 85–94%,	Zou et al. (2016)

		recognition time 0.8 s, harvesting success rate was 84–88% and harvesting time for per fruit^{-1} was 11.3–15.5 s.	
		The litchi fruit was extracted by stereo matching two litchi images in the same scene. The average recognition rates of unobstructed litchi and partially occluded litchis were 98.8 and 97.5%, respectively.	Wang et al. (2016).

Drones/UAVs in Agriculture: Drones provide platforms for cost efficient spatial data collection as compared to satellite images. This offers great data solution possibilities to monitor crop growth and development. Compared to satellites based remote sensing methods, UAV platform and light weight sensors provide better quality, higher spatial and temporal resolution images for mapping (Niu et al., 2019).

Table 13: Application of different UAVs in agriculture

Sl. No.	Application	Characteristics	Reference
1.	Sensing	Using different sensors pertaining to visible, NIR and thermal infrared rays, different multispectral indices were computed. The indices were used to assess water stress, nutrient stress, insect-pest attack, diseases, etc., in crops.	Colomina and Molina (2014).
		Thermal infrared imagery and the difference between the canopy and air temperatures were used for determining the crop water stress index. Chlorophyll fluorescence calculated using multispectral images could be used for water stress detection and monitoring.	Hoffmann et al. (2016a), Park et al. (2017), Ludovisi et al. (2017).
		RGB sensors can be used in drones to classify various weed species. Also hyper spectral sensors may be used to monitor weed as a function of the plant canopy chlorophyll content and leaf density.	Malenovsky et al. (2017), Huang et al. (2018).
2.	Mapping	Evapo-transpiration in a peach orchard was estimated by using very high resolution imagery and mapping from an UAV platform.	Hoffmann et al. (2016b), Xia et al. (2016).
		A weed mapping approach based on machine learning and UAV may be adopted for site-specific early-post emergence weed control.	Perez-Ortiz et al. (2015).
		High resolution thermal imagery can effectively generate spatial maps for assessing water status and quantifying water stress.	Gonzalez-Dugo et al. (2014).
3.	Spraying	Drones spray chemicals faster than conventional methods. It also saved the amount of chemicals applied thus reducing input cost.	Wang et al. (2022)

		Accelerometer and Gyroscope sensors were used for spraying fertilizer and pesticide; it was able to reduce time and human efforts.	Plant et al. (2000)
		The spraying cost of drone was ₹750 less ha^{-1} over knapsack sprayer. The nutrient and spray fluid requirement was also 20 times and 8 times lesser, respectively in drone based spraying.	Kanishka et al. (2022), Dayana et al. (2021).
4.	Harvesting	Drone spray increased penetration and improved nutrient translocation through uniform distribution of finer spray droplets resulting higher grain and haulm yield in green gram.	Dayana et al. (2021).
		Spectral indices, ground-measured plant height, and height derived from drone hyper-spectral images were used to predict yield in cereals.	Zhou et al. (2017), Tao et al. (2020).

VI. CONCLUSION

Digitisation in agriculture has tremendous potential in enhancing crop performance and productivity. The precise application of inputs, sustainable weed management and higher resource use efficiency makes agriculture climate resilient, sustainable and productive. It reduces the drudgery of farmers and ensures higher profitability. However, the most critical factors that limit its large-scale adoptions are technology affordability, ease of access and operations, system maintenance and supportive government policies. Research is needed to make these technologies affordable to the farmers.

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