**Digital Agriculture: Future towards sustainability**

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**Abstract**

The 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 less land, feed more people and improve farmers’ lives. 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., create 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

1. **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. Digital Agriculture includes tools that digitally collect, store, analyze and share electronic data in agriculture (Chandra and Collis, 2021). While Agriculture 4.0 brings revolutionary changes in farming, it also aims to grow more food on less land, feed more people and improve farmers’ lives (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 marks the digitalization of food and agriculture systems using artificial intelligence (Gallordo et al., 2020), Internet of Things (IoTs) (Kakani et al., 2020), drones (Dayana et al., 2021), robots (Lottes et al., 2017), machine and deep learning algorithms (Sonka, 2015, Kamath et al., 2019), sensors (Jia, 2020), etc., to create a hyper connected network of farms, machines and factories that result in 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.

1. **Status of digitalisation in agriculture**

The current global **digital farming market** is estimated to be valued worth US $18 billion (Figure 1). By 2027, it is projected to reach USD 29.8 billion. The global digital agriculture market is estimated to grow at a compound annual growth rate (CAGR) of ~10.5% over the forecast period, i.e., 2022–2027 (Anonymous, 2022a). The massive growth is attributed to the increased penetration of digital infrastructure and its growing reach to even to the rural most areas.

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Figure 1: Global overview of digitalisation in agriculture

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

1. **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 big data plays a pivotal role in the digital agricultural revolution. A variety of technological advances have created immense opportunities for big data (Sonka, 2015). Hashem et Al. (2015) defines big data as complements of techniques that require integration forms to distinguish unrecognized values from large scale, various and complex data sets. Stubbs (2016) suggested that the term “big data,” as it is applied to agriculture, is less about the size of the data and more about the combination of technology and advanced analytics that creates a new way of processing information in a way that is more useful and timely. Big data enables farmers to view all production parameters of real-time operations and improve decision-making processes (Anonymous, 2015a). Coble et al. (2016) defined the data in terms of volume, velocity, variety, and veracity, with “volume” referring to the size of the data, “velocity” measuring the flow of data, “variety” reflecting the frequent lack of structure or design to the data, and finally “veracity” reflecting the accuracy and credibility of the data.

The components of digital agriculture include (Figure 3):

Figure 3: Components of digital agriculture

1. **Application of digital technologies to enhance crop productivity**

*4.1. Cloud computing*

The practice of using a network of remote servers hosted on the internet to store, manage, and process data, rather than a local server or a personal computer is known as **Cloud computing.** The term “cloud computing” is given because the users do not really need to know who is providing those services and users consider that the services are rendered by the cloud – an unknown to them (Nath and Chaudhuri, 2012). Cloud computing is the basic infrastructure that enables intelligent farming implementations such as scalable calculations, software, data access and storage services (Kaloxylos et al., 2012, Lakshmisudha et al., 2016). Through cloud computing, large-scale data can be stored with low investment cost and instant access to this data, whenever needed, becomes possible (Chavali, 2014). A basic overview 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

*4.1.1. Agricultural marketing*

Cloud computing and big data can be used to achieve global agricultural product integration (Zhang and Rao, 2020). Using cloud computing technology, agricultural e-commerce operators can grasp consumer information instantaneously. Even if the production of agricultural products cannot be sold locally, farmers' products can meet other market needs. This improves marketing efficiency and reduces marketing 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.

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| **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 used in marketing of agricultural products, connecting farms to markets and promoting local products internationally.  |
| 3. | AgriMarket | It is used to get the market price of crops in the markets within 50 km of the device’s location.  |

*4.1.2. 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. By enabling regional weather predictions on public IaaS systems, modeling capabilities developed by the meteorological community can be executed on geographically distant resources in a timely fashion and within a trade space that allows the end-user requirements of cost and computational efficiency. Cloud computing data assist farmers in determining the day-to-day operations efficiently.

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| **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 board | The device collects, organizes and displays 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.  | Tiwari et al. (2020) |

*4.1.3. 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.

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| **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 upon N fertilizer rate for different yield objectives, timing to apply the fertilizer. 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 calculates daily irrigation, N fertilizer requirements, nutrient solution and N concentrations for fertigated vegetable crops grown in greenhouses. | Gallordo et al. (2014), Gallordo et al. (2016). |

*4.1.4. Crop management*

Different sensors can be used based on the crop characteristics that can monitor vegetative health, soil moisture, and other important agricultural characteristics at different stages of development of the crop (Tsouros et al., 2019).

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| **Table 4: Cloud computing in nutrient management** |
| **Sl. No.** | **Application** | **Characteristics** | **Reference** |
| 1. | Hydro-Tech | The Hydro-Tech is a cloud-based application for automatic real-time irrigation scheduling based on the water balance. The FAO56 approach for the estimation of ETc using real time or forecast weather is combined with continuous soil water content monitoring and remote control of the water supply network. The Hydro-Tech system was tested in commercial farms resulting in 5–20% reductions of applied water.  | Todorovic et al. (2016), Gallordo et al. (2020). |
| 2. | Imaging for yield prediction | Wide Dynamic Range Vegetation Index showed a better correlation coefficient (R=0.949) with LAI ground truth data (R2=0.902). The Modified Chlorophyll Absorption Ratio Index showed a better correlation coefficient (R=0.975) with SPAD chlorophyll ground truth data (R2=0.951). The yield predicted by using LAI and SPAD chlorophyll had a higher positive correlation with the observed yield with a R2 value of 0.822. | Shanmugapriya et al. (2022) |

*4.1.5. 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.

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| **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 is either transmitted through a long-range communication technology or is stored in a local database at the local monitoring station for eventual collection by a user who travels to the site to gather the data. | 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 produced by the Environmental Systems Research Institute, USA and GeoScene Information Technology Co. Ltd. China, with database management system along with a PC client, a web client, and a mobile app. The SMNS platform enables fast collection and analysis of regional soil quality information. Taking the spatial distribution analysis of soil organic matter in southwest Shandong province as an example, the results of cloud platform inversion were consistent with the measured sample points and interpolation analysis. It is used to analyse soil indicators in several areas producing good operational results and benefits, thereby, enhance overall crop productivity. | Zhang et al. (2023) |

*4.2. 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)

Using IoT in agriculture will improve the functionality of existing tools by making the physical world a part of the information system through advanced networked innovative systems (Ozdogan et al., 2017). IoT technology enables efficient use of resources by allowing producers to make timely and appropriate decisions with real-time and accurate data (Savale et al., 2015). Agricultural enterprises can prepare sensitive production mixes to increase harvest yields through interconnected intelligent machines and cloud computing based on big data analysis software (O'Halloran & Kvochko, 2015). Kamath et al. (2019) evaluated IoT based Raspberry Pi to categorize paddy crop and weed using the shape features separately. 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

*4.2.1. 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.

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| **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 a real time soil temperature monitoring sensor with direct cellular connection and better accuracy. 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 | A 3D crop sensor array with photosynthetically active radiation technology deployed at any location of field can monitor temperature, CO2 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 monitoring system | An IoT based monitoring system for analyzing crop environment used different sensors like temperature, humidity, soil EC and soil pH sensors. The results suggest that weather and soil monitoring can be done efficiently in real-time and at low cost.  | Jagnam et al. (2018), Lee et al. (2013) |
| 5. | Trace Genomics | Trace Genomics deals with multiple pathogens at once and models valuable information from the data. The micro-biomes in the soil are the source of main input for Trace Genomics.  | Kakani et al. (2020) |

*4.2.2. Climate condition monitoring*

IoT based help getting better insights from the data. All available data can be viewed in the date ranges to find the historical trends of data. Precise weather data collection makes water use, planting and maintenance more accurate, resource efficient and also save time, labor and money, thereby making agriculture more productive and profitable.

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| **Table 7: IoT based climate monitoring** |
| **Sl. No.** | **Application** | **Country** | **Characteristics** | **Reference** |
| 1. | allMETEO | USA | A portal to manage IoT micro weather stations and to create weather maps. The data collected is used to map the climatic conditions and provides access to the farmers; the farmers can monitor the weather predictions and plan their crops accordingly. | Kaur and Bharti (2020), Divesh et al. (2022) |
| 2. | Pycno | London | A software and sensor allowing continuous data collection and flow from the farm to 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) |

*4.2.3. 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. Different sensors such as soil moisture sensor determines soil water content, light sensor: The light sensor displays the digital values corresponding to the light intensity, humidity sensor is used for sensing the vapors in the air.
Thus, remote monitoring systems protect valuable plants from extreme temperature fluctuations, giving plants the best possible growing environment. Table 8 represents some green house automating apps.

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| **Table 8: IoT based Greenhouse automation** |
| **Sl. No.** | **Application** | **Country** | **Characteristics** | **Reference** |
| 1. | Farmapp | Australia | It is an integrated pest management based app service that combines information from geo-referenced scouting and spraying apps, soil sensors and weather stations. The information is processed, analysed and delivered back to the farmers via email, SMS, and through the platform. This information is used in planning biological controls, program spraying of a particular product, monitor pests and diseases and automates greenhouses.  | 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, CO2 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) |

*4.2.4. 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.

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| **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) |

*4.2.5. 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.

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| **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 phenomenon in IoT | - | Micro-Doppler phenomenon facilitates contact less monitoring of animals at relatively low cost solutions and minimise stress on the animal. The motion of the chest cavity is detected from the micro-Doppler phase which aligns with the respiration of the animal.  | Michie et al. (2020) |

*4.2.6. End-to-end farm management systems*

An end-to-end farm management system integrates all agricultural IoT devices and sensors. It can be installed on premises as a powerful dashboard with analytics capabilities and built in accounting and reporting features. A system like this is critical for identifying areas for improvement in agriculture.

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| **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 manage crop production. It also markets agricultural products.  |  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 records, stores and updates the data obtained from various sensors in a specific area of the crop. This enable farmers to access the information and monitor their crops. | Pandithurai et al. (2017), Gomez-Chabla et al. (2019) |

*4.3. Robotics and Un-manned Aerial Vehicles (UAVs)*

The electro-mechanical machines that operate automatically through computer programs and may contain sensors, control systems, manipulators, power supplies and software, all working together to perform a task are known as robots. Automation in agriculture creates several advancements to the industry while helping the farmers to save money and time. Weeding robot, flying robot, forester robot, Demeter, etc., are some of the exclusively used robots in agriculture (Naresh et al., 2021). Demeter is a computer-controlled speed-rowing machine, equipped with video cameras and global positioning sensors. It is capable of planning harvesting operations for an entire field by cutting crop rows, turning to cut successive rows, repositioning itself in the field, and detecting unexpected obstacles (Pilarski et al., 2002). Similarly, automatic weeding robots can improve weeding efficiency, save resources, reduce environmental pollution and improve the yield and quality of agricultural products. BoniRob weeding robot is capable of mechanical weed control in carrot and sugarbeet with weed control rate of 93.86% (Lottes et al., 2017). Kiwifruit harvesting robot based on stereo-vision have visual recognition success rate of 76.3–89.6% (Williams et al., 2019). In order to evaluate the overall performance of harvesting robots, Bac et al. (2014) reviewed 50 harvesting systems and summarized that location finding efficiency was 85%, fruit detachment 75%, harvesting 66% and rate of fruit damage was 5% only.

Unmanned Aerial Vehicles (UAVs) or Agricultural drones are used for precision agriculture, which is a modern method of farming that uses Big Data, aerial imagery and other means to optimize efficiency. In agriculture, UAVs are mainly used for harvesting, spraying, sensing and mapping. Fruit harvesting drone developed by Tevel Aerobotics Technologies of Israel, is able to pick over 90% of all fruit from trees. It enables growers to increase tree heights by 20% and thus generate additional yield (Anonymous, 2020).Application of 2% TNAU pulse wonder with 50 L ha-1 of drone spray fluid significantly recorded higher 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) demonstrated the UAV and CubeSat based multispectral sensing having potential to monitor nitrogen stress.

  

Figure 8: UAVs and robots used in farming

1. **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.

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| **Table 12: Application of different robots in agriculture** |
| **Sl. No.** | **Application** | **Characteristics** | **Reference** |
| 1. | Micro spraying | Weeds close to the crop plants can be killed with micro spraying. The position of an individual weed plant is identified through machine vision and a set of nozzles mounted close together can squirt herbicide on to the weed.  | Pedersen et al. (2008), Reddy et al. (2016)  |
| Robots can detect and spray 85‒100% of the diseased area and reduce pesticide use by 20%. | Oberti et al. (2013), Oberti et al. (2016). |
| Using plant recognition, micro-dosing and autonomous robotics in a machine vision system, spray liquid could be applied at sub-centimetre accuracy and the application rate can be reduced by two orders of magnitude over conventional broadcast spraying. | Sogaard and Lund (2007) |
| 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. | Zhaoet 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%, recognition time 0.8 s, harvesting success rate was 84‒88% and harvesting time for per fruit-1 was 11.3‒15.5 s. | Zou et al. (2016) |
| 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). |

1. **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).

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| **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). |

1. **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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