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Anish Kumar Subudhi
M.Sc. Scholar, Department of
Horticulture School of Agriculture,
GIET University, Gunupur,
Rayagada, Odisha, India

Kheyali Ghosh
Assistant Professor, Department of
Horticulture, School of
Agriculture, GIET University,
Gunupur, Rayagada, Odisha, India

Pratyush Kumar Pradhan
M.Sc. Scholar, Department of
Horticulture, School of
Agriculture, GIET University,
Gunupur, Rayagada, Odisha, India

Subhankar Panda
M.Sc. Scholar, Department of
Horticulture, School of
Agriculture, GIET University,
Gunupur, Rayagada, Odisha, India

Corresponding Author:
Kheyali Ghosh
Assistant Professor, Department of
Horticulture, School of
Agriculture, GIET University,
Gunupur, Rayagada, Odisha, India

Digital horticulture: An integrated approach of precision agriculture

**Anish Kumar Subudhi, Kheyali Ghosh, Pratyush Kumar Pradhan and
Subhankar Panda**

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Abstract

Modern agricultural methods are being transformed by digital horticulture, a revolutionary merger of precision agriculture. Initially released in the second part of the 20th century, precision agriculture aims to maximize inputs, reduce waste, and increase output through site-specific crop management utilizing data-driven solutions. Mechanized farming gave way to satellite-based systems in the past, which established the groundwork for contemporary precise technology (Gebers & Adamchuk, 2010). Decision-support systems, automated equipment, and GIS are essential elements, each with unique related purposes. Aerial drone footage is used to monitor crop health, and spectral data from remote sensing is essential for comprehending soil characteristics and plant health. AI algorithms process large datasets to produce insights that can be put to use. At the same time, sensors track environmental variables like temperature, nutrient levels, and soil moisture in real time. Accurate crop identification and resource allocation are made possible by these technologies working together, guaranteeing sustainability and profitability. The great value and variety of crops in horticulture make the use of precision equipment especially significant. Precision irrigation and fertilization are made possible by sensors, AI helps with production prediction and pest control, and drones improve disease detection and pollination efforts. This comprehensive strategy guarantees ecologically responsible behaviours, lowers labour reliance, and enhances quality. The precision farming methods are still getting rejected by farmers in developing countries due to unawareness of it, lack of government schemes and benefits with respect to the high cost of drones, sensors, and other computing devices used in precision farming.

Keywords: Artificial intelligence, crop monitoring systems, digital horticulture, machine learning, precision agriculture

Introduction

Precision agriculture is a technological farming approach that combines applied technology with controllable temporal and spatial variation principles to enhance crop performance and maintain the natural environment in every aspect of the agricultural industry. (Ahmad *et al.*, 2020) ^[5]. By precisely determining the necessary amounts of inputs, precision agriculture reduces waste and raises average yields in comparison to conventional farming. The comparatively tiny and dispersed landholdings in India are a significant problem. 58% of India's arable land is owned by a single person and is less than one hectare (Dev and S, 2014) ^[77]. Seed, soil, water, and agrochemicals (such as fertilizers) interact intricately to form the agricultural production system. Therefore, the long-term functioning of such a complicated system relies on the meticulous monitoring of all inputs. Small fields were common in agriculture before the industrial revolution (Allen and R, 1994) ^[7]. Without really measuring the variability, farmers used to have a comprehensive picture of their agricultural system. Large-scale, homogenous, mediocre agricultural methods were dominated by mechanization and the drive for more profits (Giller *et al.*, 2021) ^[48]. The late twentieth and beginning of the twenty-first centuries witnessed innovations in technology that cleared pathways towards the expansion of agriculture. These days, as agricultural profitability declines, producers search for technology that saves expenses without sacrificing output (Jack and K, 2013) ^[61]. According to Bill No. H.R. 2534 of the US House of Representatives from 1997, in the beginning, precision agriculture has been defined as

"an integrated information-and production-based farming system that has the objective at maximizing productivity, profitability, and a long-term location-specific and whole agricultural production efficiency while trimming unwanted effects on wildlife and the environment." Modern methods such as precision farming employ technological advances to reduce hazards and expenses while boosting sustainability, profitability, and performance (Belousova *et al.*, 2019). Management zones provide the use of suitable inputs to optimize management practices, hence enhancing profitability and minimizing environmental effects (Sharma and P, 2007). Precision farming is currently described as "an ecologically sustainable system solution that maximizes product quality and quantity while minimizing expenses, human involvement, and unpredictability caused by unpredictable nature" Precision farming has changed in recent years (Gebbers and Adamchuk, 2010)^[47].

Smart agriculture also means a methodology that applies the 4R (right time, right place, right method, and right amount) of agriculture. The technologies like GPS, GIS, Yield Monitoring, Remote Sensing, Variable Rate Technology (VRT), Crop Scouting Devices, Decision Support System (DSS), Farming Management Software, Auto-Steer and Guidance Systems, and Sensor Technologies are the major branches of precision farming (Yadav and Sidana, 2023)^[156].

The development of sensor technology, which when paired with protocols that connect mapped variables to suitable farming management activities, including growing, sowing, fertilization,

herbicide treatment, and harvesting, makes precision agriculture feasible (Monteiro *et al.*, 2021)^[88].

Nowadays, artificial intelligence combined with various new developmental technologies like drones, sensors, automated systems, machine learning, and leaf analysis by using graphical interpretation are more feasible towards meeting the global agriculture, food, and production demands.

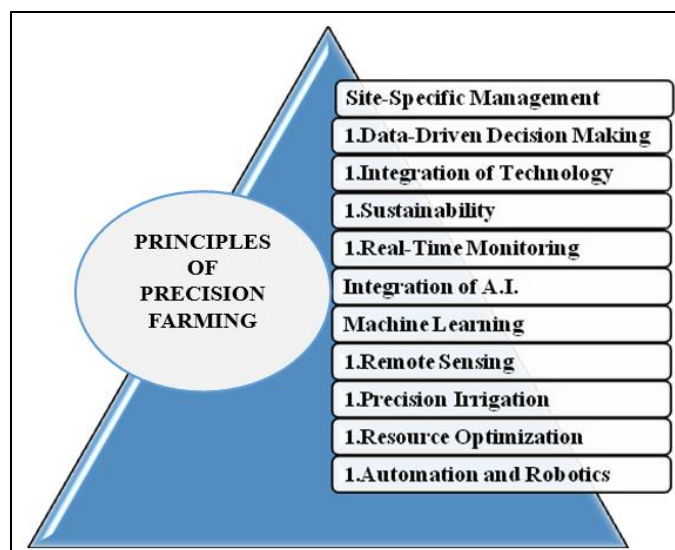


Fig 1: Principles of precision farming (Adi Narayana *et al.*, 2024)

Table 1: Historical references denoting advances towards modern farming practices

Topic	Key Highlights
Geostatistics in Soil	• Origin in 1970s-1980s by soil scientists. • Focused on soil moisture, hydraulic properties (Nielsen <i>et al.</i>, 1973). • Applied to soil property mapping (Webster & Burgess, 1984).
Variable Rate Fertilizer	• First computer-controlled spreaders (1985-1987). • Transitioned to "site-specific farming" in the 1990s. • Optimized input use; challenges: costs vs. benefits.
Management Zones	• Defined by uniform yield-limiting factors (Doerge, 1999). • Based on soil texture, organic matter, and remote sensing.
GPS in Agriculture	• Initially used for location tracking (1980s). • Differential GPS improved accuracy. • Auto-navigation and real-time yield monitoring are enabled.
Automated Navigation	• First tractor auto-steering with RTK GPS (1996). • Reduced overlaps/gaps; improved efficiency. • Modern systems integrate multiple sensors.
Yield Monitoring	• Early methods used engine speed as a proxy. • Modern systems use GPS and advanced sensors. • Challenges: inaccuracies during turns, time lags.
Spatial Variability	• Linked yield to soil properties (Karlen <i>et al.</i>, 1990). • Temporal variability is often greater than spatial (McBratney & Whelan, 1999).
Variable Rate Herbicide	• Optical sensors detect weeds (1990s). • Machine vision reduced herbicide use by 66% to 80%. • Technologies include Detect Spray, Weed Seeker.
Variable Rate Irrigation	• Controlled nozzles on pivots deliver precise water. • Developed for water conservation (1990s). • Challenges: data interpretation, wind distortion.
Remote Sensing	• Focused on crop health, nitrogen stress (1990s-2000s). • Key metric: NDVI (assesses biomass, canopy structure).

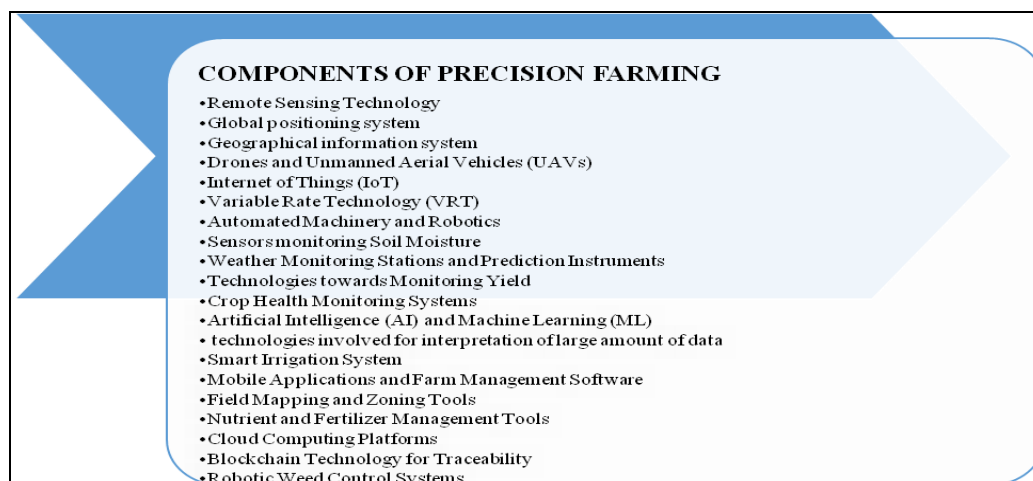


Fig 2: Components of Precision farming (Yadav and Sidana, 2023) Precision Agriculture Technologies Adoption in Developed vs Developing Countries

1. Rates of Adoption

The adoption rate is substantially greater in developed nations. According to Leonard (2014), 80% of grain growers in Australia employ automated guiding, while 60% of farmers in the UK use PA in some capacity, mostly GPS steering (Norris, 2015). In developing countries, adoption rates are lower; Brazil reports only 20% adoption overall (Albuquerque, 2017), while in Turkey, only 6% of combines and cotton harvesters are equipped with yield monitors (Keskin *et al.*, 2017)^[67].

2. Technology Diversity

Developed countries adopt a broader range of technologies, such as variable-rate applications, auto guidance, yield monitoring, and GPS mapping (Schimmelpfennig & Ebel, 2011)^[125]. Developing countries primarily rely on basic tools like soil sampling, manual guidance, and navigation aids (Helm, 2005; Akdemir, 2016)^[6, 57].

3. Farmer Usage

In developed nations, large-scale adoption is common across regions and crops, with 83% of US agricultural input dealers offering GPS guidance systems (Erickson & Widmar, 2015)^[15]. Adoption in developing countries is often localized and crop-specific. For example, laser levelling is primarily used in rice farming in India (Mondal and Basu, 2009)^[87].

4. Economic Barriers

High costs pose minor barriers in developed countries, where farmers generally have access to subsidies and advanced

equipment (Schimmelpfennig, 2016)^[125]. Developing countries face significant financial challenges, as seen in Russia, where PA adoption remains slow due to high costs (Anonymous, 2013).

5. Focus Areas

- Developed countries focus on advanced automation, for example, variable-rate fertilizer treatments and sowing (Lowenberg-DeBoer, 2015)^[75].
- Turkey's GNSS-based navigation systems are an example of how developing nations prioritize core technology (Keskin *et al.*, 2017)^[67].

7. Infrastructure

- Developed countries benefit from strong institutional support and infrastructure for technology adoption (Fountas *et al.*, 2005)^[41].
- Developing countries often lack the necessary infrastructure and technical training, slowing adoption rates (Verma, 2015)^[146].

8. Growth Potential

- Developed countries have mature markets with ongoing optimization and innovation (Robertson *et al.*, 2012)^[116].
- Developing countries, such as Brazil and China, show significant growth potential as they adopt new technologies (Bongiovanni & Lowenberg-DeBoer, 2005)^[75]

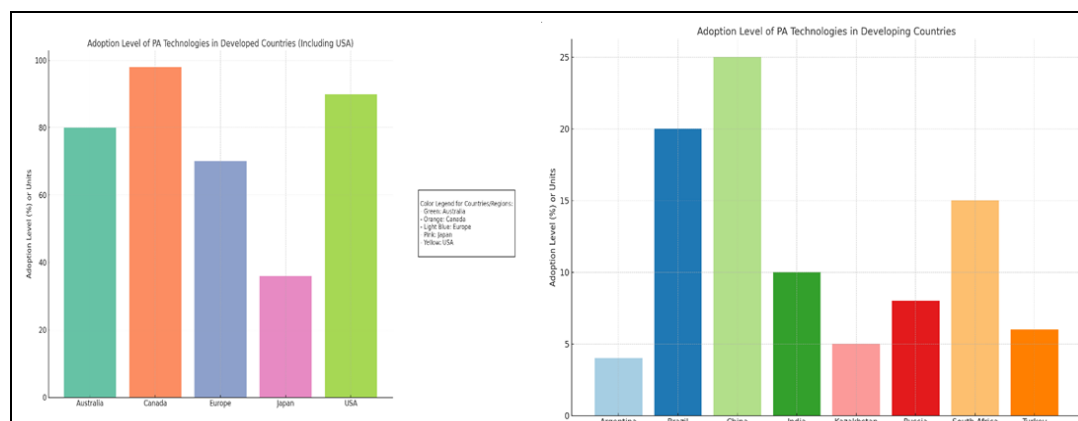


Fig 3: (A) Graph of developed countries in adoption of Precision agriculture (B) Graph of developing countries in adoption of Precision agriculture

How are the components of Precision farming implemented in agriculture?

A. GPS (Global Positioning System)

For the precise determination of location in the crop field, two categories of interest emerged at that time, which we might think of as ideologies that influence field location decisions. A radio-based triangulation system with strategically positioned beacons was the initial concept.

(Palmer, 1991)^[101]. The second idea was the GPS, which was in the late 1970s only used for military purposes (Tyler 1993; Larsen *et al.*, 1988)^[71, 140]. The first idea had so many disadvantages like losing of signal during topography estimation, the amount of time needed to set up beacons in the field, place them, and modify their placements, among other things (Auernhammer and Muhr 1991)^[10]. The second philosophy was a success but has lacked so many things that further improvement and changes occur in GPS. When the military began using GPS in the early 1990s, it could only achieve an accuracy of 3-5 meter using C/A code processing (Tyler 1993)^[140]. A GPS receiver that is fixed in place is necessary for differential correction. When using a GPS receiver, a civilian user without the differential correction resource can only reach a range of 10-100 meters. Differential correction gained popularity in agriculture in the 2000s, after military selective availability was discontinued.

How a differential correction in GPS works?

A technique called differential correction is used to increase the accuracy of GPS signals by lowering errors brought on by satellite or atmospheric interference (Balaei and A. T., 2007)^[12]. A ground-based reference station that offers real-time adjustments to GPS signals is the basis for the DC's operation (Dana and P. H., 1997)^[28]. According to Yu *et al.* (2009)^[158], a fixed location is a ground-based reference station that continually receives GPS signals and computes precise locations based on satellite data. When the reference station's known

location differs from its GPS-calculated position, the difference is referred to as an error signal (Han *et al.*, 2001). GPS application in precision agriculture by field mapping, guidance system, variable Rate Technology (VRT), yield monitoring, and irrigation management. DGPS technology enhances the precision of agricultural operations, leading to improved efficiency, profitability, and sustainability.

The three components that make up GPS are as follows

- Satellites:** which function similarly to stars in a constellation.
- Ground stations:** Satellites are monitored and managed by ground stations. Additionally, ground stations pinpoint their position.
- Receivers:** These devices are always on the lookout for satellite signals. Even the precise position may be determined within a fraction of an inch using highly sophisticated receivers. The satellite-based Global Positioning System works with a minimum of 24 satellites in the sphere. The satellites are positioned nearly 12,500 miles (20,000 km) from the level of the ground. These satellites do their work in any circumstances at 24*7 (Çelikkileket *et al.*, 2025).

Interesting GPS Facts

- The Decca Navigation System and LORAN served as the foundation for the initial concept of the Geo Positioning System. During World War II, both aided long-distance ship and aircraft navigation (Rankin and W, 2014)^[113].
- The United States owns 31 GPS satellites. Every twelve hours, each GPS satellite completes a rotation of the planet (Kumar *et al.*, 2002)^[70].
- The Soviet equivalent, GLONASS, has 24 satellites. At 11,900 miles above the ground, they are in a quicker orbit that lasts 11 hours (Emenonyeet *et al.*, 2025)

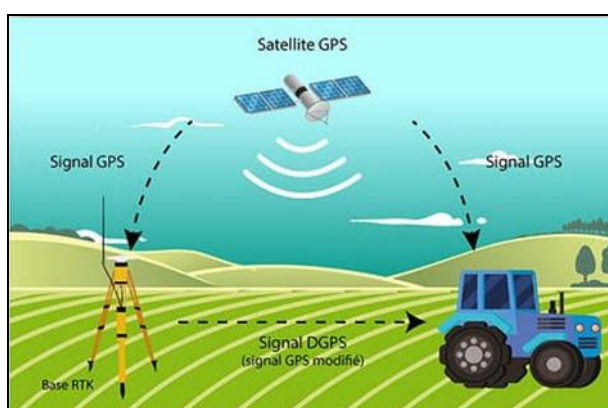


Fig 4 and 5: Indicating how GPS works in the Agriculture Sector

B. Geographical Information system (GIS)

A computer-based system is used for collecting, organizing, processing, and displaying the spatial data recognized as GIS. GIS helps to collect and combine the spatial information from several sources, such as satellite pictures, existing files, different sources, and databases. In the end, all the technology and methods it able to provide user assistance and help them to understand geographical information, patterns, trends, and correlations between the databases.

Components of GIS

- **Hardware:** Computers and devices used for processing and displaying geographic information.
- **Software:** Tools that perform data analysis, visualization, and mapping.
- **Data:** Spatial (location-based) and attribute (descriptive) data.
- **People:** Users and analysts who interpret and apply GIS data.

- **Methods:** Processes and techniques for analysing geographic information effectively.

Applications of GIS in agriculture

GIS applications in agriculture include smart agriculture, crop monitoring with management, soil analysis, water resource

management, yield prediction, climate impact assessment, land use planning, pest and disease management, supply chain optimization, and farm planning and development.

An image illustration of GIS in agriculture

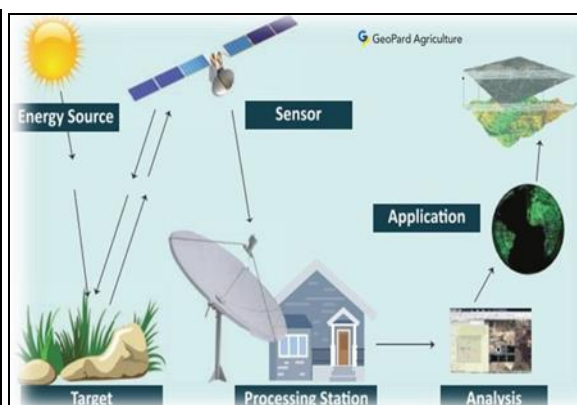


Fig 6 and 7: Illustration of GIS application

C. Remote sensing technology

The science of collecting information on areas from a particular distance without physically making contact with the area. It is used to collect or gather information by using space technology to monitor earth's resources.

Components of Remote Sensing

1. Source of energy

The electromagnetic energy source, usually the Sun or a man-made source such as radar systems.

2. Atmosphere

The medium through which electromagnetic radiation travels. Atmospheric conditions may affect the transmission of energy.

3. Target (Object or Area)

The region or feature on Earth's surface that is being seen, including soil, plants, or bodies of water.

4. Sensor

The device that captures reflected or emitted radiation, often located on satellites, drones, or aircraft.

Data Transmission and Processing System

1. Systems that process raw sensor data into interpretable formats, such as images, maps, or numerical data.
2. **User Interpretation and Application:** Final analysis and application of the processed data for specific purposes, like agriculture, forestry, or urban planning.

How Does Remote Sensing Work in Agriculture?

1. **Data Collection:** Sensors capture reflected sunlight or emitted radiation from crops, soil, and other surfaces.
2. **Processing:** The data is transmitted to ground stations, processed into images or maps, and analyzed using software.
3. **Analysis and Application:** Insights about crop health, soil conditions, water availability, or pest outbreaks are derived from the processed data.
4. Crop tracking, soil analysis, irrigation control, yield forecasting, disease and pest identification, precision farming, and climate and weather monitoring are some of the agricultural uses for remote sensing.

Table 2: Types of remote sensing

Type of Remote Sensing	Category	Description	Examples
Based on Energy Source	Passive Remote Sensing	Determines the amount of natural energy that is reflected or released from the Earth's surface, usually sunlight.	Optical sensors, thermal sensors, radiometers, and spectrometers.
	Active Remote Sensing	Emits its energy and measures the reflected signal.	Light Detection and Ranging (LiDAR), Radio Detection and Ranging (RADAR), and Sonic Detection and Ranging (SODAR).
Depending on Platforms	Remote Sensing from the Ground	Sensors placed close to the target on ground-based platforms.	Cameras on tripods, handheld thermal cameras, and ground-based LiDAR systems.
	Airborne Remote Sensing	Sensors mounted on aerial platforms.	Aerial photography cameras, LiDAR systems on aircraft, drone-mounted multispectral sensors.
	Spaceborne Remote Sensing	Sensors on satellites orbiting the Earth.	Satellite-based optical sensors (e.g., Landsat), microwave sensors (e.g., RADARSAT), thermal infrared sensors.
Based on Sensor Types	Optical Sensors	Detect visible, infrared, or near-infrared radiation.	Multispectral cameras, hyper spectral imagers.
	Microwave Sensors	Measure longer wavelengths unaffected by cloud cover or time of day.	RADAR systems, scatterometers, altimeters.
	Thermal Sensors	Capture emitted thermal radiation to study surface temperatures.	Thermal infrared radiometers, thermal cameras.

How remote sensing works in crop fields or sectors of agriculture

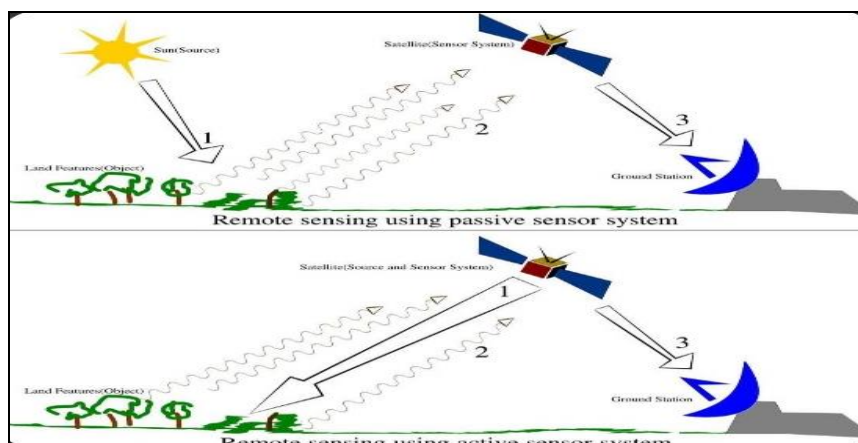


Fig 8: Illustration of remote sensing application

D. Technology based on variable rate

Because VRT enables effective fertilizer, pesticide, and herbicide administration, it has a significant impact on precision farming. Variable application rates, precise seeding, planting optimization, economic savings, and fewer environmental effects are also made possible by it.

Variable rate herbicide application



Fig 9: Stafford and Miller had created a variable rate herbicide applicator in 1993

The major yield reduction in agriculture is caused by weed and their microclimate in crop fields. Weeds typically appear in patches across crop fields, and when their numbers get too large, they significantly reduce production and vigour (Coble and Mortensen 1992). Variable rate applications of pre-emergent or post-emergent herbicides were quite popular before the introduction of Roundup Ready crops (Wiles *et al.*, 1992) [152]. To spray herbicides more effectively and at greater dosages in weed-dense regions, Thompson *et al.* (1990, 1991) [135] and Guyer *et al.* (1986) [53] proposed mapping weed sites using techniques like machine vision or remote sensing. Fields with recurrent weed patches benefited greatly from this, but real-time mapping was challenging since it was hard to tell weeds from crops. A spot sprayer that uses red and near-infrared reflectance to identify weeds was proposed by Felton and McCloy (1992) [38]. UAV and GPS technology were first used to target mapped weed areas in early work by Stafford and Miller (1993) [133], but map-based systems were subsequently hampered by legal limitations. Real-time detection became the norm when Johnson

et al. (1995) [63] found that weed patches were dynamic. Weed Seeker (1998) and machine vision technologies (1997-2002) are examples of sensor-based systems that have reduced the usage of herbicides by 63-85% and 66-80%, respectively. The effectiveness and sustainability of herbicide application were greatly improved by these improvements.

2. Variable rate irrigation

Another major problem of agriculture production is inadequate irrigation during different developmental stages of crops that leads to yield reduction and loss in plant vigour. The right amount and right time, along with the right method, help to maximize growth. The over irrigation leads to a water-logging situation along with nutrient leaching from surface runoff and insufficiency in irrigation, leading to drought.

A technique utilizing centre pivot devices for variable rate irrigation (VRI) was patented by McCann and Stark (1993) [83]. They mapped irrigation zones on a microprocessor and utilized soil samples or aerial images to determine which zones need varying amounts of water. Then, they used solenoid valves to operate each nozzle. King *et al.* (1996) verified that this system successfully modified nitrogen and water applications. A comparable VRI system for linear irrigation was created by Fraisse (1994) [44], and in South Carolina, center pivot systems with multiple manifolds were enhanced by Omary *et al.* (1997) and Camp *et al.* (1998) [99] to give up to eight water rates. A commercial farm was equipped with VRI controllers by Evans *et al.* (1996) [37], who divided fields into 30 zones with two to four nozzles each. Using soil and climatic data, a potato growth model estimated water requirements. Despite its effectiveness, handling geographical data and wind-distorted spray patterns presented complications.

E. IoT (Internet of Things)

The need for food has grown dramatically due to the world's expanding population, making it difficult to produce enough food given the planet's finite resources. Precision Agriculture (PA) and other cutting-edge technology are being incorporated into farming methods to address this. PA uses near/remote sensing methods and Internet of Things (IoT) devices to track crops at different phases of development. It gathers and examines a great deal of information, such as temperature, insect presence, water levels, soil nutrients, and chlorophyll content. Based on current crop requirements, soil properties, and weather projections, farmers may use this information to make accurate agronomic decisions, such as the kind and quantity of fertilizer

to use. A Wireless Sensor Network (WSN), which monitors environmental characteristics through networked wireless nodes, serves as the foundation of PA. Transceivers, microcontrollers, sensors, and antennae make up these nodes, which send data to a cloud system or gateway. The size and cost of sensors have decreased due to WSN improvements, making them suitable for widespread agricultural application. These sensors enable the monitoring of various crop needs that differ depending on the location and environmental circumstances. (wang *et al.*, 2006) [148]. WSN applications include cyber-physical frameworks, which combine physical, software, and hardware elements to perceive and react to crop conditions (Abbasi *et al.*, 2014) [2]. Potato crops have been monitored using such systems in three layers: decision (data analysis for actionable insights), network (data transmission), and physical (data gathering). Despite the exponential growth of connected devices, IoT-based agriculture confronts issues such as cloud congestion, latency, bandwidth limits, and sporadic internet access. Fog and edge computing are examples of emerging technologies that try to address these problems. By distributing computational work closer to the devices, fog computing improves service quality while saving energy and bandwidth. In simulations, a six-layer "Fog of Everything" (FOE) structure that incorporates virtualization and peer-to-peer communication has shown lower failure rates and more energy efficiency (Baccarelli *et al.*, 2017) [33]. With the use of WSN and fog computing, IoT in agriculture has enormous potential to maximize resource utilization, boost yields, and sustainably satisfy future food demands.

Artificial intelligence of things (AIoT) in precision agriculture

Precision agriculture is important for maintaining and balancing global food production, which should be met towards global food demand. In recent decades, technical advancement in artificial intelligence with an association with the Internet of Things eradicates various constraints of crop production. AI and IoT-enabled applications are increasingly implemented for

precision agriculture applications such as crop growth monitoring, weed removal control, pest and disease detection, planting, crop yield estimation, targeted spraying and pollination, smart irrigation and nutrient management, field analysis, and plant phenotyping. IoT-based applications that employ machine learning and deep learning models, for instance, are frequently used to evaluate soil quality and nutrients as well as identify fruits, vegetables, weeds, pests, and illnesses. Such data aids in improving crop management techniques. A combination of two precise technologies as IOT and AI preferred as AIOT. AIOT is still at the stage of research stage and needs more development. And faces many more struggle and obstacles to work, like data collection errors, unable to catch ai algorithms, can't process sources or data also unable to process computing capabilities.

F. Yield Mapping

Making spatial maps of the variations in agricultural production across fields is known as yield mapping. Originally developed

by Schueller and Bae (1987) [126], before GPS, early techniques employed microwave range for locating and engine speed to estimate grain flow. However, inaccuracies due to wheel slippage prompted advancements like grain auger volume measurements (Bae *et al.*, 1987; Searcy *et al.*, 1989) [126]. Modern systems, such as deflection-based grain flow monitors (Vanischen & Baerdemaeker, 1991), enhance precision by mitigating signal distortion. Errors in yield mapping—like swath overlap and turnaround inaccuracies—can be reduced using centimeter-accuracy GPS systems (Pierce *et al.*, 1997). Soil factors, such as depth to argillic horizon, elevation, and organic matter, significantly affect crop yield variability (Karlen *et al.*, 1990; Sudduth *et al.*, 1996) [65]. Temporal factors, including precipitation, also play a role, with year-to-year variations often surpassing spatial ones (McBratney & Whelan, 1999) [82]. Spatial yield maps often fail to predict future variability accurately. Lamb *et al.* 1997 demonstrated that past spatial yield patterns could explain only half the variability in subsequent years. Similarly, according to Blackmore *et al.* (2003) [43], yield variability varies from year to year., emphasizing in-year management over historical patterns. A crucial distinction lies in yield versus crop response. Mamo *et al.* (2003) highlighted that spatial variability in nitrogen (N) fertilizer response differs from yield patterns. Optimizing variable-rate N applications based on soil N supply rather than yield could enhance efficiency and reduce fertilizer use (Scharf *et al.*, 2006).



Fig 10: Elite company yield monitor device for yield mapping

G. Drone Technology

Drones, also known as unmanned aerial vehicles or, in the early era of drone development it also called flying robots, were initially developed for military use in the 1800s. Unlike other aerial devices, drones are remotely controlled, lightweight, and pilot-free. Guided by software, they perform diverse tasks such as military operations, photography, agriculture, and more. With the ability to fly up to 400 meters, drones equipped with HD cameras and GPS can capture stunning images. In agriculture, specialized drones help farmers improve crop management and productivity, making them valuable tools for both large and small-scale farming (Newcome L R, 2004).

History of drones

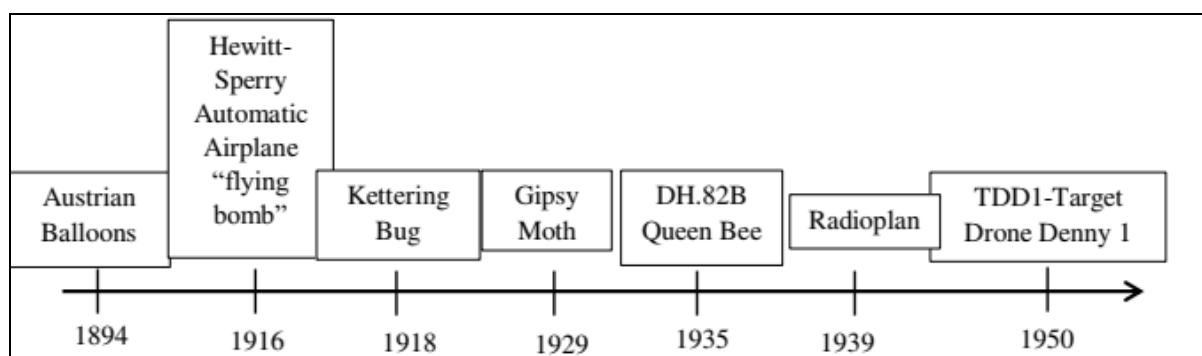


Fig 11: Timeline of drone development in early years

The name drone at the beginning of drone exploration is linked to or, we can say taken from drone bee from honeybee colony. The link is likely the drone bees' work by taking the command from queen bees without making their own decisions, so drone function is mainly like that a command-based programme is incorporated to the drone and it is controlled by a remote in that all the functional aspects are present so that a person without physically controlled the machine can operated from a specific direction or distance. The machine in the early era of precision

farming was called an unmanned aerial vehicle because it operated without any pilot (Joiner, 2018).

Types of Drones

In the world of technology, where drones are sold, they offer a wide variety or range of drones from considering factors including physical features, purpose of drone usage, range of their flight, and weight of the drone (Joiner, 2018)

Table 3: Drone categorization based on flight range and weight (Hassanalain and Abdelkefi, 2017) ^[56]

Types of drones	Range of the drone's weight	Range of drone flight
Mini and micro drone	Equal or less than 5kg	Ranges from 25km-40 km
Heavy and medium-sized drones	Equal or less than 500kg	Ranged from 70-300km
Combat UAV aircraft	Less than 500 kg	Flight range less than or equal to 1500km
Lightweight medium ranged drones.	Weight of drone ranges from 50kg -100kg	Flight range is from 70 km-250km
Small and light weight drones	Weight ranges from 5-50kg	Flight ranges from 10 km-70 km
Medium-sized with heavy-weighted drones	Weight ranged from 300 kg to 500 kg	Flight ranges from 70 km to 300 km
Large endurance with heavy-weighted UAVs	Weight is less than or equal to 1500kg	Flight ranges from less or nearly equal to 1500km
Average-sized and average-weight drones	Range of drone weights from 100-300kg nearly or equally	Fight ranges from nearly equal to or from 150 km-1000 km

Table 4: Categorization of drones by number of rotors or propellers

Drone type	Characteristics
Single blade drones	• Appearance similar to helicopter • Drone monitored with the help of a roter, and it's attached to its tail • User interface is simple and easy to control it
Three propeller drones	• These drones are lighter in weight, the design is compact, and they can be foldable • Camera-like load can be carried by these tri-copters
Four-bladed drones or Quadcopters	• For lifting aircraft, 4 propellers are present • Can be easily repaired or maintenance is ease • Affordable price, faster, have more powers and can be easily manufacturable
Eight-bladed or eight-roter drones	• It flies higher concerning capturing images and footages and has installed with 8 motors if any 2-3 motors died during flight the drone can't be crashed and easily controllable • It's generally expensive with large-sized drone
Fixed-winged drones	• Wings are very similar to airplane • Generally used for long-distance flights • These drones are used for monitoring, agriculture, field mapping • Generally higher cost than octocopters • Special training is needed to fly these types of drones

Drones used in the agriculture sector

The recent development in the agriculture sector that transforms the perspective towards farming by implementing the digital technologies like the principle and components of smart farming make it easy for doing farming operations. The availability of different types of drones and their type accordance to their usage

they provide a variable of applications like aerslspraying, crop monitoring, data analysis, aerial photography and image illustration and processing and can be used for fertilizer application. Drone accounts for 60-70% of studies done in crop fields. Drones like Agras MG-1, roter drones, Yamaha RMAX, etc.

Table 5: Features and specifications of drones for spraying in the agriculture sector (Shahrooz *et al.*, 2020) ^[128]

Properties	Yamaha RMAX	6-rooter UAV	DJI Agras MG-1
Maximum speed	6-8m/s	10-16m/s	8-10m/s
Capacity of tank	14-16 litres	10-12 litres	9-10 litres
Weight of drone	Approximately 100kg	10-12 kg	8-10 kg
Drone cost	75-85 lakhs	7-17 lakhs	18-20 lakhs
Nozzle number	4	4	4
Rooter or propeller number	1	6	8
Duration of flight	Nearly 1 hour	Varies between 10-40 minutes	Depending on the load, approximately half an hour

Sensors and their uses in agriculture

Sensors are the cornerstone of precision agriculture (PA), enabling the collection and tracking of vital information to maximize crop yield. Physical characteristics such as soil nutrients, water levels, temperature, insect presence, and plant chlorophyll content are measured by these sensors. Processing of the gathered data yields practical suggestions for crop management, including the exact kind and amount of fertilizer required. Agriculture sensor integration is based on Wireless

Sensor Networks (WSNs). Each WSN is composed of sink nodes that process and transmit data to the cloud or mobile devices and source nodes that collect data. Sensors are nowadays crucial to manifest the precision agriculture because sensors nowadays are affordable, small in size, and also doing a variety of works like collecting and manipulating environmental data. By providing precise, real-time monitoring, these tools promote better crop health and effective resource use.

Table 6: Wireless nodes utilized in the field of agriculture (Naranjo *et al.*, 2017) ^[33]

Name of sensor	Parameters to be captured
Soil moisture sensor (ECH ₂ O)	Temperature of soil, moisture of soil, EC
Soil sensor (Probe2 Hydra)	Salinity status, moisture level, EC of soil, temperature of soil
Moisture sensor of soil (MP406)	Moisture and temperature of soil
Electrical conductivity sensor (EC250)	Temperature, salinity, moisture, conductivity
Portable pogo sensor of soil	Capturing moisture and temperature of soil
Wetness sensor (237 leaf)	Captures moisture, temperature, and wetness of plant
Chlorophyll sensor named YSI 6025	Parameters like photosynthesis measured
MSO (Met station one)	Parameters like speed of wind, pressure, temperature, and humidity of air it measures
Leaf temperature sensor (LT-2M)	Measure plant temperature
Leaf wetness sensor LW100	Parameters like temperature, moisture, wetness of plant
Temperature sensor 107-L	Temperature of air
Hydrogen sensor SenseH ₂ TM	CO ₂ , temperature of plant, wetness of plant

Precision Agriculture application in horticultural crops:

- 1. Soil and Field Management** - Managing soil and specific areas of the farm effectively.
- 2. Watering Plants** - Giving plants the right amount of water using advanced systems.
- 3. Fertilizing Crops** - Adding nutrients to the soil where and when needed.
- 4. Pest and Disease Control** - Spotting and treating pests and diseases early.
- 5. Harvest Prediction** - Estimating how much fruit or vegetables will be ready to harvest.
- 6. Weather Monitoring** - Adjusting farming practices based on local weather.
- 7. Using Machines and Robots** - Automating tasks like planting, pruning, and picking.
- 8. Storing Produce** - keeping harvested fruits and vegetables fresh for longer.
- 9. Checking Plant Health** - Monitoring crops for signs of stress or poor growth.
- 10. Helping Pollination** - Supporting pollinators like bees or using technology to assist.
- 11. Weed Control** - Managing weeds efficiently in specific areas.
- 12. Saving Energy** - Reducing electricity or fuel use in farming processes.
- 13. Managing Greenhouses** - Automating temperature, light, and humidity in greenhouses.
- 14. Using Data for Decisions** - Making smart choices using collected data.

- 15. Sorting and Grading:** Arranging fruits and vegetables according to their size and quality.

Managing orchards with precision agriculture

Precision agriculture in fruit crops aims to increase economic efficiency and production by managing each site differently. To address physical, biological, and chemical aspects and lessen environmental consequences while enhancing agricultural outcomes, key activities include data collecting, identifying orchard variability, and making well-informed choices (Zhang & Kovacs, 2012) ^[55].

Effective fruit crop management involves key practices like thinning, pruning, and irrigation to improve fruit size, quality, and yield. Thinning ensures that only seven percent flowers of apple are retained towards harvest, preventing overcrowding and enhancing fruit quality (Greene & Costa, 2013; Dennis, 2000). While manual thinning is costly, mechanical thinning can reduce labour needs if flower intensity is accurately assessed (Glozer & Hasey, 2006). Pruning shapes the canopy for better light interception, directly impacting fruit production and quality (Rom, 1991). Measuring canopy structure helps select the best pruning strategies for better production (Castillo-Ruiz *et al.*, 2015; Miranda-Fuentes *et al.*, 2015) ^[46, 124]. Deficit irrigation uses mild water stress to optimize fruit quality while conserving water, requiring precise monitoring to match tree needs (Mu *et al.*, 2018). Overall, precision tools like structural maps improve efficiency, sustainability, and profitability for growers (Mu *et al.*, 2018).

Techniques that gather sensor data about targets from a distance

using instruments including image sensors, radar, sonar, and satellite arrays are referred to as remote sensing (RS) (Usha & Singh, 2013^[141]). Recent studies that analyse data from several platforms have shown how effective it is in managing orchards (Barbagallo *et al.*, 2009; Garcia-Ruiz *et al.*, 2013^[146]; Salgadoe *et al.*, 2018). Manual observation (MO), handheld detection (HD), sensor networks (SN), ground vehicles (GV), unmanned aerial vehicles (UAVs), aerial sensing (AS), and spectral satellite sensing (SSS) are among the methods that are suitable for specific orchard management tasks such as yield prediction, disease detection, thinning, and spraying throughout the fruit tree growth cycle.

UAVs are becoming more and more useful for real-time orchard monitoring at appropriate geographical, spectral, and temporal resolutions, thanks to recent developments in sensor downsizing (Berni *et al.*, 2009^[14]; Caruso *et al.*, 2019^[24]; Torres-Sanchez *et al.*, 2018; Valente *et al.*, 2019)^[136]. Equipped with thermal sensors, multispectral sensors, and LiDAR systems, UAVs offer advantages over ground-based platforms, including portability and real-time field map generation, as well as over satellite-based remote sensing, having greater data-acquisition probabilities in cloudy areas and being less weather-dependent (Campos *et al.* ^[22], 2019; Matese *et al.*, 2019^[81]; van der Wal *et al.*, 2013)^[143]. Additionally, UAVs may be used in high-risk situations, produce geo-referenced photos, and offer quick data collection (Handique *et al.*, 2017^[54]; Saldana Ochoa & Guo, 2019)^[121]. Effective monitoring of small to medium-sized orchards is ensured by striking an ideal balance between flying speed and data quality, despite limits in battery life and operational speed as compared to manned platforms (Garcia-Ruiz *et al.*, 2013)^[146].

UAV and unmanned aerial vehicles' role In orchard management practices

The restrictions and needs of the application determine the type of UAV to use for orchard management. The most popular UAVs in orchards are multi-rotor models, which have benefits like hovering, GPS-based navigation, vertical and horizontal flying, and small-space operation.

They are easy to control and provide high maneuverability, with optical sensors achieving centimetre-level 3D resolution at a 70 m altitude (Caruso *et al.*, 2019)^[24]. However, they have shorter flight times and slower speeds compared to fixed-wing UAVs, which offer longer flight durations, faster speeds, and higher payload capacities but lack hovering capability and may cause image blurring, addressable with fast-shutter imaging sensors.

Different types of sensors equipped in UAVs:

Although they have shown promise in orchard management, the five sensor types utilized in UAVs—RGB, thermal, multispectral, hyperspectral, and LiDAR—have several drawbacks (Díaz-Varela *et al.* ^[30], 2015; Tu *et al.*, 2018). Hyperspectral sensors, while capable of high spatial resolution, are limited by size, cost, and geometric calibration issues, affecting their adoption (Vanbrabant *et al.*, 2019)^[144]. LiDAR, though promising for geometric trait measurement, remains largely unexplored in this domain (Díaz-Varela *et al.*, 2015)^[30]. RGB sensors lack essential camera and radiometric calibration, reducing accuracy, particularly in geometric estimations (Tu *et al.*, 2018). Multi-modal sensing, which integrates different sensors on the same UAV, offers the potential to improve detection accuracy by combining unique data traits (Kesture *et al.*, 2018). To get compaction and compatibility and size reduction, these features are needed to implement in sensors to retrieve

benefits. (Hadas *et al.*, 2019)^[51]. To retrieve high-quality pictures, extraction of qualitative and quantitative data, and sensor-based drones, these features are needed for sensor development. (Vanbrabant *et al.*, 2019)^[144].

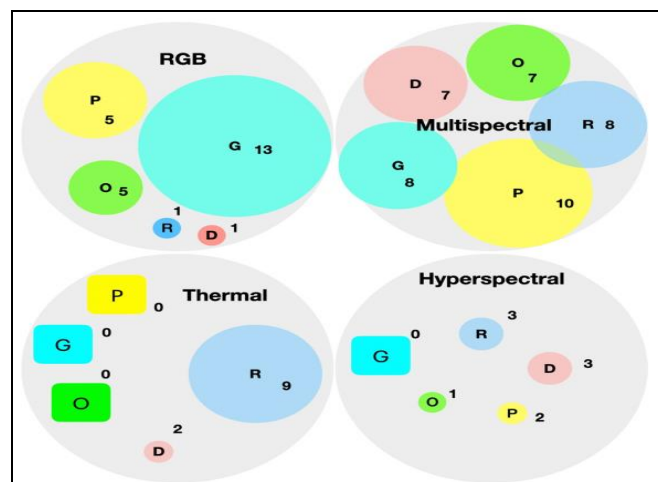


Fig 11: The figure's vibrantly coloured circles' regions show the percentage employed in comparable applications; rounded rectangles stand for zero, and a certain number of pertinent items are also indicated. "G" stands for geometric and biophysical characteristics (light blue), "P" for productivity applications (yellow), "D" for disease detection (orange), "O" for other applications (green), and "R" for resource efficiency in orchards (dark blue). These acronyms are the category of application initials.

1. Observation and Monitoring

Stress indicators like illnesses, pests, water scarcity, or nutritional shortages can be detected by UAVs fitted with thermal and multispectral sensors (Zhang & Kovacs, 2012)^[55]. Additionally, they offer aerial photography to measure canopy uniformity and density, which aids in assessing the general health and production of trees (Torres-Sánchez *et al.*, 2014)^[136]. Timely treatments that minimize potential losses are ensured by early diagnosis of issues such as fungal infections, insect infestations, or mechanical damage (Zhang & Kovacs, 2012)^[55].

2. Accurate Use

UAVs with sprayer attachments can be used to apply fertilizer and pesticides, reducing waste and adverse environmental consequences (Sinha *et al.*, 2020)^[130]. Targeted distribution boosts efficiency and ensures successful applications even in hard-to-reach orchard areas (Hunt *et al.*, 2013)^[59].

3. Data Collection and Analysis

The high-resolution image of fruits, fruit size, color, and harvesting indices are needed to be input in UAV programmes (Torres *et al.*, 2014)^[136]. For proper orchard management, the integrated collected and retrieved data from drones with respect to the GIS functions help in making productive maps for effective orchard management (Hunt *et al.*, 2013)^[59].

4. Environmental Monitoring: Sensor-based drones capture parameters like temperature, humidity, photoperiod, and wetness, which helps to gather information to ensure strategies to measure plant protection and irrigation that estimate microclimate data (Hunt *et al.*, 2013)^[59]. To estimate water requirement for crop cultivation, like efficiency of water along with scheduling irrigation soil mapping needed through which soil moisture mapping is done (Hunt *et al.*, 2013)^[59].

5. Pollination Support

UAVs can monitor and document pollinator activity, helping evaluate pollination efficiency and coverage within orchards (Zhang & Kovacs, 2012)^[55].

6. Labour Efficiency and Cost

Numerous orchard chores are automated by UAVs, which minimizes reliance on manual labour and permits resource optimization (Sinha *et al.*, 2020)^[130]. Long-term cost savings are achieved by early issue detection and effective resource use (Torres-Sánchez *et al.*, 2014)^[136].

Remote sensing application in horticulture

Interestingly, India is one of the few countries using land-based observations and satellite technologies for sustainable agricultural operations, including horticulture. In a 1970 coconut withering experiment in India, remote sensing was initially used (Ray, 2016)^[114]. For uses including crop production estimation, precision farming, drought monitoring, and climate impact assessment, Indian academics have refined digital image processing and created proprietary software since then (Navalgund and Ray, 2000^[94]; Panigrahi and Ray, 2006; Navalgund *et al.*, 2007)^[95]. ISRO and other organizations have implemented projects that have institutionalized these techniques in agriculture (Parihar and Manjunath, 2013)^[103].

Key application of remote sensing in Horticulture

- **Crop Insurance:** By validating planted crops, satellite data (NDVI) helps lower insurance fraud.
- **Monitoring Soil Moisture:** Soil moisture is measured using both active and passive sensors, which is essential for weather forecasting and drought analysis.
- **Crop Health and Yield Estimation:** (Hao *et al.*, 2011^[55]; Jensen, 2000^[62]; Usha *et al.*, 2013)^[41] NDVI and multispectral photography evaluate crop health, forecast yields, and distinguish horticulture crops from other vegetation.
- **Early detection of pest and disease** outbreaks can be facilitated by variations in reflectance in stressed plants (Johnson *et al.*, 1996)^[63].
- **Abiotic Stress Monitoring:** Chlorophyll variations brought on by stress can be identified using reflectance data (Usha *et al.*, 2013)^[41].
- **CHAMAN Program:** A MIDH initiative that uses geo-informatics to estimate area, plan horticulture, and track diseases in 12 states (Mahala Nobis National Crop Forecast Centre, 2014).

Key elements of Remote sensing used in Horticulture

- **NDVI and Multispectral Imaging:** Crucial instruments for evaluating the health of plants and estimating yield.
- **Institutionalization of Remote Sensing:** Programs like CHAMAN and MNCFC ensure systematic implementation.
- **Geo-informatics in Horticulture:** Enables area estimation, disease monitoring, and site-specific crop planning.
- **The role of ISRO:** Research and development in horticulture is supported by sophisticated satellite systems and mapping capabilities.
- **Integration of Active and Passive Sensors:** Bringing together the advantages of both technologies to get the best possible outcomes.
- India uses space technology and remote sensing for horticulture, focusing on crop health, yield estimation,

disease detection, and abiotic stress monitoring. Programs like CHAMAN and ISRO's contributions support area estimation and planning. Challenges include limited fruit crop applications, spectral overlaps, and sensor resolution trade-offs. Satellite advancements enhance precision horticulture.

Precision spraying systems for fruit trees

Lowering the risk of pesticide use is one of the primary challenges that harms the ecology, the environment, and human health. By providing the right amount and dose at the target area, the precision spraying system is one of the most efficient technical solutions for pesticide administration, preventing overuse and toxicity (Oerke *et al.*, 1994)^[98]. This is necessary to sustain insect infestation and pest population. Since crop losses of up to 100% can result from the improper management of insects, pests, diseases, and weeds, fruits depend on pesticides for reliable production. However, because pesticides can pollute soil, groundwater, and air, endangering the environment, human health, and animal welfare, their usage in orchards has come under fire. Furthermore, tree fruit producers must pay hundreds to thousands of euro's per hectare for pesticides, which accounts for around one-third of overall production costs (Weinzierl *et al.*, 2015)^[151]. Most pesticide waste comes from applications to the spaces above, under, and between tree canopies. Pesticide waste and usage may be significantly reduced by carefully and selectively applying pesticides to tree canopies.

What is Precision Spraying?

Precision spraying involves applying pesticides or other chemicals only where and when they are needed, using technologies like sensors and GPS to optimize application rates and minimize waste. For instance, Esau *et al.* (2014)^[36] were able to reduce agrochemical use from 9.90% to 51.22% by using precision spraying technology to avoid applying pesticides to bare spot areas in wild blueberry fields. Despite improvements, precision spraying in tree fruit orchards still confronts obstacles such as drift, chemical loss, and limited large-scale viability. The camera, ultrasonic, and laser sensing technologies that are currently in use are restricted and have poor real-time performance. Nozzle type, spraying distance, droplet size, canopy structure, wind, temperature, and humidity are the important parameters in precision spraying. Future work should focus on bridging technological gaps to spray orchards effectively and efficiently.

Chemical Sprayers in Tree Fruit Orchards Evolution of Sprayer Technology

- Early designs included hand-boom, horse-drawn wagons, and steam-powered sprayers (Lodeman *et al.*, 1916)^[73].
- Air blast sprayers gained popularity in the 1940s due to labour shortages (Potts and S.F., 1946)^[107].
- Innovations like mist blowers and handguns allowed efficient pesticide application (Fleming, G.A, 1962)^[40].

Modern Sprayer Designs

- **Air Jet Models:** Enabled ground-based spraying into tree canopies (Randall and J.M,1971)^[112].
- **Air Blast Sprayers:** Axial-fan sprayers, suitable for older orchards with large canopies, face limitations with smaller, modern orchards (Fox *et al.*, 2008&Cross and Patternation,1991)^[43, 27].
- **Tower and Tunnel Sprayers:** They improve canopy coverage but have high costs and limited adaptability (Chen

- and Y, 2010).
- Precision Sprayers: Sensor-guided systems reduce chemical use and off-target deposition (Boatwright *et al.*, 2020)^[17].

Challenges with Conventional Sprayers

- Older sprayers waste up to 50-70% of pesticides due to inefficient matching with modern orchard tree sizes (Brown *et al.*, 2008).

The technological development of sprayers for orchard spraying

Category	Sprayer Types	References
Accurate Sprayers	Intelligent sprayers and sensor-guided air blasters	Ludeman and E.G,1916 ^[107] Fleming, G.A, 1962 ^[40]
Contemporary Air Blast Sprayers	Tunnel sprayers and tower sprayers	Randalland J.M,1971 ^[112] Travis <i>et al.</i> , 1987 ^[137] Fox <i>et al.</i> , 1992 ^[42]
Models of air jets	Plane jet sprayers and polar jets	Peterson <i>et al.</i> , 1994 Walklate <i>et al.</i> , 2000 ^[147]
Designs of Early Sprayer	Handguns, early mist blowers, boom sprayers, and steam-powered sprayers	[Ludeman and E.G,1916 ^[107] Rose and G.E., 1955 Fleming, G.A, 1962 ^[40]



Fig 12: (A) Constant rate air blast sprayer system (B) Precision spraying system

AI in Horticulture

India's unique soils, temperatures thereby and agro-ecological zones promote the development of a broad spectrum of horticulture crops, which boost the economy through raising productivity, creating jobs, and providing raw materials for food processing. By using AI in horticulture, high demand may be satisfied despite a lack of land. AI helps with weather forecasting, irrigation optimization, disease diagnosis, pest management, yield forecasting, harvesting automation, post-harvest loss reduction, and fruit quality improvement for processing organizations. Strong mathematical methods and programming tools are used to create artificial intelligence. American computer scientist John McCarthy initially proposed it in 1956.Models of artificial intelligence (AI) and machine learning (ML) evaluate agricultural data, such as weather, soil, and water use, to maximize planting, irrigation, harvesting, and pest management. The food supply chain, crop health, and resource management are all improved by these technologies, which also provide customized solutions and boost productivity and product quality.

1. Utilizing AI to Forecast Soil Fertility

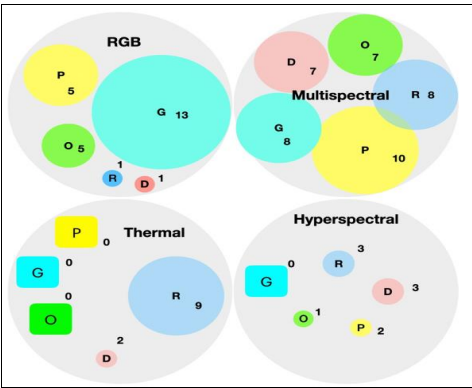
Crop health depends on critical elements, including soil nutrients, pH, moisture, and temperature, but they are presently measured with labour-intensive techniques. By actively monitoring soil conditions, AI technologies like drones, unmanned aerial vehicles, and computer vision models simplify these procedures. By connecting leaf patterns to soil flaws, tools such as Plantix by PEAT, a deep learning program, may detect nutrient deficits (Varshitha and Choudhary, 2021)^[145]. An ANN-

- Conventional broadcast spraying fails to adjust for variables like weather, tree density, or missing trees, leading to significant losses (Edward,2001)

Precision Spraying Benefits

- Uses real-time canopy data to optimize pesticide application, reducing wastage and environmental contamination. (Chen and Y, 2010 and Boatwright *et al.*, 2020)^[17].

based system was created by (Palaniappan *et al.* 2019)^[100] to analyze soil characteristics and suggest appropriate crops.



2. AI in Crop Production

By anticipating environmental changes and facilitating prompt responses, like early harvests, AI tackles issues like temperature rises and frost events. As evidenced by Sentiment's methods for maximizing basil growth, greenhouse applications involve automated monitoring and management of environmental parameters (Sahni *et al.*, 2021)^[119]. Using meteorological data, neural network models, such as those developed by Robinson and Mort (1997)^[117], can reliably forecast frost. Srbínovska *et al.* (2014)^[132] and Qiu *et al.* (2014)^[110] developed sophisticated systems that automate greenhouse conditions for the best agricultural yield.

3. Application of AI in Assisting Pollination

Shrinking natural pollinator populations threaten food supply, and AI solutions are emerging to assist pollination. Monash University used AI and computer vision to track pollinator species, enhancing strawberry crop yields. Chen and Li (2016) developed robotic micro-air vehicles for autonomous pollination, employing real-time field data and thermal sensors to optimize the process.

4. Application of AI in Automated Irrigation

By automating processes based on current environmental and soil moisture data, artificial intelligence (AI) improves irrigation efficiency. Technologies that improve water utilization include electro tensiometers for demand-based fertigation (Contreras *et al.*, 2021)^[26] and soil sense by Proximal Soil Sens Technologies Pt. Ltd., which offers irrigation guidance through mobile applications (Manaware, 2020)^[80]. By measuring trunk variations and water status, respectively, dendrometers and drone-mounted cameras enhance irrigation even more (Santesteban *et al.*, 2016; Hahn *et al.*, 2021)^[53, 124].

5. AI's Use in Crop Phenotype Determination

AI replaces labour-intensive conventional approaches by streamlining the collection of phenotypic data for breeding techniques. With 99.9% tree count accuracy, Ampatzidis *et al.* (2019)^[9] showed that UAVs with sensors can efficiently track phenotypic changes in citrus rootstocks. Apple tree crown features are analyzed using deep learning models, such as those employed by Wu *et al.* (2020)^[153], which help with growth monitoring, machine harvesting, and precision spraying.

6. Application of AI in Disease Diagnosis

Plant diseases cause up to 40% of global crop losses (Fenu and Mallocci, 2021)^[39]. AI-driven systems enhance early disease detection and treatment, improving yield. Examples include drone-based vegetation indices for disease mapping (Patel *et al.*, 2013)^[104], grape vineyard monitoring using sensors (Patil and Thorat, 2016)^[105], and smartphone-assisted illness diagnosis with 99.35% accuracy (Mohanty *et al.*, 2016)^[86]. Deep learning systems like Plantix diagnose plant diseases with 95% accuracy (Manaware, 2020)^[80].

7. AI in Field Management

AI optimizes pesticide application, lowering labour and chemical use; UAVs with pre-mapped routes improve spraying efficiency; robots such as "See & Spray" use computer vision for targeted weed spraying, saving 90% of herbicide (Bhavana and Bhagwan, 2021)^[115]; and autonomous systems such as Agrobot Srishti use sophisticated algorithms to identify and remove weeds (Debnath, 2020)^[29].

8. Application of AI in Produce Maturity Identification

AI guarantees accurate ripeness evaluation for the best crop. Systems that use ANN and computer vision, such as Yossy *et al.* (2017)^[157], can classify mango ripeness with 94% accuracy. For determining the maturity of crops, including apples (Ma *et al.*, 2021), tomatoes (Qi Binget *et al.*, 2015), and bananas (Saputro *et al.*, 2018), hyperspectral imaging is frequently utilized. According to Al-Sammaraie *et al.* (2022)^[8], methods like RGB image processing forecast orange sweetness based on red color intensity, and NIR spectrophotometry determines the amount of sugar in grapes (Gutierrez *et al.*, 2018)^[49].

9. Application of AI in Yield Forecasting

AI reduces manual labor and time by enabling accurate production predictions through automated fruit-counting systems. To increase productivity, systems employing deep learning and image processing architectures recognize and count fruits for harvest planning and yield estimate (Lomte *et al.*, 2019; Maheswari *et al.*, 2021)^[74, 78].

10. AI in Harvesting

AI-driven harvesting robots help reduce labor shortages and expenses. With the use of cameras and sensors, these robots can differentiate between fruits and leaves, select fruits with the least amount of damage, and use sophisticated path-planning algorithms for effective operations (Kitamura *et al.*, 2005; Xiong *et al.*, 2020). High-value crops are handled delicately, thanks to robotic systems like Vegebot and soft grippers (Navas *et al.*, 2021; Birrell *et al.*, 2019)^[69, 154].

11. Application of AI in Fruit Grading

AI-based grading systems leverage computer vision and fuzzy logic to classify and grade fruits with high accuracy. Image processing techniques extract features like size and shape, while machine vision systems reduce human errors and ensure consistent quality (Kavdir & Guyer, 2003; Mustafa *et al.*, 2009)^[66, 91]. Advanced systems like TOMRA sorting machines use AI to enhance sorting and grading efficiency (Sahni *et al.*, 2021)^[119].

12. Using AI to Reduce Postharvest Losses

AI may be used to reduce post-harvest losses brought on by microbial infections, bruising, and moisture loss. To ensure longer shelf life and less spoiling, hyperspectral imaging and neural networks identify interior damage, improve storage conditions, and forecast deterioration risks (Morimoto *et al.*, 1997; Nagata *et al.*, 2006)^[89, 92].

13. Application of AI in Quality Assessment

AI enables non-destructive quality assessment by analyzing parameters like moisture, pH, and spoilage. Techniques like image classification, electronic noses, and sensor-based systems identify defects and predict shelf life accurately. These advancements improve product safety and consumer satisfaction (Sanaeifar *et al.*, 2014; Megalingam *et al.*, 2019)^[123, 111].

14. AI application in Processing Industry

AI streamlines food processing with self-optimizing cleaning systems and augmented vision sensors. These systems detect residues, optimize cleaning resources, and ensure only suitable products enter the processing line, improving efficiency and hygiene (Sahni *et al.*, 2021)^[119].

15. Application of AI in Aeroponics

AI-driven aeroponic systems employ sensors to monitor temperature, humidity, pH, and water levels. Real-time data comparison and alerts through mobile applications help maintain optimal growth conditions, promoting sustainable farming (Priyanka *et al.*, 2020).

16. AI types used in the agriculture sector (Dotaniya *et al.*, 2024)^[32]

The AI types or their classification is based on the complexity level, and another classification is based on the functionality level.

a) Strong artificial intelligence and weak artificial intelligence are the two major components of complexity-classified AI. By their name, we can calculate their level of potential compared to the intelligence of humans.

1. **Weak AI:** It is excellent at doing operations and tasks at a specific level, and it works by its specialized knowledge. The most common AI implemented in day-to-day life is an example of weak AI is Alexa or Siri.
 2. **Strong AI:** By the name itself, it's measurable how much capability the strong AI can optimize in the field. It's much more powerful and advanced than weak AI. This AI has a feature to understand, and on its own, it can learn and implement a variety of activities compared to the level of human intellect. It's still under process and needs many more programmes and algorithms that have to be implemented to make it more advanced and easier for user interface to access it for agriculture operations.
- a) The other type or classification of AI is based on the functionality, and it composes only one type of AI, i.e., Symbolic AI. As it names it sounded like an old-fashioned name or it has a goofy name. It's basically like a programme or an algorithm that is mostly found or implemented in programming computers that calculate the data by using the reasoning procedure and knowledge implied in its programme to judge the calls for data estimation. It's mostly like a rule-based functioning AI.

Applications of Remote Sensing in Horticulture

India is home to a variety of crops, and remote sensing is crucial to measure these crop data by properly utilizing satellite technology and integrated technology of ground-based stations (Ray, 2016) ^[114]. In 1970, a coconut withering experiment in India was the first known application of remote sensing. Since then, the development of proprietary software and improvements in digital image processing have been greatly aided by Indian researchers (Navalgund and Ray, 2000^[94]; Panigrahi and Ray, 2006) ^[95]. Precision farming, crop acreage estimation, agricultural water management, drought monitoring, and watershed development are some of the horticultural uses of remote sensing (Parihar and Manjunath, 2013) ^[103]. Many of these techniques, tested in practical field conditions, are now institutionalized.

Key Applications

1. **Crop Insurance:** Remote sensing, using satellite imagery and NDVI (Normalized Difference Vegetation Index), helps verify seeded crops and prevent insurance fraud (GIS Geography).

2. **Soil Moisture:** Soil moisture is measured using both active and passive sensors, which is crucial for drought evaluation and weather forecasting. NASA's Soil Moisture Active Passive (SMAP) research employs both strategies for optimal outcomes (GIS Geography).

3. **Crop Conditions and Canopy Measurement:** NDVI is employed to assess crop health, chlorophyll content, and canopy water stress. This method also predicts soil properties and aids in managing crop canopies (Smart *et al.*, 2000; Schumann, 2008) ^[127].

4. **Yield Estimation:** Remote sensing enables yield predictions for annual crops and some horticultural crops using aerial imagery and spectral indices (Maja and Ehsani, 2010) ^[79].

5. **Pest and Disease Detection:** Variations in plant pigments and spectral reflectance can be used to identify pests and illnesses early. Citrus canker and tomato late blight are two examples (Borengasser *et al.*, 2001) ^[119].

6. **Monitoring Abiotic Stress:** By tracking variations in chlorophyll reflectance, remote sensing methods identify how plants react to abiotic stressors such as drought, salt, and temperature swings (Carter, 1993) ^[23].

Machine learning

To meet the food demand for fulfilling the growing population, the 4th wave of revolution now begins that is towards the digital revolution with precision farming composing IoT, ML, satellite technology, and artificial intelligence (Saini *et al.*, 2024) ^[120].

History of Machine Learning

A science or technology that implements or provides an ability to the computer to learn and expand its knowledge without being programmed. In simpler the computer has its ability to learn new pieces of knowledge without any program (Arthur Samuel, 1959). The turning test for machine intelligence is a research paper written and published by Alan Turing in the early to mid of. 1950, in this paper, he proposes the major concepts of machine learning (Alan Turing, 2009). 36 ML techniques, considering a total of 80 implementations from which NN, RF, SVM, and DT were the most frequently implemented.

- The process of ML has three components which are generalization, data imputation and the last one is model building.
- According to the task of learning, machine learning has two types, i.e., supervised and unsupervised learning.

1. **Supervised learning:** There is a general guideline with the corresponding rule provided so that the maps, data input, and output interpretation are easily done because, in supervised learning, some data and their example are pre-programmed.

2. **Unsupervised learning:** Previously, in supervised learning, the machine was trained and tested, but in this type of machine learning, there is no such data, training, or testing, and pre-programmed data are not provided. This type of distinction is absent here. The learner has the goal to set by inputting data here to discover some hidden features or patterns.

Machine learning in precision agriculture

The data or information called big data needs large storage and also the capability of editing, interpreting, and analysing that has given challenges to the users of precision tools, but with the help of AI and the body of machine learning it is possible to manage and manipulate such larger amounts of knowledge or information or can say data (Helm *et al.*, 2020) ^[58]. The incorporation of precision tools with machine learning is a primordial factor in the development of a bright future in food production. AI, sensors, drones, GIS, GPS, and monitoring systems are helpful for machine learning to estimate, calculate, interpret, and process the input information and also helpful for identifying key problems, timely management, and some hidden beneficial factors. Towards reducing labour drones and robots are enabled in fields (A. Sharma *et al.*, 2021). Prediction of harvesting and yield, detection of pest and disease infestation, detection and interpretation of data about the weed microclimate in crop fields, and identification and recognition of crops and quality attributes of crop are the four major parts or sectors of agriculture that are explored by machine learning. In machine

learning, there is a networking system called an artificial neural network, and its processing factor is similar to the human brain processing system, and like the brain neural, once it is trained according to a similar pattern, in the future, it predicts, solves complex problems into simpler solutions and ANN accuracy of problem solving has increases with addition of more data to it (Mishra *et al.*, 2016)^[85]

Problems in the use of machine learning

Wang *et al.* identified challenges in four stages of agricultural Big Data, including multiple data sources, low precision, slow processing, long collection times, high complexity, and missing data. The key focus areas are data cleaning, consolidation, and storage (Wang *et al.*, 2019)^[149]. The programming of machine learning varies from different to organization, so the problem is that the data is malfunctioning and changes when it goes from one organization to another. The results are greatly varying, and it happens due to different hardware used for data collection (Priya and Ramesh, 2020)^[108]. On the other hand, another challenge raised was the velocity or speed with which data is collected, but processing and visualization can't proceed with that speed (Priya *et al.*, 2018)^[109].

Limitations of precision farming

25-30 years above the precision farming used in the agriculture sector and its precise use to maximize production, obtaining maximum output, towards reducing the negative environmental impacts. The fact remains that after implementing precision agriculture then people still choose traditional methods of farming. People always show the positive side of things, but they forget to bring up the negative side of things. In developing countries like India because people still choose traditional methods of farming because, in India-like countries, farmers are unaware of the smart farming methods because of the lack of extension services of precision farming, low land area for farmers, high cost of precision farming tools, lack of government schemes and the lack of funding towards precision farming implementations. In comparison to developed countries, they lack manpower, so it's easier for their people to adapt and implement precision farming tools in day-to-day life, but in developing countries, there is not lack of manpower and due to high cost of implementing precision tools it's still a drawback towards adoption of precision farming.

Conclusion

According to the global crisis that is referred to as climate change and growing population, the need of food demand and farming practices precision farming principle and components are the major beneficial factor to mitigate these problems arise. To maximize production, generate higher profit, increase the amount of yield, and maintain a healthy relationship between humans and the environment, these majors are necessary. The GIS, GPS, remote sensing, drone, AI, sensors, and Machine learning are the networks that change the perspective of farming technology. But still, the developing countries are lacking in adopting the smart technology than the developed countries much more emphasisation is still needs to develop the farming style in developing countries. These countries lack in adoption due to the higher cost of the tools like drones, sensors, AI, and also the government schemes and benefits. They are unaware that these much more awareness should spread among farmers and people. It brings a major impact in horticulture. The ongoing development of digital technology and its use in horticulture portend a bright future for precision farming, supporting a robust

and creative agricultural industry. Enhancing these technologies' cost and accessibility, guaranteeing their widespread use and future research should focus on developing algorithms for even greater accuracy and efficiency (Zhang *et al.*, 2021).

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