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19. Future Sustainability through Precision Agriculture

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Abstract:

Precision agriculture is a technology- and information-driven management approach that examines the field's temporal and spatial variability and methodically tackles it to maximize output, profitability, and environmental sustainability. The agricultural industry has seen a change with the introduction of precision agriculture, which emphasizes the use of data-driven tactics for resource optimization and decision-making. This is a new idea in agriculture that calls for careful use of inputs at the appropriate time, location, and quantity to maximize yield, increase profitability, and lower hazards. Technology, decision support systems, and data and information are the three primary components of precision agriculture. The four steps of the precision cycle are data acquisition, data access, decision-making, and decision-taking. Utilizing technologies such as the global positioning system, global information system, remote sensors, yield monitors, guiding technology, variable-rate technology, hardware, and software, this management system is called "site-specific management." Precision farming aims to improve the precision of agricultural input and method application by matching them to particular crop and agro-climatic conditions. By reducing production costs, this strategy seeks to increase output, optimize profitability, maintain sustainability, and save land resources.

Keywords:

Future, Precision Agriculture, Site-specific management, Sustainability

19.1 Introduction:

19.1.1 What is Precision Agriculture?

Precision farming, often known as precision agriculture, is a modern technique that makes use of technology to improve several aspects of the farming process. With precision agriculture, producers can now guarantee long-term food production with little human intervention and improve environmental stewardship, making it a crucial tool in modern society. The careful control of planting, fertilizing, and harvesting processes with a high degree of accuracy and precision is known as precision agriculture. Using state-of-the-art tools including sensors, drones, GPS guidance systems, and data analytics, this method collects and examines information regarding crop variability in the field. Using precision agricultural techniques, farmers can allocate resources like water, fertilizer, and pesticides with knowledge and confidence.

By employing a targeted and data-driven approach, agricultural practices can be tailored to the specific conditions of a particular region, leading to increased output and less environmental impact. Farm output is increased with precision agriculture. More precise control of inputs allows farmers to increase yields while conserving costs. Farmers that tailor their practices to each field area can increase sustainability, minimize waste, and allocate resources as efficiently as possible. According to Thilakarathna and Raizada (2018), precision agriculture also makes it possible to monitor crop health in real time for pests, illnesses, and nutritional deficiencies.

19.1.2 History of Precision Agriculture:

In 1980, the notion of precision agriculture (PA) surfaced, pertaining to the application of methods to address field variability (Burg et al., 2019). Driven by the principles of PA and industry 4.0 (I4.0), a number of words, including agri-food 4.0, digital agriculture, smart agriculture, and agriculture 4.0 (A4.0), aim to denote the application of developing technologies in agriculture.

Liu et al., (2020) have classified agricultural technological advancements into four distinct phases, collectively referred to as the shift from Agriculture 1.0 to Agriculture 5.0.

Agriculture 1.0 refers to the period of conventional agricultural techniques from ancient times, when farmers mostly relied on human labor and animal power for cultivation and employed domestic hand tools, to the end of the 19th century (Liu et al., 2020).

Agriculture 2.0 refers to the period between 1784 and almost 1870, when agricultural machinery was employed for soil tillage, planting, weeding, irrigation, and harvesting, increasing food output and decreasing manual labor (Liu et al., 2021). The 20th century's "industry 2.0" phase began with the shift from primary steam power to oil and gas power. The energy and transportation industries' advancements allowed for the long-distance delivery of agricultural products. As a result, remote communities began to communicate with one another and new agricultural markets where farmers could sell their produce arose (Liu et al., 2021). Mass production saw the installation of the first assembly line, which greatly boosted productivity and efficiency (Zhai et al., 2020). Livestock meat production utilised the first agricultural mass production method. These advancements all contributed to the large-scale, intensive animal husbandry industry. The period of farming known as "The Green Revolution" era, or Agriculture 2.0, started in the late 1950s when new agronomic management techniques, synthetic fertilizers, and pesticides were used to agricultural fields, and farmers manually operated a variety of machinery (Zambon et al., 2019).

As a result, across the board, yields, productivity, and returns rose (CEMA, 2017a). Despite the fact that mechanization made productivity and efficiency higher, excessive use of chemicals, water, and fossil fuels resulted in environmental degradation. Indeed, humankind is still wreaking havoc on the planet today, with such severe consequences that it is altering the climate in several regions of the globe. Additionally, relying on electronics and information technology, the first programmable logic controller (PLC) was employed in industry in 1969 (Yülek, 2018).

The development of "Precision Farming," or Agriculture 3.0, was made possible by advancements in electronics and computation. Thanks to these advancements, agricultural systems are now operating more efficiently, requiring less energy to run machinery, less water to irrigate, and less pesticides in the field (Ahmad & Nabi, 2021). "Precision Agriculture is a management strategy that gathers, processes, and analyses temporal, spatial, and individual data and combines it with other information to guide site, plant, or animal-specific management decisions to improve resource efficiency, productivity, quality, profitability, and sustainability of agricultural production," states the International Society of Precision Agriculture (PA) definition. (ISPA, 2021). Even if every technological revolution has had an impact on agriculture, it should be highlighted the digital transformation in the agriculture sector started with PA. Today, the agricultural sector is experiencing a new revolution, called Agriculture 4.0 from with the affecting of digital technologies also in "Industry 4.0" entered our life in 2011.

Based on the literature, there is a distinction between precision agriculture and Agriculture 4.0 applying agricultural inputs in areas with the highest production potential. However, Agriculture 4.0 aims to build a value chain that completely integrates and engages technologies and agricultural processes. It does this by managing farms based on in-depth knowledge of particular contexts and scenarios, going beyond field variability analysis (Sott et al., 2021).

Furthermore, Agriculture 5.0 is the general notion if this process includes a robot structure with AI algorithms on the system (Zambon et al., 2019). According to this idea, the farm employs autonomous decision-support systems and unmanned operation tools, as well as precision agriculture concepts.

19.2 Fundamentals of Precision Agriculture:

19.2.1 What is 4 R’s?

Precision agriculture (PA) represents a revolutionary approach to farming, transforming traditional practices through the integration of cutting-edge technologies. It operates on the principles encapsulated in the 4 R’s: applying the Right Input, at the Right Rate, to the Right Place, and at the Right Time. This framework guides farmers in optimizing the use of various crop inputs, including water, nutrients, pesticides, and seeds. By adjusting these inputs based on the spatial and temporal variability of field conditions and crop requirements, farmers can enhance efficiency and resource utilization (Njoroge, 2022).

1. Right Input: Precision agriculture (PA) revolves around the concept of the “Right Input,” which spans critical aspects of farming practices. For instance, examples include crop selection, where careful consideration of climate, soil conditions, and market demand guides the choice of suitable crops.

2. Right Rate: The concept of the “Right Rate” in precision agriculture encompasses various aspects aimed at optimizing input usage for enhanced agricultural practices. Therefore, determining the optimal input rate is a crucial, and this involves recognizing field variations. Variable-rate input applications, facilitated by technologies like Variable Rate

Irrigation (VRI), play a pivotal role in this process. VRI, for instance, allows the adjustment of water application rates based on specific landscape features, preventing overwatering and significantly enhancing water use efficiency.

3. Right Place: In precision agriculture, the concept of "Right Place" extends beyond a mere location on the field, it involves a nuanced understanding of Spatial Variability. This entails the identification and comprehension of diverse field characteristics, such as soil types, moisture levels, and nutrient distribution. These insights serve as the bedrock for informed decision-making in agricultural practices. A pivotal tool in precision agriculture is Variable Rate Technology (VRT), which allows for the application of inputs at variable rates across distinct zones within the field based on specific needs. This targeted approach optimizes the utilization of resources, contributing to enhanced agricultural productivity. he importance of precise nutrient placement cannot be overstated, as it directly impacts the uptake and efficiency of nutrient fertilizers.

4. Right Time: Precision agriculture emphasizes the significance of executing various agricultural activities at the right time to enhance overall efficiency and productivity. This entails a strategic approach to timing across multiple facets of agricultural practices. In the realm of precision agriculture, the timing of planting is a critical determinant of crop success. Ensuring that crops are planted at the optimal time is essential for maximizing yield. This involves taking into account factors such as the growth stage of the plant, prevailing climatic conditions, and logistical considerations related to field operations. Another crucial aspect is the precise timing of irrigation. Implementing well-defined irrigation schedules is imperative for ensuring water efficiency in agricultural practices.

19.2.2 Key Concepts and Technologies in Precision Agriculture:

Precision agriculture in worldwide has been gradually evolving, incorporating advanced technologies to enhance productivity and sustainability. At its core, precision agriculture leverages data and technology to make farming more accurate and controlled. The integration of remote sensing, GIS, VRT, robotic, AI, drones (UAV) and sensors represents a transformative approach to traditional agricultural practices, enabling more efficient resource use and better decision-making.

1. Remote Sensing: Satellite devices have been widely used for PA since the 1970s. Unmanned aerial vehicles (UAVs) and airplanes are examples of aerial platforms that have been utilized in PA recently. Agriculture has benefited greatly from remote sensing technology, which makes it possible to remotely monitor crop health, soil conditions, and weather patterns (Seelan et al., 2003). Farmers now have access to previously unthinkable levels of detail about their land because to drones and satellite imagery. A precision farming technique called remote sensing makes use of sensors installed on satellites or spacecraft to track variations in the light's wavelength from fields and crops that are expanding. It aids in understanding the field by tracking changes in both space and spectrum over time at high resolution. Table 1 shows some applications of remote sensing in modern agriculture.

Table 19.1: Remote sensing applications

Satellite	Application in Precision Agriculture	References
SMAP (2015–present), Rapid Eye (2008–present)	Water management	Hao et al., 2019; Mobasheri et al., 2007; Siegfried et al., 2019; Zhou et al., 2018
Triple Sat (2015–present), Landsat 8, Pleiades-1A (2011–present, Pleiades-1B (2012–present)	Crop growth	Chua et al., 2020; Dong et al., 2016; Kokhan and Vostokov, 2020; Romanko, 2017
GeoEye-1 (2008–present)	Nutrient management	Amaral et al., 2015; Sai and Rao, 2008; Shaver et al., 2017
KOMPSAT-2 (2006–present), SMAP (2015–present)	Crop yield	Cao et al., 2016; Hao et al., 2019; Lee et al., 2011
Worldview-3 (2014–present)	Weed management	Caturegli et al., 2015; Mudereri et al., 2019

2. GPS & GIS: GIS technology makes mapping and geographical data analysis possible, which enhances remote sensing. Agricultural GIS uses have included crop planning, pest and disease control, and soil mapping. The ability of GIS to precisely pinpoint variations within fields makes it an effective tool for increasing crop yields and reducing waste. The GPS system, which consists of 24 satellites orbiting the planet, uses radio signals that are interpreted by a ground receiver to pinpoint exact locations on the planet. GPS enables precise mapping of farms with a 95% accuracy rate within 10–15 meters. When used in conjunction with appropriate software, it gives farmers information on the health of their crops and pinpoints certain regions that need inputs like pesticides, fertilizers, or water. The quantity and geographic distribution of invasive species infestations on a land base can be evaluated using GIS analysis, which can help in the development of effective control methods for that specific species. The mapping of weed infestations inside an annual crop has implications for future management strategies, weed dynamics research, and targeted pesticide treatments. Land managers can select the most successful method for managing invasive species by examining the extent and spatial distribution of infestations (Abdellatif et al., 2021). Table 2 shows some example applications for those.

Table 19.2: GIS & GPS applications

Field	Application	References
Crop field	Yield monitoring, yield forecasting, crop pattern monitoring	Al Gaadi et al., 2016; Memon et al., 2019; Santosh & Suresh, 2016
Soil	Soil quality and fertility assessment	Abdellatif et al., 2021; Singha et al., 2020
Pest and disease	Detection and management	Lou et al., 2013; Roberts et al., 2021; Santoso et al., 2011; Yang, 2020
Weed control	Weed detection and management	Golmohammadi et al., 2020; Xie et al., 2012

3. VRT: According to specific crop requirements and site circumstances identified by sensor systems and prescription maps, variable rate (VR) platforms adjust the amount of seed, fertilizer, pesticides, irrigation, and drainage applied to various fields (Franzen et al., 2016). By avoiding excessive applications in less sensitive zones, VR fertilization makes it easier to tune applications to soil nutrient supplies and yield potentials. Similar to this, by focusing on active compounds according to tracked pest pressure, VR chemigation lowers the need of pesticides. Water management is additionally enhanced by automated drainage control devices that measure soil moisture. Table 3 shows example applications.

Table 19.3

Field	Applications	References
Soil	Assessment of soil property, organic matter, pH, soil texture, electrical conductivity	Al-Shammary et al., 2019; Bousbih et al., 2019
Weed control	Weed detection and management	Andújar et al., 2012
Crop	Yield monitoring, seeding applications	Manasa et al., 2023

4. Robotics: Robot market: Robot Applications Diversifying: Agricultural robots are employed in animal husbandry, horticulture, row cropping, and orchard management, among other farming activities. Agriculture will unavoidably need to advance agricultural robot technology between the 1.0 and 5.0 eras. Its main objective is to solve the issues of less labor, precision, safety, comfort, and green operation that are difficult to achieve with traditional agricultural machinery and equipment, as well as to fill in the gaps left by many traditional forms of agricultural machinery (Qi et al., 2016). However, robotic agriculture provides benefits such as costs reductions, optimization of yields and quality concerning the productive capacity of each site, better management of the resources, and protection of the environment. Most of countries like Japan, China and Indonesia apply this technology for agriculture and countries like Sri Lanka, Bangladesh have some barriers like capital, technology and skill affect (Mu et al., 2022).

Table 19.4: Robotic application in precision agriculture

Applications	Key findings	References
Crop monitoring	Crop health and disease detection, yield monitoring, weeding	Ahmadi et al., 2020.
Livestock	Poultry farming	Qi et al., 2016.
Pollination	Autonomous flower pollination	Strader et al., 2019.
Fruit harvesting	Kiwi fruit harvest	Mu et al., 2020.

5. AI: Over the past 20 years, there has been a noticeable advancement in the use of information technology (IT), also known as agricultural information technology (AIT), to agricultural operations (Yoosefzadeh-Najafabadi et al., 2021). The agricultural industry has recently shown a great deal of interest in artificial intelligence (AI) due to its ease of use in leveraging large amounts of data from unmanned aerial systems (UAS). Artificial intelligence (AI)-based technologies support the growth of productivity across industries, including agriculture, by addressing issues with weeding, irrigation, crop yield, soil content detection, crop monitoring, crop establishment, and other related issues. AI could be applied to reducing environmental pollution, conservation and recycling since natural resources are significant social and environmental concerns. There are some barriers occurred in AI technology adaptation. Those are a lack of top management support, a lack of AI skills, employee fear of change, barriers in security and limited technology capabilities, human interference is becoming less, dataset requirements (Tace et al., 2020).

Table 19.5: AI application in agriculture

Applications	Key findings	References
Predictive analytics	Supports risk management and precision farming. Application in crop yield estimation.	Yoosefzadeh-Najafabadi et al., 2021.
Crop monitoring and irrigation	Smart irrigation systems use AI and ANN	Tace et al., 2020.
Disease detection	High accuracy in disease detection through AI.	Fang et al., 2020.
Genomics and plant breeding	AI enhances gene expression and cultivar selection.	Pallante et al., 2022.

6. Drones (UAV): Drone technology is a remarkable advancement that has the potential to revolutionize the way agricultural routines and manual labor are performed. Drone technology is being used by agricultural businesses around the world to revolutionize farming. Today's farmers face a number of complex factors that affect how successful their farms are. Water availability, wind, temperature changes, the presence of weeds and insects, different growing seasons, and other factors are all included. Consequently, farmers are resorting to advanced drone technology in order to address these issues and offer prompt and effective answers (Abdollahi et al., 2021).

Table 19.6: Drone application in agriculture

Applications	Key findings	References
Weeding	Identification of weeds and weed management	Huang et al., 2018.
Disease identification	Detection of Ganoderma disease in oil palm	Izzuddin et al.,2020.
Pollination	Impact of autonomous pollination in date plams	Rehna and Inamdar, 2022.

7. Sensors: Sensors have become crucial in contemporary agriculture, as they furnish farmers with useful information that can be utilized to enhance crop productivity, optimize resource allocation, and safeguard the environment. The sensors gather data on several aspects, encompassing soil moisture, temperature, nutrient levels, and plant health. Subsequently, this data can be scrutinized to detect potential issues and formulate remedies. For instance, sensors can be employed to identify initial indications of illness or pests, enabling farmers to promptly intervene and impede their propagation. Sensors can additionally be employed to enhance irrigation efficiency by gauging soil moisture levels and activating irrigation systems as needed. Implementing this method can effectively conserve water resources and mitigate the risks of over-irrigation, which can lead to agricultural damage and water pollution (Khang, 2023). Sensors can contribute to environmental protection, in addition to enhancing crop yields and optimizing resource utilization. As an illustration, sensors can be employed to oversee the quality of water and identify contaminants. Subsequently, this data can be utilized to avert the infiltration of pollutants into water bodies. Sensors can additionally be employed to detect greenhouse gas emissions originating from agricultural activities. Subsequently, this data can be utilized to formulate tactics to mitigate emissions. In general, sensors play a crucial role in contemporary agriculture. They furnish farmers with the necessary data to make well-informed decisions that can enhance agricultural productivity, optimize resource utilization, and safeguard the environment (Kumar et al., 2021).

Table 19.7: Sensor application

Field	Application	References
Soil sensors	Soil moisture, pH, nutrient, temperature, electrical conductivity monitoring	Lloret et al., 2021; Yin et al., 2021
Crop sensors	Crop growth and plant health monitoring, crop yield prediction	Kim and Lee, 2022; Rayhana et al., 2020; Talaat, 2023
Weed control	Weed detection, weed mapping, herbicide application	Andújar et al., 2012; Da Costa and Mendes, 2020; Pflanz et al., 2018

Field	Application	References
Weather sensors	Monitor rainfall, wind speed, temperature, humidity	Abdollahi and Pradhan, 2021; Mangano et al., 2022; Messina and Modica, 2020
Pest and disease management	Target pesticides applications	Huang et al., 2018

19.2.3 Challenges:

The integration of precision agriculture technologies, spearheaded by the advancements in AI and IoT, presents a promising avenue for transforming the agricultural landscape. However, this transition is not without its challenges, particularly in the realms of technical issues and scalability (Krishnababu et al., 2024).

- High initial costs
- Technical Difficulty
- Data management
- Dependence on Technology
- Data Privacy and Security
- Risks to the environment
- Scale of Adoption
- Limitations in rural place

19.2.4 Advantages:

Precision farming offers a range of benefits that can revolutionize agricultural practices, but it also faces significant challenges that need to be addressed for widespread adoption (Kushwaha et al., 2024).

- Increased Crop Yields
- Environmental Sustainability
- Data-Driven Decision Making
- Improved Crop Quality
- Reduced Soil Compaction

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