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Recent Trends in Precision Agriculture: Applications & Challenges in Precision Farming

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Abstract

Agricultural products for food production are expected to increase by 70% in 2050 to cater for the rising population. However, conventional agriculture (CA) practices cause unpredictable production, resource overutilisation, and unregulated waste production, while affecting climate change through greenhouse gas emissions. Precision agriculture (PA) is one of the fastest-growing agriculture technologies. PA strives to improve agricultural productivity, land-use efficiency, production costs, environmental quality, and food supply sustainability. Despite expanding research on new technology adoption, PA continues to suffer from a lack of agreement on its conceptualisation. Thus, this study examined agricultural developments from the conventional era to the current PA trends, with a focus on precision farming. This initiative would assist farm managers and agriculture analysts in identifying PA implementations and current PA technology for adoption while providing decision-making support.

Discipline: Agriculture & Information Technology; Spatial Technology.

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1 Introduction

Concerns about food security have long plagued many developed and emerging economies worldwide. The deterioration of crop yield essentially affects food security. Factors such as population growth, decreasing arable land for crop production, water scarcity, climate conditions, and a declining or aging farmer population have worsened this issue [1]. Enormous demand for food production must be served cost-effectively without wasting resources such as water and electricity. The world's population is projected to be 34% larger than the year 2020, which may hit 9.6 billion people by 2050 [2]. The demand for agricultural products for food production is expected to increase by 70% in the same year to cater to the rising population [3]. At the same time, the agricultural sector must address severe challenges due to conventional farming practices that lead to erratic production, overuse of resources, and unrestrained waste production [4]. Precision agriculture (PA) is a recent advancement that addresses these challenges through farm management approaches to optimise yield productivity.

In [5],[6], [16]-[18], PA has been proven to have significantly improved conventional agriculture (CA) practice and consequently improved crop yield. However, a variety of stressors, including rapid population growth, natural resource depletion, environmental pollution, crop diseases and climate change, pose increasing threats to the global agricultural sector that need to be addressed in PA. The Internet of Things (IoT) and advanced machinery are among the most common technologies adopted for effective farming. A need also arises to integrate the current PA practice with the use of cutting-edge technology, such as artificial intelligence (AI). Table 1 summarises the recent reviews in the field of PA based on their agricultural application areas. Despite the abundance of literature on this subject, this research highlights the theoretical gaps in other advanced engineering concepts that can be integrated with the current PA practice. A review of PA technologies is presented and thus provides insights for other researchers to utilise the information in the PA sector.

Table 1: Summary of recent PA reviews.

Author	Year	Area	Research Focus	Research Gaps
Chin et al. [9]	2023	Traceability	The automation of plant disease detection using drones. Presented an identification of common diseases, pathogens, crop types, drone categories, stakeholders, machine learning (ML) tasks, data, techniques to support decision-making, agricultural product types, and challenges of drone-based plant disease identification in literature.	Decision support system for plant disease detection. Drone/unmanned aerial vehicle (UAV) communication technologies.
Shin et al. [10]	2022	Traceability	Machine vision-based automation in detecting stress and diseases on crops, leaves, fruits, and vegetables.	Real-time detection Decision support system for machine vision-based automation. Cellular communication technologies
Corwin et al. [5]	2019	Traceability	Monitoring tool to address soil spatial variability mapping. Also presented a characterisation of spatial variability of soil salinity using georeferenced soil electrical conductivity (ECa).	Machinery coordination. Decision support system for crop sampling and monitoring and disease inspection.
Mavridou et al. [11]	2019	Traceability	Machine vision applications in PA, support fruit grading, fruit counting, yield estimation, and plant health monitoring. Also, focus on machinery coordination and agricultural harvesting robots.	Communication technologies Drone/UAV applications
Rivera et al. [12]	2023	Information-driven crop production	Reviewed light detection and ranging (LiDAR) technologies for crop cultivation. Categorized LiDAR applications into crop-related metric estimation, tree and plant digitisation, vision systems for object detection and navigation, and planning and decision support.	Cellular wireless communication technologies such as 3G, 4G Long-term Evolution (LTE) and 5G.

Author	Year	Area	Research Focus	Research Gaps
Verma et al. [13]	2020	Information-driven crop production	Multimedia data collection and decision-making ability approach in PA with IoT sensors along with wireless communication technologies.	Wireless sensor network (WSN). Cellular wireless communication technologies such as 3G, 4G LTE and 5G.
Thakur et al. [7]	2019	Information-driven crop production	WSN technologies adopted for PA as well as available sensors and communication technologies.	Cellular wireless communication technologies such as 3G, 4G LTE and 5G
Méndez-Vázquez et al. [14]	2019	Site-specific farming	Pest detection management control using site-specific zoning techniques. An unmanned aerial system (UAS) is used to capture georeferenced data using high-resolution multispectral images.	Site-specific monitoring (nutrients and diseases). Site-specific spraying (herbicides, pesticides, fertiliser). Site-specific irrigation. Hyperspectral imaging.
Norhashim et al. [15]	2023	Field robotics	UAV for PA in Malaysia based on technical requirements (weight, wing span, wing loading, range, maximum altitude, speed, durability, and engine type), as well as sensors and data processing methods. Applications of UAVs are mostly for weed mapping, crop growth and health monitoring, crop production estimation, and crop spraying.	Combination of several advanced machineries for robust and efficient robotic systems. Cellular wireless communication technologies such as 3G, 4G LTE and 5G.
Gonzalez-De-Santos et al. [8]	2020	Field robotics	Advanced machinery with the utilisation of different types of sensors for specific purposes. Translation of automated factory concept into automated farm utilizing advance machinery.	Mobile robots such as UAVs and UAS
Saiful et al. [6]	2020	Field robotics	Specific advanced machinery of robotics and vehicles to execute specific agricultural operations (planting, inspection, spraying, and harvesting) according to its limitation capabilities	Combination of several advanced machineries for robust and efficient robotic systems. UAV for monitoring, spraying, seeding, etc.
Martin et al. [16]	2020	Fleet management	Field operations in agriculture, focusing on the optimization of agricultural machinery's movement in sugarcane production. Approaches based on spatial division configuration, route planning, and cost parameters (fuel and time consumption) were presented.	Cellular wireless communication technologies such as 3G, 4G LTE and 5G Real-time vehicle, machinery detection and coordination and operational information.

PA applications have proven successful in diverse agricultural sub-branches, including precision horticulture (PH), precision farming (PF), precision livestock farming (PLF), and precision viticulture (PV). These sub-branches are illustrated in Figure 1. PH is a production management approach in which precise inputs and practices are implemented at precise locations within an orchard or particular sites with the intention of 'doing the right thing', 'at the right time' and 'in the right way' [17]. PH normally involves the cultivation, processing, and marketing of fruits, vegetables, flowers, medicinal, aromatic, and ornamental plants [18]. PLF is described as the implementation of process engineering principles and methods in livestock farming to automatically monitor, model, and manage animal production. PLF also involves the conversion of bio-responses into pertinent information that can be easily applied to various management aspects focusing on both animals and the environment [19]. PLF tools are designed to be a completely automated management system that provides reliable data and warnings based on continuous animal monitoring [20]. Meanwhile, PV refers to the method of using site-specific techniques in vineyard production to enhance grape quality and yield while reducing negative environmental impact [21]. PV focuses on maximising the oenological potential of vineyards, particularly in regions where high-quality wine production standards are enforced [22].

In this research, PF is the main focus in which this article reviewed the recent trends and challenges in PF. PF is practiced in both small and large farms, implying a management strategy to increase productivity and economic returns while minimising the environmental impact [23]. The rapid development of recent technological advancements in information and communication technology (ICT) and geographic science provides tremendous opportunities for the development of optimised distributed information systems for PF. This strategy will ensure their ability to meet the nation's food security needs in the face of diminishing natural resources, particularly land and water. Applications of PF can be further classified into five sectors, including traceability, information-driven crop production, site-specific farming, field robotics, and fleet management [24]. Thus, this research aimed to gather the existing knowledge on technologies used in the PF sector, categorised based on the five sectors, and to review the existing PA technologies implemented from early techniques to their current agricultural practices.

This paper is structured as follows. Sections 2 and 3 thoroughly describe the CA and PA from the PF perspective, respectively. Section 4 discussed the state-of-the-art of PA technologies in PF. Further recommendations and practical considerations are also provided. Finally, Section 5 presented the review conclusion. Table 2 lists the acronyms used in the paper.

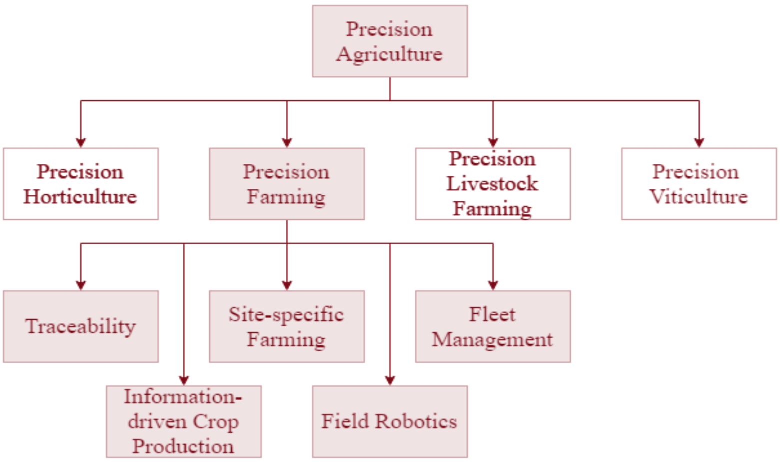

Figure 1: Precision agriculture categorization [24].

Table 2: Definitions of acronyms and notations.

Acronym	Definition	Acronym	Definition
AI	Artificial intelligence	PLF	Precision livestock farming
CA	Conventional agriculture	POI	Points of Interest
DL	Deep learning	PV	Precision viticulture
GIS	Geographic information system	SSDC	Site-specific disease control
GPS	Global positioning systems	SSNM	Site-specific nutrient management
ICT	Information and Communication Technologies	SSWM	Site-specific weed management
IoT	Internet of Things	UAV	Unmanned aerial vehicle
ML	Machine learning	VRA	Variable rate application
PA	Precision agriculture	VRT	Variable rate technology
PF	Precision farming	WSN	Wireless sensor network
PH	Precision horticulture		

2 Literature Review

2.1 CA Background

Studies on the origins of farming history can be traced back to the 1930s through archaeological excavations and investigations. The study by Tauger [25] showed that early humans in the Neolithic Revolution developed agriculture approximately 10,000 years ago in response to a seasonal climate following the end of the last ice age. Agriculture has played an important role in the advancement of human civilisation. Even though early farming techniques were influenced by local climate conditions, most farmers continued to plant on the same field year after year until the soil nutrients were depleted. Agricultural techniques such as irrigating, intercropping, and crop rotation have improved farming productivity over time. It is a primitive form of agriculture that heavily relies on local cultures, instruments, natural resources, organic fertiliser, and the farmers' cultural practices [26]. North Africa, East Africa, and West Africa are amongst the poorest countries in the world, with subsistence and small-scale traditional agriculture remaining the mainstays of their economies [27]. However, farming has changed dramatically over the last few centuries, and many countries have shifted towards CA practices [28].

CA is the most common form of agriculture, where farmers typically utilise synthetic chemical inputs that include fertilisers, pesticides, herbicides, and other continuous inputs. CA techniques were developed in the late 19th century but were not widespread until after the Second World War [29]. However, half of the world's population notably continues to practice CA [26]. In countries that practice CA, synthetic chemical resource inputs are handled uniformly across fields, ignoring the naturally occurring spatial variability of soil and crop conditions between and within fields [5]. Consequently, CA is usually resource and energy-intensive.

2.2 CA Issues

CA adopts tedious manual crop inspections, whereby human experts constantly monitor crops to detect diseases early and prevent them from spreading. However, farmers with hectares of land experience difficulty reaching every nook and cranny of a crop for regular inspection [30]. Additionally, these manual assessments can be time-consuming and cost-intensive [31].

The presumption of soil nutrient classification in CA is that a sampling point indicates the status of the specified region and that variances within it are distributed randomly [1]. However, intensive laboratory testing for soil nutrients such as nitrogen, phosphorous, and potassium is time-consuming [32]. The collection of a huge number of soil samples involves the laborious task of gathering soil chemicals and requires expert laboratory operators, increasing cost and time. These limitations led to undersampling, which renders it inaccurate for the estimation of soil fertility in large crop areas.

Currently, 70% of the global water consumed is used for crop irrigation [31]. However, a water management control system that allows continuous flooding of water to provide the best growth environment for crops (e.g. rice), is seriously lacking [33]. In addition, risks of groundwater contamination and other environmental threats exist as a result of the excessive usage of herbicides, fertilisers, and pesticides in agriculture.

Herbicides are substances used to keep the growth of unwanted plants at bay. Application of herbicides in CA is the most common practice of weed control. However, farmers tend to spray the same amount of herbicides over the entire crop, even in weed-free areas. Overuse of herbicides will eventually result in the mutation of weeds into herbicide-resistant ones. These weeds will compete with crops for available resources such as water and space, causing losses to crop yields and their growth [31].

In addition, insufficient blanket spreading of fertiliser without discrimination and reference to the plant's condition, as well as available soil nutrient content, can damage crop growth. It will ultimately result in inconsistent fertiliser distribution, either undersupplying needed nutrients to the plants, which will negatively impact plant development or oversupplying it, which will increase input costs and create negative environmental consequences [1].

Conventional crop spraying utilises manual air-pressure and battery-powered knapsack sprayers, which may lead to major pesticide losses. This insufficient method of pesticide crop spraying is not only time-consuming but can also lead to untimely spraying [31]. Besides that, the dependency on manpower methods causes inefficient labor costs.

In a nutshell, CA adopts tedious manual crop inspection and soil nutrient sampling that results in either under-sampling or over-sampling. Moreover, the blanket spraying method can cause groundwater contamination. Legitimate concerns about the adverse environmental impact and production output from the use of CA methods should therefore be addressed. As such, CA practices are being actively transformed by adopting PA, a more precise and reliable approach to collecting, storing, restoring, and analysing field data.

3 Precision Agriculture in Farming

3.1 PA Background

A wide range of stressors pose increasing challenges to the global agricultural sector, including a rising population, resource depletion, pollution, crop diseases, and climate change. PA is a viable approach for addressing these issues with the adoption of variable rate application (VRA) into farming activities [34]. VRA is an aspect of PA that automates the application of materials such as fertilisers, chemical sprays, and seeds to the land. The application of these materials is determined through precise data collection from on-field sensors, maps, and GPS that identify and monitor the characteristics of a specific area of land [35].

3.2 PA Application and Technologies

VRA in PA can be further classified into five agriculture applications, including traceability, information-driven crop production, site-specific farming, field robotics, and fleet management. The following subsections briefly explain these applications. Meanwhile, the summary of these application technologies is tabulated in Table 3.

3.2.1 Traceability

In agriculture, traceability refers to all stages of data collection, classification, conservation, and implementation related to relevant processes in the food supply chain. Its purpose is to provide assurance to customers and other stakeholders on the origin, location, and background of the product, as well as to be used in crisis management in the event of food quality and safety concerns [36]. Accordingly, product tracking and traceability, especially for on-farm operations, have emerged as one of the most crucial matters in PA research. The use of a Geographic Information System (GIS) as a PA tool will provide facilities for improving traceability information by linking it to agro-environmental situations, including soil quality, crop productivity, pest control, disease control, and local properties [36].

An example of a GIS application can be found in [37], through the web application Web Paddy GIS. This web-based application decision support system (DSS) is capable of storing, managing, analysing, and visualising all information on a single platform. The architecture of Web Paddy GIS was developed by using free and open-source software. Therefore, the platform may be remotely accessed by users using their smart phones. The data stored on the database server contains agricultural information, plot location information, and information on pests and diseases.

Lamanna et al. [38] presented a study on nuclear magnetic resonance profiling based on GIS data to evaluate the spatial variability of metabolic expression in durum wheat fields in Italy. The presented solution is used to adapt agronomic practices for providing water and nutrients to areas depending on the metabolic expression of durum wheat at three different vegetation stages.

The use of Global Positioning Systems (GPS) on agricultural machinery provides location and time information for all treatments. Given that the use of GPS-enabled smartphones has become increasingly common, farmers can maximise it in the field by taking images of suspected pests or diseases and sending them to the internet cloud. With the GPS coordinates of the spot where the picture was taken, the potential desirable treatment will then be computed in the cloud system based on crop information such as type of crop, planting date, and expected harvest date. These pieces of information are initially stored in the cloud [39].

Abu Bakar and Bujang [1] reviewed how the integration of GPS-enabled mapping devices with sensors helps identify and analyse sampling sites by using these geo-statistical tools. Satellite images or aerial photography may be used to perform GPS mapping functions. Apart from using GPS-based devices for crop sampling, GPS data can also be applied to shipping documents so that the product's origin (region, farmer, field) can be tracked and the buyer can be assured of the veracity of the origin claims [39].

3.2.2 Information-Driven Crop Production

Crops have initially been managed in CA under the presumption of standard soil, nutrient, moisture, weed, and insect conditions. The application of chemicals, irrigating, fertilizing, and performing such treatments have all been over- or under-applied due to uniform and untargeted application. However, advances in crop growth modeling, as well as in the use of software for monitoring and collecting data from farms, have opened the way for a new field of insights to aid PA decision-making [1]. The advent of GPS and Global Navigation Satellite Systems (GNSS) has enabled the practice of PA, which employs information technology to bring data from multiple sources to crop production decisions. The fundamental pieces of knowledge required to identify the geographic position of phenomena are critical. This is because the geographical and temporal variability of soil and crop variables between and within fields is the factual basis for PA. The purpose of georeferenced data collection is to provide accurate information about the spatial and temporal variability of crops to facilitate the best decision-making by PA to increase yield production [2].

Sensors and automation are vital applications in the agricultural sector. An example of its usage is to track the health and performance of the farm [40]. The adoption of remote sensing in agriculture has resulted in the systematic collection of data across vast geographical areas [2]. Remote-sensing applications in agriculture refer to non-contact measurements of electromagnetic radiation that interact with soil or plant content. The application of remote sensing focuses on a wide range of endeavors, including crop yield, crop nutrients, water tension, plant disease infestations, and soil properties such as organic matter, moisture, clay content, pH value, and salinity [41]. The platforms for making these measurements often use satellites, aircraft, tractors, and hand-held sensors. However, cloud cover also severely limits the availability of remote-sensing imagery from satellite and airborne platforms, whereas ground-based remote sensing is less affected by this constraint. Additionally, higher spatial and spectral resolution remote sensing data are often prohibitively expensive [41].

Ismail et al. [42] proposed an IoT-based paddy monitoring and advisory system called e-Padi, as shown in Figure 2. By using microcontrollers to control the wireless network and sensor nodes on an IoT-enabled platform, the prototype offered continuous monitoring of the paddy field area as well as warning and advisory reports. All collected data from the sensor nodes will be stored in a database management system, allowing users access to it via tablets, smartphones, or computers. The techniques from this research are frequently implemented in PA to increase crop productivity through real-time monitoring of crop environment parameters. Besides, with the implementation of PA, the dependency on manpower is reduced and costs are efficiently utilised.

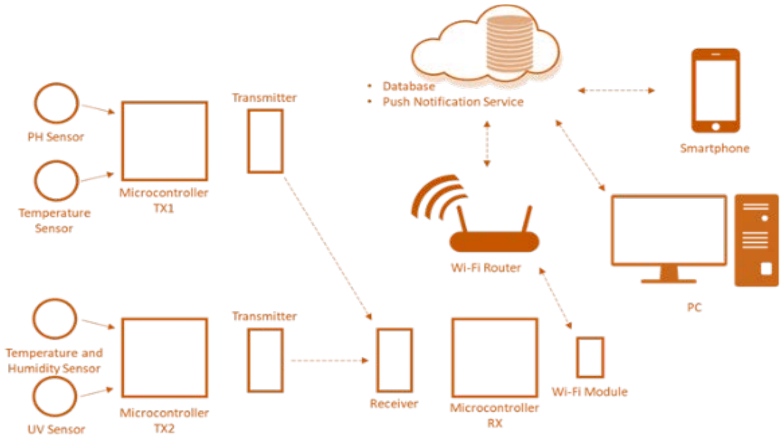

Figure 2: The e-PADI System [42].

Sharma et al. [43] presented a fuzzy logic-based identification algorithm for determining a suitable cropping window and minimum pest growth based on data collected from a wireless IoT-enabled sensor network deployed in medium-grass vegetation, such as rice and sugarcane crops. The experiments were conducted in an agricultural field in Madhya Pradesh, India, in which the deployed IoT sensors collected moisture, rainfall, and temperature data for the area. The solution aimed to help farmers identify appropriate planting seasons through IoT applications, as well as prevent pest development and take proactive precautions to achieve maximum crop yields.

3.2.3 Site-Specific Farming

Site-specific farming is the practice of managing specific areas within fields rather than the entire field. The management procedure is to identify and quantify variations between the fields, document these differences at particular sites, and use this information to handle improvements in management or inputs [44]. In other words, site-specific farming is the act of doing the right thing, at the right time and at the right places. Site-specific farming uses numerous methods for managing resources, including water, herbicides, fertilisers, and pesticides.

Site-specific weed management (SSWM), presented in [31], refers to the spatially variable rather than uniform application of herbicides over the entire region. Selective herbicides eradicate particular weed species while causing minimal damage to the target crop. In this sense, the sector is divided into management areas, each of which is assigned a unique management strategy. This process, in turn, will reduce the total crop inputs, and herbicides will be applied in a more targeted manner. This scenario is ideal because weeds usually spread only across a few areas of the field, and applying uniform management is thus a waste of herbicides.

Another SSWM approach was presented by Li et al. [45], who proposed a smart weed-control system that utilised a real-time sensing system for the automatic localisation and recognition of vegetable plants. In particular, the authors developed a system that accurately distinguishes vegetable plants, such as tomato and pak choy, from weeds in a real-time manner by using an integrated sensing system consisting of camera and color mark sensors. Through real-time identification, an effective weed eradication method can be performed.

Conventional fertiliser applications conducted by farmers may not meet the crop requirements and are not resource-efficient. Farmers often inefficiently apply fertilizers with regard to the amount and type of fertiliser at a particular stage of crop development. Thus, an appropriate nutrient management strategy could help boost the low recovery efficiency of fertilizer that results from excessive usage. Site-Specific Nutrient Management (SSNM) was developed as an integrated nutrient management strategy through a web application decision-support software called Rice Crop Manager (RCM), presented in [46]. The quantitative relationship between nutrient supply and crop demand, which differ enormously in space and time, was considered. SSNM serves to recommend the application of an acceptable amount of fertilizer to the rice crop at the appropriate growth stage through RCM. The SSNM was studied in irrigated ecosystems and demonstrated a substantial improvement in rice yield throughout Asia.

Precise nutrient administration may be enabled by quantifying the site-specific nutritional status of the soil [1]. The objective is to create an on-site model by using aerial images to map out the plantation areas for nutrient distribution. The aerial images provide an accurate determination of spatial variability, allowing for the identification and analysis of subsequent sampling sites. The nutrient distribution model for the particular sampling sites will then be obtained by utilising geo-statistical tools. With this method, the soil preparation process can be sped up by removing the need for time-consuming manual sampling and labor-intensive laboratory research.

Crop health is a critical consideration requiring monitoring, as crop diseases may result in substantial economic losses due to decreased yield and quality. Crops should be monitored continuously to identify pathogens early and prevent them from spreading, as they are known to alter the biophysical and biochemical characteristics of crops. However, manually inspecting an entire crop will take months. Thus, the implementation of an automated disease detection system is necessary. By analysing crop imaging data to monitor improvements in plant biomass and health, pathogens can be identified early on, allowing farmers to interfere and minimize losses for a possible higher yield achievement [31]. The information would be beneficial for the implementation of site-specific disease control (SSDC), an application of pesticides on crops using variable rate applications. It has the benefit of using less pesticide when adhering to the recommended application rate for a diagnosed disease, such as fungicides [47].

3.2.4 Field Robotic

A significant number of studies have been conducted in recent years on the applications of mobile robots for farming activities such as planting, inspection, spraying, and harvesting. In PA, automation and robotics have become a few of the main frameworks that focus on minimising the environmental impact whilst maximising agricultural produce [6].

Agricultural operations must be carried out by using a variety of robots and vehicle systems, depending on the type of land and service criteria. For example, a tractor is highly capable of traversing across muddy surfaces. However, the tractor's massive structure restricts its application to a small area. Thus, agricultural operations in the small area must be executed by mobile robots. The implementation of these mobile robots in agriculture can be categorised based on different agricultural operations, including planting, inspection, spraying, and harvesting. Naik et al. [48] proposed an autonomous seeding robot that has been designed using the Agribot platform, an automated system for measuring soil moisture, weather and crop data based on IoT technology. Additionally, this tool is capable of visualizing real-time results, performing analytics, and generating automatic reports. An infrared (IR) sensor was also used to track the state of the seed tank and detect crop rows. Hence, the proposed technique enables an efficient seed sowing.

Park et al. [49] designed a fruit-and-vegetable harvesting robot that can harvest a variety of fruits and vegetables without any additional or complex control. The designed robot's performance was verified through lab and field experiments, which showed a promising success rate of 80.6% and a total harvesting time of 15.5s.

3.2.5 Fleet Management

Agricultural fleet management is the process by which farmers or machine contractors make choices on resource distribution, scheduling, routing, and real-time tracking of vehicles and materials. Fleet management techniques are employed to assist in decision-making to optimise certain aspects for the more efficient performance of the tedious management task [50]. Additionally, fleet management encompasses the method of supervising the usage and operation of machines. Also, the administrative functions associated with them, such as the coordination and dissemination of tasks and related information address heterogeneous scheduling and routing issues.

Achillas et al. [51] developed a voice-driven fleet management system called V-Agrifleet. The system features a voice-driven functionality and facilitates information sharing between all machine-to-machine pairs in the fleet. For example, during a harvesting process, the harvester operator could identify on the map the location and operating status of a selected transport device, such as whether it is traveling to the depot or to a field, whether it is carrying a load or not, or whether a malfunction has occurred. Along with locating transport trucks and farm equipment, the application offers a concise image of the operating status of both main (e.g., harvesters) and secondary (e.g., transport) groups. Each operator offers real-time information exchanged amongst all authorised users through formalised voice commands during distinct events of the service, such as when loading is complete or when harvesting in a field is complete. By using the V-AgriFleet app, the fleet is contextually conscious of each unit's operation and therefore adapts the configuration to their detected statuses by empowering them with decentralised decision-making capabilities.

Table 3: Summary of VRA in PA.

Application of Precision Farming	References	Technologies	Summary
Traceability	[37]	GIS	A decision support framework capable of storing, managing, analysing, and visualising all types of knowledge (agriculture data, plot data and pest and disease data) on a single platform
	[38]	GIS	Uses nuclear magnetic resonance profiling on GIS data of durum wheat fields to evaluate metabolic expression of durum wheat for selective watering and herbicide spraying
	[1]	GPS	GPS implemented on agricultural machinery helps coordinate location and time information for crop sampling purposes.
	[1]	Satellite imaging	GPS mapping functions
	[39]	Aerial photography	
Information-driven crop production	[42]	IoT-based monitoring and advisory system	The integration of microcontrollers and sensor nodes on an IoT-enabled platform for crop monitoring
	[43]	IoT-based monitoring and advisory system	Utilized an IoT-based sensor network to collect environmental data and proposed a fuzzy logic algorithm based on the data to determine suitable cropping window with minimum pest growth for crop production
	[2]	GPS	Collecting georeferenced data to impose on crop production decisions
	[2]	GNSS	
	[41]	Remote sensing	A systematic data collection of crop nutrients and health conditions over large geographical areas
Site-specific farming	[31]	SSWM	Selective herbicides spraying on crops according to management zones
	[45]	SSWM	A weed control system that utilizes camera and color sensors for automatic localization and recognition of vegetable plants
	[46]	SSNM	A system recommendation on the application of a suitable amount of fertilizer to crops at the appropriate growth stage
	[47]	SSDC	Pesticides are applied to crops in small amounts that do not surpass the application rate suggested for the detected disease.
Field robotics	[48]	Agribot	The Agribot platform was used to develop an autonomous seeding robot. An infrared (IR) sensor was used in this production to track the state of the seed tank and to detect rows.
	[49]	Harvesting robot	Designed a universal fruit-and-vegetable harvesting robot
Fleet Management	[51]	Voice-driven fleet management system	A decentralised decision-making platform for agriculture machinery and transportation that integrates voice-activated capabilities and facilitates information sharing between the fleet's machine-to-machine pairs.

4 The Rise of Precision Agriculture in the Farming Industry

The history of PA demonstrates that it has been driven more by technological developments than by advances in information analysis and decision support. For example, when GPS and yield monitors were first implemented in PA, they were seen as technical advancements that could be applied to existing agriculture machinery to increase its value. The incorporation of GPS into agricultural machinery paved the way for many other technical advancements in PA. However, a current shift seems to have occurred in PA towards a greater emphasis on data analysis and decision support systems.

Variable rate technology (VRT) combines both physical and digital technologies, such as on-farm machinery, drones with the integration of artificial intelligence (AI), machine learning (ML), deep learning (DL), and hyperspectral imaging [35]. These technologies aid in the development of information analysis and decision support systems in PA. VRT refers to a technology that enables variable rate application of materials in PA [52]. It is one of the most notable advantages for agriculture to come out of the era of digitisation.

4.1 Applications and Technologies

Similar to VRA, VRT in PA can also be further classified into five agriculture applications, including traceability, information-driven crop production, site-specific farming, field robotics, and fleet management. The following subsections present an overview of these applications. Meanwhile, the summary of these application technologies is tabulated in Table 4.

4.1.1 Traceability

The normalised difference vegetation index (NDVI) is a graphical tool used for crop monitoring through satellite or multispectral cameras that uses light reflectance in the visible and near-infrared (NIR) wavelengths to evaluate the amount and health of vegetation in an area [53]. The data collection stages, primarily in crop monitoring and mapping functions, are evolving from conventional multispectral imaging into hyperspectral imaging. Hyperspectral imaging is a more sophisticated technique than multispectral imaging in that it can acquire a precise spectral response to target features [41].

Hyperspectral imaging can detect subtle variations in ground covers and their evolution over time [54]. The more specificity in a scene, the more likely it is that unique crop characteristics and physiological characteristics can be identified. It is now possible to recognise and identify crop pathogens, pests, and nutrient deficits in vegetation, owing to the potential of comparing spectral signatures with variations in plant physiology [55]. Hyperspectral imaging can also identify and classify different types of weeds, wild vegetation, and crop varieties. Each species of vegetation and variety of crops has its unique spectral signature. However, owing to spectral resolution limitations, the retrieved variables' accuracy is frequently limited, and early signals of crop stresses, such as nutrient deficiency and crop disease cannot be detected effectively and promptly. Nevertheless, hyperspectral imagery functions are better than multispectral imagery to facilitate a more accurate and timely crop physiological status detection [54].

Hyperspectral data may be analysed by using ML and DL algorithms because they can efficiently process a large number of variables [54]. Researchers have used different ML and DL algorithms with hyperspectral images for agricultural applications [54]. ML and DL have a versatile and effective computational approach for processing the massive volume of data contained in pre-processed hyperspectral images. Although ML and DL models are powerful, one must still bear in mind that large-quantity and high-quality training datasets limit power outperformance [56].

An example of hyperspectral data applications in precision farming utilising ML is presented by Zhang et al. [57]. The authors presented a quantitative estimation of wheat stripe rust, one of three major wheat rust diseases, by using fractional order differential equations to improve the spectral information and reduce noise while the Gaussian process regression (GPR) ML model is used to construct models for estimating the severity of wheat stripe rust disease. Conversely, Li et al. [58] presented a study for predicting the anthocyanin content in mulberry plants through hyperspectral imaging, least squares-support vector machine, and extreme learning machine models. Falcioni et al. [59] adapted AI algorithms in combination with hyperspectral imaging for the accurate classification of eleven lettuce plant varieties.

4.1.2 Information-Driven Crop Production

Smart crop monitoring through the use of IoT technology is the latest state-of-the-art feature in precision farming, with the aim to optimise resource use and crop development through real-time, accurate, and location-dependent adjustments [60]. The more IoT sensors used to track the data points of crop conditions, the higher the possibility of predicting and foreseeing various crop changes and making faster and better decisions. Several technical challenges exist with the massive use of IoT applications in farm management, such as reliability, scalability, and data transparency issues [61]. These issues happen because diverse and high-dimensional data streams from sensors should be ingested in real-time, delivered, and analysed, usually in a short time, to meet the demands posed by several agricultural applications [2]. Hence, these IoT sensors exploit the 5G technology's low power transmission and reliability given that PA relies heavily on event monitoring that demands data stream processing and consequently requires lower latency and higher bandwidth [62]. Therefore, the superfast 5G network will play a critical role in this PA application [4].

With the advent of smart crop monitoring integration with cloud computing and IoT technologies, a challenge arises in dealing with large-scale analysis of agricultural data [13]. Big data are expected to play an essential role in the PA domains. High-performance, scalable learning systems for data-driven discovery can turn farm management systems into AI systems, providing richer real-time recommendations and automation of several agricultural procedures [2]. Raw and unstructured data captured via several pre-configured IoT sensors are sent to the cloud for processing with the help of big data analytics. The processed result simultaneously and automatically reaches the customers. In agriculture, the decision-making trends have been passed down through generations of farmers; but now, with the advent of advanced computational technologies and complex data processing capabilities, the massive data being captured daily can be exploited to establish a Decision Support System (DSS) for smart farming [13]. The collaboration of Big Data with Cloud Computing and IoT technologies has transpired a new range of applications spanning the area of agriculture [13]. Although big data are widely used in agriculture, they are only relevant in some instances, depending on the farm and its degree of technology acceptance [63]. Kamilaris et al. [64] cited 34 works where big data were used in agricultural applications. Factors such as climate changes, crops condition, and farmer's decision-making, play an important role in adopting big data practices.

4.1.3 Site-Specific Farming

Precision irrigation techniques presented in [31] is a water management site-specific technique that aims to improve the efficiency of water use so that the resource is applied effectively in the right places at the right time and in the right quantity. Detecting the areas where major irrigation is needed can help the farmers save time and water resources.

In addition, a water management model mentioned in [1] is capable of monitoring and scheduling daily crop water requirements within an observed grid. This GIS user-interface technique linked with the water management model as shown in Figure 3 is capable of assisting and improving the decision-making process in water management based on parameters such as the irrigation requirement, rainfall, effective rainfall, and drainage requirement.

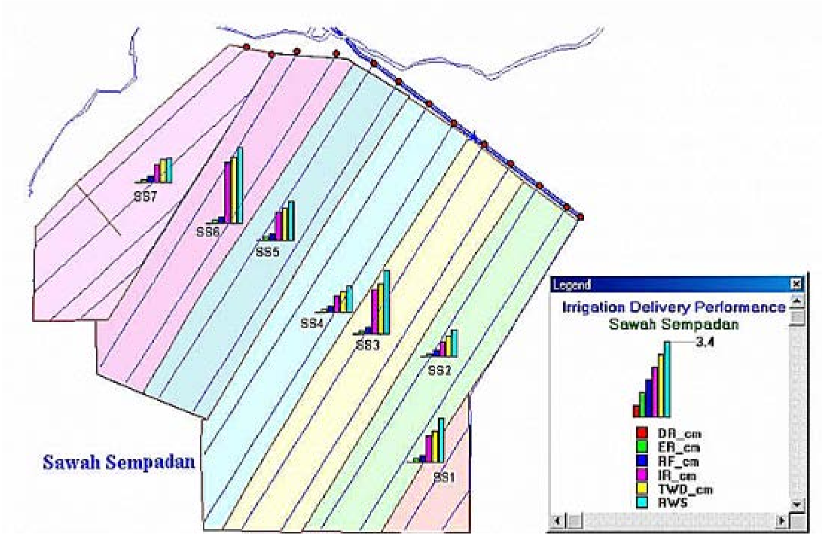

Figure 3: GIS-based computer model to compute spatial water requirement [1].

Targeted spraying of herbicides, fertiliser and pesticides is also a major contribution in site-specific farming to ensure the right amount of chemical is applied at the right time to obtain optimal yield and minimise its negative impact on the environment. Stajnko et al. [65] proposed a targeted spraying method on an apple orchard that selectively delivers pesticide spray with respect to the characteristics of the targets. The density of an apple tree canopy was detected by ultrasound sensors controlled by a microcontroller. The analysis focused on the detection of appropriate thresholds on 15 cm ultrasound bands, which corresponded to maximal response to tree density, and this feature was selected for accurate spraying guidance. The employment of this method showed a reduction in the amount of spray delivered by up to 48.15%.

Apart from using pesticides, biological solutions are being implemented to control the excessive usage of chemicals in agriculture practice [66]. Metarhizium Anisopliae is an Entomopathogenic Fungi (EPF) that acts as an environmentally friendly biological control agent for rhinoceros beetles [67].

An example of crop health monitoring by using intelligent site-specific farming technology was presented by Devi et al. [68]. In particular, the authors proposed an intelligent bean cultivation approach that utilises computer vision, IoT, and spatio-temporal DL strategies for real-time discrimination between healthy and diseased bean leaves, weed detection, and process control, as well as site-specific water sprinkling.

4.1.4 Field Robotics

Advanced technology allows the deployment of autonomous robotics. UAVs, commonly referred to as 'drones', are the latest advanced equipment in the field of robotics. Drones are typically associated with military, industrial, and other advanced operations; however, with recent advances in sensor and information technology over the last two decades, the application of drones has expanded to include agricultural applications [30]. Drones are manufactured to become smarter, thereby widening their scope of application in the agricultural sector. Drones provide comprehensive benefits that help to accurately monitor food crops, especially large agricultural crops [3]. Drones can carry out regular air monitoring of crops to identify their status at regular intervals. Site-specific disease control can be implemented by integrating UAVs. UAV-based data processing technologies use crop imaging information to identify changes in plant biomass and their health. Moreover, utilisation of pesticides, water, and fertilisers can be accurately monitored. Such a process is possible because UAV targeting helps in the timely and highly spatially resolved spreading of fertilizer [31].

4.1.5 Fleet Management

Fleet management views prescriptive maintenance and real-time environmental adjustments, aimed at improving performance and extending the useful life of farm equipment and other assets, as well as decreasing the risk of mold, fire, and other threats. Currently, fleet management tools focus on real-time insights not only to improve logistics but also to reduce costs, and create stronger digital connections amongst all the stakeholders. Current fleet management also aims to protect valuable assets, including staff, equipment, inventory and land by identifying the conditions that present a hazard to health, safety or productivity at an early stage [60].

A global telematics platform provider called 3Dtracking proposed an agriculture fleet management system based on a case for industry-specific software solutions [69]. The use of a telematics platform enables farmers to view their farms in accordance with various points of interest (POI). Real-time agricultural transport and machinery, including field robotics detection and operational information, are made available with this tool. Additional features of reports and alerts for the management of these agricultural transport and machinery are implemented allowing for efficient fleet control decision making. Additional functionality for fuel tracking was embedded, and the data is being used to measure and provide insights such as distance covered or working hours in relation to fuel usage. Fuel dispensing at the farm fuel depot is also added to provide further monitoring of fuel usage in relation to work achieved in the fields. This added procedure helped improve the management of fuel and avoid theft or waste in the case of vehicles idling unnecessarily. With further studies and developments in the future, features such as driver's authentication, behaviour, working hours, and fuel consumption would improve agriculture productivity as a whole.

Table 4: Summary of VRT in PA.

Application of Precision Farming	References	Technologies	Summary
Traceability	[41]	Hyperspectral imaging	Identification of unique physiological crop traits to identify crop diseases, pests, and nutrient deficiencies
	[54]	ML and DL algorithms	Tools for analysing a large number of variables from information captured by hyperspectral imaging.
Information-driven crop production	[61]	IoT technologies	Utilisation of many IoT sensors to track the data points for higher possibilities of predicting and foreseeing various farms' changes to make faster and better decisions.
	[4]	5G communication technology	To ensure real-time data execution with low latency for crop monitoring IoT sensors.
	[63]	Big data	Raw and unstructured data captured via several pre-configured IoT sensors are sent to the cloud for processing with the help of big data analytics.
Site-specific farming	[31]	Precision irrigation techniques	A water management site-specific technique to improve the efficiency of water use by monitoring and scheduling daily crop water requirements.
	[65]	Targeted spraying of herbicides, fertilizer, and pesticides	A programmable ultrasonic sensing system for targeted spraying in orchards that showed a reduction in the amount of spray delivered
	[68]	DL	A tool for crop-monitoring (real-time discrimination between healthy and diseased leaves, weed detection, and process control)
Field robotics	[30]	UAV	Crop monitoring, disease control and crop spraying at regular time intervals
Fleet Management	[69]	Fleet management system utilizing telematics platform	Provides real-time agricultural transport and machinery detection and operational information with 3D POI.

4.2 PA Issue and Recommendations

Agriculture production is heavily reliant on water and soil factors, both of which must be used more efficiently. These resources are managed effectively with the help of PA practices through a set of information technologies (IT) such as GPS, remote sensors, UAV, ML, DL, and many other options [70]. PA is equipping farmers with effective instruments for achieving productivity in agriculture. Different types of sensors, positioning and navigation systems, and variable rate technology are well-known components of PA. Drones and robots are promising tools that enable farmers and managers to collect information or perform particular actions, including irrigation and fertiliser spraying in remote areas or tough conditions [24]. PA adoption can be substantially improved if a combination of more precise and robust sensors specialised for each activity and the end-users (farmers) is applied. This process is done to receive quantified information about the farm profit augmentation and the positive sustainability impact, combined with reduced investment cost [47].

The implementation of PA is not limited to one or two technologies or innovations, as certain technologies and innovations may be applicable in one field but not in others. A useful, practical, and suitable transition to technology is necessary. Each field should have its own set of technologies, such as crop planting methods and customized fertiliser application technology. PA's objective was to achieve site-specific management (SSM) through cost-saving agriculture methods to increase yield production [1]. Table 5 summarises the issues and future recommendations that can help improve PA practices.

Multiple possible future research lines exist in the context of PA, focusing on technologies that have not been researched as often, such as the utilisation of hyperspectral imaging with UAV for crop mapping, which requires further sampling. Although UAVs are currently used in the agricultural sector, their integration with hyperspectral imaging has not been extensively used in PA due to their limited accessibility outside of the scientific community. The acquisition, processing, and evaluation of hyperspectral imaging continue to be difficult tasks due to its large data volume, high data dimensionality, and complex information analysis. Performing a comprehensive and in-depth study of hyperspectral imaging technologies for agricultural applications is therefore advantageous [54].

Table 5: PA Issues and Future Recommendations.

Methods	Issues	Recommendation
Utilisation of hyperspectral imaging with UAVs for crop mapping	Challenging data acquisition, processing, and evaluation of hyperspectral imaging hinders its integration of imaging technologies with UAVs	Perform a comprehensive study on hyperspectral imaging, which requires further sampling
Adopting 5G communication for easy-access to data storage and real-time application	Advances in communication technologies with the implementation of 5G networks in all countries	Mobile operators across the globe should largely contribute to smart agriculture by building out their digital networks to support 5G networks
DSS for crop management	A farmer's lack of PA skills is a major element preventing IT adoption in the agriculture sector. Farmers usually opt to implement hasty trial-and-error tactics, which significantly raise the adoption cost	Introducing a tool or framework that encompasses the required PA knowledge that directly supports the decision-making process of selecting the appropriate technology for a farmer's needs
The integration of hardware and software	The generation of a massive amount of crop data to be processed creates research opportunities. It could help identify new advancements in the context of PA using a variety of methods, providing farmers with useful insights on how to increase yields	Specific attention should be given to research on the optimised methods of PA application to primarily reduce undesired yield and improve the carbon footprint of crops

All countries are expected to introduce 5G networks in all fields; hence, Internet prices are expected to decrease significantly and connectivity will improve [71]. Investment costs for PA are predicted to substantially decrease due to 5G use, which would benefit farmers. Farmers would be well equipped for smart farming, as they would be able to predict and prevent crop diseases via their cell phones. If the implementation of 5G is largely adopted, mobile operators are then required to contribute significantly to smart agriculture by expanding their physical networks to support PA applications. For instance, large sensors will be able to gather data in the field and store it in the cloud, where it can be analyzed whenever convenient [4].

Another essential aspect that future research should focus on is the need for farmers to acquire additional PA knowledge. It has become one of the significant factors discouraging them from implementing IT in their fields. Accordingly, a tool or framework that encompasses this required knowledge and that directly supports the decision-making process of selecting the appropriate IT for a farmer's needs without relying solely on trial-and-error strategies that further increase adoption costs would be highly desirable [70]. The information that the crops offer can only be turned into profitable decisions when they are efficiently managed. PA is growing rapidly owing to recent developments in data management, as data has become a vital component in modern agriculture, assisting farmers with critical decision-making. [63]. Hence, farmers should have a DSS for their crop management decision [1].

The integration of software and hardware solutions has resulted in the generation of a massive amount of data that can be processed by using a variety of methods, providing farmers with useful insights on how to increase crop yields [47]. Considering that the adoption of innovation solutions promises exponential growth in PA application, further research should be carried out to improve the carbon footprint of crops. All these research opportunities could help to identify new advancements in the context of PA [70]. Hence, specific attention should be given to research on the optimised methods of PA application to primarily reduce undesired yield.

PA is forecast to hit USD11,107 million by 2025, rising at a 13.97% compound annual growth rate from 2019 to 2025 [72]. Although advancements in precision agriculture encourage the adoption of innovative solutions, the practice's implementation is constrained by several challenges. The main factors affecting the adoption of PA are as follows [24]:

a) Political and legal support
b) Decision support systems and user interfaces
c) Experienced research team works
d) National educational policy
e) Success in commercialisation of the PA system

The adoption of advanced technologies in PA continues to be critical for progressing towards new and sustainable agriculture capable of illustrating the maximum potential of data-driven management in addressing the complexities of food production in the 21st century. Agriculture 5.0 is a priority over the next decade for the majority of large agricultural machinery manufacturers. Hence, governments, researchers, and industry enablers play a critical role in aiding farmers in agricultural management systems through digital solutions powered by robotics and artificial intelligence [63].

5 Conclusion

To meet the expanding population, agricultural products for food production are predicted to increase by 70% by 2050. However, conventional practices show many signs of inefficiency that negatively impact the environment and yield production. PA is one of the fastest-growing agricultural technologies. PA strives to improve agricultural productivity, land-use efficiency, production costs, environmental quality, and food supply sustainability. Despite expanding research on new technology adoption, PA continues to suffer from a lack of agreement on its conceptualisation. Thus, this research aimed to synthesise the literature on the adoption of agricultural technologies in the farming sector from its conventional era to its current practices. This work has shown that with PA practices, using full mechanisation of high-tech equipment can reduce agricultural inputs through site-specific applications as it better targets inputs to the spatial and temporal needs of agriculture crops. This research provides readers with an overview of the evolution of PA throughout the years, categorised based on five major PA applications. Farm managers and agricultural analysts may find the information in this work beneficial in identifying PA implementations as well as in deciding the PA technologies to be adopted.

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