

# Emerging Line of Research Approach in Precision Agriculture: An Insight Study

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**Abstract**—The present state of agriculture and its demand is very much different than what it used to be two decades back. Hence, Precision Agriculture (PA) is more in demand to address this challenging demand. With consistent pressure to develop multiple products over the same agricultural land, farmers find PA's adoption the best rescue-based solution with restricted resources. PA accelerates the yield and potentially assists in catering up the demand of scarcity of demands of food. With the increasing adoption of PA-based technologies over farming, there are best possibilities to explore efficient farming practices and better decision-making facilitated by real-time data availability. There is an evolution of various novel technologies to boost agricultural performance, i.e. variable rate technology, Geomapping, remote sensing, automated steering system, and satellite positioning system. Apart from this, it is also observed that Internet-of-Things (IoT) and Wireless Sensor Network (WSN) have been slowly penetrating this area to accelerate PA's technological advancement. It is noticed that the adoption of sensing technology is a common factor in almost all the techniques used in PA. However, there is no clear idea about the most dominant approach in this regard. Therefore, this paper discusses existing approaches concerning standard conventional PA and sensing-based PA using WSN. The study contributes towards some impressive learning outcomes to state that WSN and IoT are extensive to boost PA.

**Keywords**—Precision agriculture; smart farming; wireless sensor network; internet-of-things; remote sensing; variable rate technology

## I. INTRODUCTION

Technological advancement has penetrated agriculture in the present time, right from small to large scale farming [1]. Two decades back, the Global Positioning System (GPS) usage permits the farmers to collect necessary farming data, which facilitates autonomous steering control system development [2]. However, the present times make use of more advanced technologies, e.g., fixed solutions for Internet-of-Things (IoT), aerial devices, sensors, etc., to carve the progressive path of Precision Agriculture (PA). The prime goal of PA is to achieve, i) opt for the appropriate crop to ensure increased quality yield and make more revenue in the commercial market, ii) using the proper data to assess the performance of the farming land, iii) improve the economics of farming and another offer better sustainability towards the environment, and iv) making a prediction of climatic fluctuations and taking necessary countermeasures to protect from upcoming threat towards agriculture [3]-[5]. The significant beneficial aspect of

PA is minimizing and controlling crop waste and adverse influence over the environment. Farmers are facilitated with the appropriate anticipated yield for their farming land. Investigation towards PA could offer potential insight towards solving the crisis of food demand globally [6]. Farmers are now able to identify the beneficial aspects of PA introduced by IoT. The return of investment and quality of decision-making can be ensured by adoption PA by business owners. There is the inclusion of various metrics to carry out PA, e.g., fertilizer input, a sample of soil, nutrient availability of soil, rainfall level, temperature, etc. [7].

Acquisition of this information via sensors can lead to precision decision-making by the farmers. It can also furnish various real-time data of their farming land, identifying specific production patterns or identifying any associated risk factors during cultivation and harvesting season. Adopting PA also facilitates exclusive access to the agricultural records via cloud-based resources where the data can be accessed anytime and anywhere [8]. It also leads to an adequate formulation of measures towards crop protection. Usage of sensors can quickly identify the health statistics of a plant concerning soil pressure, presence of chemicals, environmental impact, pest, etc. [9]. This information leads to a better decision in planning for fertilizer input by the farmer. The most potential benefit of PA is associated with irrigation management. Any form of the crop demands an adequate water supply in appropriate quantities and channel them throughout the farming land. Usage of various controllers, actuators, and sensors further offers relevant water supply statistics for better irrigation management. To effectively operational, PA demands the use of progressive technologies, i.e., usage of sensors [10], precision farming software [11], connectivity protocols [12], and location monitoring tools [13]. Irrespective of PA's known benefits, it is still yet to get a discloser about the research progress regarding more insights over challenging state of farming, minimal resource waste, identifying the unique pattern of production or risk. Therefore, this manuscript offers an exhaustive review of standard and upcoming potential PA approaches to provide a more precise research state. The significant contributions in the proposed paper are described as follows:

- The present state of conventional approaches in PA is highly scattered. So this paper contributes towards offering a compact discussion of conventional standard approaches concerning its taxonomies.

- Presents an elaborative discussion of all the potential implementation carried out in present times towards conventional standard approaches in PA.
- Discussion about the existing approaches carried out by Wireless Sensor Network (WSN) to identify the strength and weaknesses.
- Presents a compact discussion about existing research trends to have a real picture of existing approaches, targeted issues, and technological adoption.
- Contributes towards more in-depth insight of the study findings concerning learning outcomes to visualize the clear picture of PA approaches

The remaining sections of the proposed manuscript are organized as follows: Section II discusses the essentials of precision agriculture concerning all standard taxonomies and conventional research-based approaches. Since WSN is identified as upcoming technology and IoT in precision agriculture, Section III discusses various techniques used in WSN in precision agriculture; Section IV discusses the research trend. In contrast, Section V highlights about learning outcome of this manuscript. Finally, Section VI summarizes the overall contribution of the proposed review study and briefs about future work direction in precision agriculture based on study findings.

## II. PRECISION AGRICULTURE

Precision Agriculture (PA) targets improving crop production with the adoption of advanced technologies. This concept deals with improving agricultural management based on various scientific observations [14]. The primary aim of precision agriculture is to construct an appropriate decision-making system capable of optimizing productivity without consuming expensive resources [15]. It is believed that crop production is significantly affected by the terrain features studied in the phytogeomorphological mechanism [16]. The evolution of the phytogeomorphological mechanism is due to the realization that the hydrological factors of farmland are controlled by geomorphic components [17]. The proliferation of various satellite navigation systems has further boosted the adoption of precision agriculture [18]. Adopting such a navigation system helps localize an appropriate location of the agricultural land suitable for production. Such geographic information obtained from satellite navigational system also furnishes spatial information of land concerning actual contents required for cultivation viz. potassium, manganese, pH level, nitrogen level, moisture level, crop yield, etc. [19]. A sensory-based satellite navigation system helps further more data collection, right from a degree of water in the soil to the level of chlorophyll. More granularity can be obtained from hyperspectral imaging in this regard. At present, there are different forms of variable rate technology (e.g., sprayers, seeders) that are used along with satellite images for optimizing the resources [20]. However, the current advances in technologies are more inclined to use sensors planted within the soil. This sensor can directly forward the aggregated data to the user autonomously without any dependency on human interactivity.

The adoption of airborne vehicles is also used in precision agriculture due to their cost-effective nature and does not require specialized skills to make them airborne. Such approaches make use of photogrammetric techniques by using different forms of the camera (for both color and hyperspectral images) are used over airborne vehicles to extract information associated with the field images [21]. The images obtained by this technique can be used for evaluating the different forms of vegetative index [22]. Apart from this, a different form of other information, e.g., the elevation of land, can also be captured by airborne vehicles subjected to various conditions of sophisticated software models for constructing topography [23]. Therefore, a better probability of enhancing crop cultivation can be achieved by studying such a topography map. This information can be used for improving the inputs towards healthy cultivation, e.g., growth regulators, different types of chemicals, fertilizers, water, etc. Therefore, using different forms of technologies in precision agriculture is used to study crop science, accelerate the economics associated with the production, and protect the environment by controlling different possibilities of risk and agricultural footprints.

### A. Standard Taxonomies of Technologies in PA

The novel approaches of agricultural practices are now facilitated by the advent of different technologies in PA. The optimization is now possible for PA for both profitability and productivity based on decision-making and real-time information over the field. The prime targets of the technologies used in PA are mainly to control the agricultural input along with environmental protection. On this basis, it is seen that there are five standard taxonomies of precision farming, including 1) Satellite Positioning System, 2) Variable Rate Technology, 3) Geomapping, 4) Automated Steering System, and 5) Remote Sensing as in (Fig. 1).

In *Satellite Positioning System*, the prime technological contributor is the Global Positioning System (GPS), mainly using data associated with geo-references of production and auto-steer system. The agricultural machines (e.g., tractors) are better controlled with accuracy using GPS inbuilt within the machine. The farming operation is improved when the driver is provided with error-free information with machine movement patterns (Fig. 2).

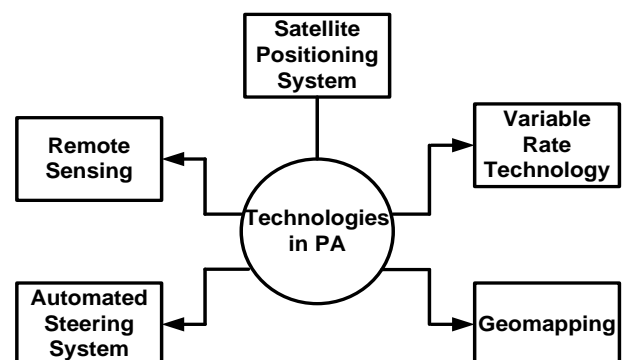


Fig. 1. Standard Taxonomies of Technology used in PA.

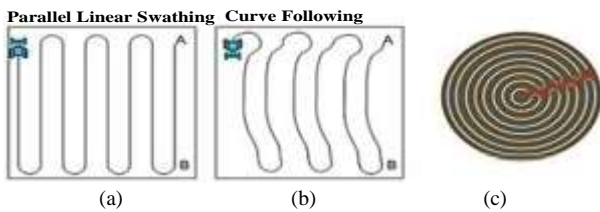


Fig. 2. Patterns of Field Traffic enabled by GPS. a) Linear-Parallel Pattern, b) Curve Pattern, and c) Circular Pattern.

In Variable Rate Technology, the agricultural inputs are controlled by farmers. Adopting this standard technology offers planting density to be optimized while increasing the applicator rate's efficiency towards nutrients and pest protection. This significantly minimizes the farming cost as well as effectively control the adverse impact on the environment. When variable rate technology is integrated with application equipment, the system offers precise information about the field's location and appropriate time for obtaining input for rates corresponding to the region-specific application. Fig. 3 highlights the soil map used for variable-rate technology to find the different nutrients needed in the soil.

In Geomapping and Remote Sensing, sensors are usually used to construct a map with the different crop and soil conditions, e.g., pest, soil pH, type of soil, nutrient level of the soil. Sensors are attached to different machines and vehicles to be dominantly used for creating soil maps. Sensors collect the information from the field and GPS to assess the health statistics of crops and soil. This information is then passed on to a specific location in an area. Farmers can carry out identification of specific events or any significant alteration in the properties of soil. Fig. 4 highlights the mapped field which is used by the sensors built over the agriculture machine.

In the Automated Steering System, the vehicles used in agriculture are involuntarily steered by the navigation system. This technology reduces human-related errors while controlling the movement of the vehicle. It also permits effective management of the field by providing overhead tuning and controlling the machinery based on edge information. The existing system uses differential correction for real-time kinematics to offer accuracy in the form of centimeters. Fig. 5 highlights overlapping factors of auto-steering system and manual machine.

However, to offer higher accuracy for the machinery over the deployed path, installing a specific communication system with a base station is required. A precise point positioning system does not require any form of data communication in the auto-steering system [24]. On the other hand, machinery can also be allowed to be moved using GPS based navigation system.

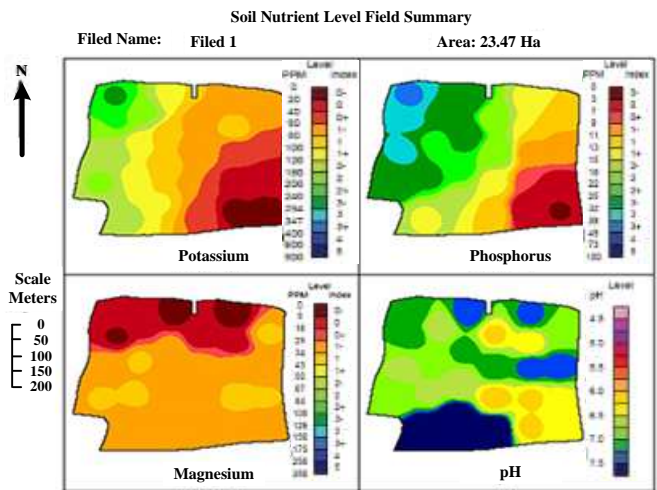


Fig. 3. Usage of Soil Map for Analyzing the Level of Nutrients in the Soil, a) Presence of Potassium, b) the Presence of Phosphorus, c) Presence of Magnesium, and d) the Presence of pH.



Fig. 4. Geomapping and Remotely Sensed Soil Map with its Properties from the Sensor Fitted in the Machine.

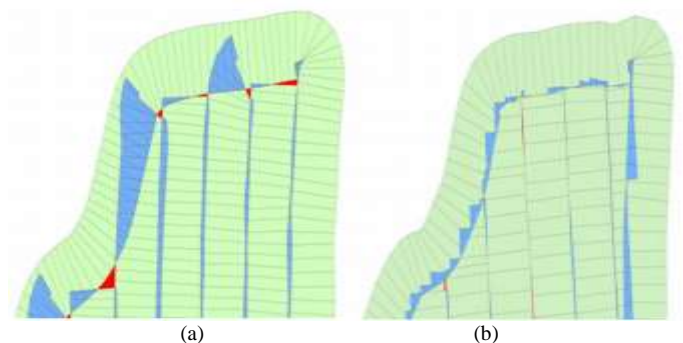


Fig. 5. Automated Steering System. (a) Manual Machine Guided Field Overlapping (Blue), b) Auto-Steering based Field Overlapping.

### B. Review of Studies on Conventional PA Technologies

This section discusses the various research work being carried out towards different standard technologies in PA briefed in the prior section.

- *Satellite Positioning System:* This approach uses two prominent techniques, i.e., GPS (Global Positioning System) and GNSS (Global Navigation Satellite System). It is found that GPS, when integrated with the robotic application, could significantly contribute towards PA. However, the GPS signal's availability could be impacted due to occlusion towards GPS-enabled Real-Time Kinematic (RTK) in farming. This problem is addressed in Levoir et al. [25] by evolving out with a smart rover that uses sophisticated image processing and statistical analysis to perform localization tasks by the rover. Further studies show that integrating GPS with the sensory application could improve the data acquisition with more accuracy (Rodriguez et al. [26]). A prototype was developed for herbicide ballistic technology integrated with sensors and GPS to automate data acquisition. Prototyping-based modeling is evolving in an existing system where GPS is integrated with a micro-electromechanical system. The idea was to offer a precise steering angle of the agriculture vehicle (Si et al. [27]). An unscented Kalman filter did the computation of the steering angle. Existing study towards the adoption of GPS has mainly emphasized achieving better accuracy for the receivers (Dabove et al. [28]). It should be noted that GPS is an integral section of GNSS with variable ranges of transmission frequency. Literature has also studied the adoption of GNSS towards precision farming (Marucci et al. [29]); however, it does not work effectively in hilly regions. There is still a better possibility of improvement when the GNSS system is combined with different technologies to overcome this issue. GNSS is also found with various artifacts, e.g., multipath error, atmospheric interference, satellite configuration (Stombaugh et al. [30]).
- *Variable Rate Technology:* This kind of technology is used for managing crop production specific to the farming region (Rubio and Mas [31], Ayaz et al. [32]). The recent work carried out by Nordblom et al. [33] have used variable rate technology in PA focusing on nitrogen fertilizer input. The study integrates such application with Geographic Information System (GIS) and rainfall data to determine the reason for waterlogging in a specific geographic area. The study has also simulated data distribution of financial risk in predictive mode to signify variable rate technology. A similar direction of work is also carried out by Steffani [34], where a statistical model is used for analyzing lint. The idea is to emphasize adequate control over the environment and maximization of profit, as discussed in the study of Kweon et al. [35]. A study carried out by Colaco [36] has analyzed the impact of this technology on yield, the fertility of the soil, and fertilizer consumption. The study outcome shows that

the variability factor can successfully achieve increased production without much dependency on excessive fertilizers. A study carried out by Nawar et al. [37] highlights that this technology, when integrated with region delineation management approach then it could lead to better efficiency in farming in contrast to application with uniform rate. At present, the implementation of variable rate technology is further boosted by the proliferation of novel solutions by manufacturers of farming equipment. The work carried out by Thomasson et al. [38] has discussed the frequently adopted manufacturers using crop sensors associated with this technology of nitrogen fertilizers. The study also suggests using automatic differential harvesting as another promising actuation process for promoting the harvesting process over the field. Adoption of differential harvesting process is reported in Sethuramasamyraja [39], where infrared sensors were used over vineyards to analyze the quality of graph based on anthocyanin present in berries. The implementation is carried out as follows viz. i) anthocyanin contents of the grapes are sensed, ii) a certain level of the threshold for this content is considered to generate a quality map for this data, and iii) forwarding the generated map to the user (harvester).

- *Geomapping and Remote Sensing:* There are various forms of Geomapping and remote sensing approaches used towards PA (Kim et al. [40]). This approach leads to the generation of agroecological zones where different attributes are subjected to analysis (Muthoni et al. [41]). The imageries obtained from satellite images are studied for boundary delineation using feature extraction and image segmentation method (North et al. [42]). The existing study has also witnessed increased adoption of Sentinel-2 data in PA (Sharifi [43]) for analyzing nitrogen usage. Nitrogen is the essential input for PA has also been studied by Yao et al. [44] using an active crop sensor. Apart from these conventional approaches, the advanced integrated approach of drone technology and Internet-of-Things are also deployed in precision farming (Uddin et al. [45]). Another interesting study carried out by Xu et al. [46] has used data from cameras and terrestrial laser scanning to monitor crop health in PA. The majority of the approaches associated with Geomapping and remote sensing are associated with capturing the field image followed by performing analysis. Proximal sensing is most recently integrated with remote sensing from multiple sources to study the leaf area index (Asad et al. [47]). This work connects the health statistics of the leaf with the topographical map of the earth. This model has three distinct modules viz. i) data processing with semantic segmentation of ground images, ii) training using deep learning model, and iii) performing prediction. The study outcome suggests that it is capable of performing better prediction even with images with low resolution.

The current study has also discussed spectral feature usage, where the prime challenge is to address the issues associated with data collection and training. This issue is addressed in Ashourloo et al. [48], which carried out a comparative study of different variants of spectral bands. The outcome shows support vector machine to be useful for large scale of data using time-series approach. However, such an approach is less utilized for computing as well as predicting yield. This problem is addressed in the work of Fieuzal et al. [49] considering leaf area index. The data considered for this analysis is from synthetic aperture radar, where multiple sources are considered for analysis for evaluating a crop's dry mass. A similar study is also carried out by Zalite et al. [50], where time series is considered. The study limits its evaluation from the wetlands, which is another research challenge found in current times. The prime cause of this challenge is spectral similarity and the degree of heterogeneity involved in landmasses. A study to address this challenge is seen in Hemptararasuwan et al. [51], where quantitative analysis is carried out over historical data. The study implements a classification approach by combining three standard approaches, i.e., Mahalanobis distance, maximum likelihood, and decision tree. The outcome shows a decision tree to offer better classification performance. A study concerning leaf area index is also carried out by Pan et al. [52], where water content information is also used for modeling. The emphasis on water attributes was also seen in the study of Patil et al. [53]. The current study also claims that useful classification can be carried out using a PA's deep learning approach (Sun et al. [54]). From an approach perspective, the random forest has also registered itself to be assisting in the classification of satellite images of land (Zafari et al. [55]). In such an approach, a unique classifier is designed for constructing a similarity kernel. There are also studies where correlated factors, e.g., development stage and fractal dimension, are studied (Shen et al. [56]). Such study mainly explores different factors that affect production, i.e., soil background and different farming practices. A unique study carried out by Dong et al. [57] has used chlorophyll index for assessing the internal processing of crops in PA. The study carried out over simulated environment shows the potential linear correlation among different variants of vegetation index. The study contributes towards the impact of red edge reflectance associated with chlorophyll during

photosynthesis. Such models emphasize the internal processing of plant nutrients but do not focus on balancing them. Balancing the nutrient demand is essential when it comes to the management of agricultural land in PA. Such an approach was discussed by Gimenez et al. [58], where remotely sensed data is integrated with the model for land management. The study contributes towards yielding useful information associated with farm practices and balancing the nutrients demands on it. Existing studies have also evolved with a unique clustering approach on its features over the standard scale to assess the monitoring of crops in PA (Yuzugullu et al. [59]). The work carried out by Ali et al. [60] has developed a model for remote sensing where multitemporal attributes have been used for evaluating biomass. The study has used an integrated machine learning approach where neuro-fuzzy logic, neural network, and linear regression have been used over remotely sensed data to extract biomass estimates.

- *Automated Steering System:* The research work towards this approach is mainly associated with developing agricultural machinery to give them a direction towards its orientation. The existing system has used fuzzy logic (Duan et al. [61]), manual priority (Fu et al. [62]), renewable energy (Ghobadpour et al. [63]), proportional integral derivative (Liu et al. [64], Yin et al. [65]), designing electro-hydraulic circuit (Mungwongsa et al. [66]), field robots (Gonzalez-de-Santos et al. [67]), and automatic pilot system (Wang et al. [68]). The idea of the majority of such implementation orients about developing a system that can assist the agricultural machinery to accomplish specific objectives while farming. It reduced iterative human efforts and can undertake a specific task that is not feasible for humans to carry out for a given constraint of extensive agricultural lands. However, most of the approaches are associated with hardware-based development, and less advancement is done on the computational model.

Table I highlights the summary of the most significant conventional PA-based approaches studied above-concerning issues, methodology, advantages, and limitations connected to them.

TABLE I. SUMMARIZATION OF THE EXISTING STUDIES IN PA [SPS: SATELLITE POSITIONING SYSTEM, VRT: VARIABLE RATE TECHNOLOGY, GRS: GEOMAPPING AND REMOTE SENSING, ASS: AUTOMATED STEERING SYSTEM

	Author	Problem	Methodology	Advantages	Limitation
SPS	Levoir et al. [25]	High complexity localization, occlusion of GPS	Autonomous GPS-based rover vehicle, image processing, statistics	Higher accuracy	Lacks standard benchmarking
	Rodriguez et al. [26].	Data acquisition	Prototyping by integrating sensor and GPS	Assists in differential data acquisition	Lacks comparison with the existing system, does not consider signal unavailability in GPS
	Si et al. [27]	Calculating steering angle of farming vehicle	Prototyping with gyroscope, unscented Kalman filter, GPS	Higher accuracy	Involves higher computation to compute steering angle
	Dabove et al. [28]	Receiver effectiveness with GPS	Discussion of different variants of GPS-based receiver and antenna	Simplified discussion	It does not conclude the best performing receiving in adverse environmental condition
	Marucci et al. [29]	Effectiveness of using GNSS	An experimental model combining RTK with GNSS	Improved accuracy of trajectories	It does not deal with heterogeneous environments of farming
VRT	Nordblom et al. [33]	Search for the reason for waterlogging	Simulation-based study	Simplified probability model, risk analysis	Region-specific study
	Steffani [34]	Risk analysis of cotton production	Statistical modeling	Simplified risk analysis	Region-specific study
	Kweon et al. [35]	Testing of organic matter of soil	Prototyping, field study, sensors, linear regression (multivariate)	Comprehensive analysis	Computational complexity is higher and not addressed
	Colaco& Molin [36]	Fertilization of citrus	Discussion of variable rate fertilization, yield map	Reduction in input,	Study-specific to region and crop
	Nawar et al. [37]	Zone delineation management	Discussion of various techniques and their contribution	Pin-pointed findings to prove increased yield	It does not discuss the inclusion of high-end analytics
	Thomasson et al. [38]	Automation technologies	Discussion of robotics and automation in PA	Discusses the importance of robotics in PA	It does not discuss the significant approach
GRS	North et al. [42]	Boundary delineation	Image segmentation, feature extraction	Higher suitability towards the classification of land	Area-specific study
	Uddin et al. [45]	Health monitoring of crop	Drone with IoT, dynamic clustering of data	Wide applicability, cost-effective	Hypothetical model
	Xu et al. [46]	Health monitoring of crop	Scanning with terrestrial laser, cloud data	Higher precision	It does not support heterogeneous modeling
	Asad et al. [47]	Index area mapping of leaf	Deep learning	The prediction does not demand high image resolution	Iterative mechanism,
	Ashourloo et al. [48]	Data collecting during remote sensing	Time-series, support vector machine	Assists in involuntary crop mapping	Training time is higher.
	Fieuzal et al. [49]	Lack of well-sampled data in time series, analysis of leaf area index	Combined analysis of satellite data and agrometeorological data	Effective simulation of temporal feature	Study restricted to specific crop (sunflower)
	Hempattarasuwan et al. [51]	Wetland classification	Integrated classification approach	Decision tree found to offer higher accuracy	This leads to computational complexity
	Pan et al. [52]	Analysis of multispectral data	Integrating leaf area index and water content, neural network	Good accuracy	It does not include the environmental uncertainty factor
	Patil et al. [53]	Water productivity assessment	Energy balance for surface	Lower predictive errors	Specific to desert farming
	Zafari et al. [55]	Classification of land	Randomized tree, kernel	Able to solve high-dimensional data	Study-specific to support vector machine
	(Shen et al. [56]).	Crop type classification	Deep learning	Reliable map generation	Does not address the computational complexity of training.

	Dong et al. [57]	Assessing vegetation index	Algorithm for extracting reflectance of active chlorophyll	Capable of assessing the impact of vegetation impact	Study-specific to chlorophyll
	Gimenez et al. [58]	Classification of land usage	Integrating remotely sensed data with a model of land management	Increasing accuracy in the information of land usage	Increased processing time
	Ali et al. [60]	Biomass estimation	Machine learning	Enhanced estimation approach	Accuracy depends upon the amount of trained data, presence of anomalies from the satellite signal
ASS	Duan et al. [61]	Real-time control on machinery	Fuzzy Logic	Improve accuracy in steering	It depends upon ruleset construction
	Fu et al. [62], Liu et al. [64], Mungwongsa et al. [66]	Automated steering	Electro-hydraulic steering, sensor	Reduced response time	Lacks smart feature
	Ghobadpour et al. [63]	Automated steering	Renewable energy system	Discusses increasing trend	It does not highlight the effective approach
	Gonzalez-de-Santos et al. [67]	Intelligent farming	Robotics	Discusses autonomous robots	Research gap not identified
	Wang et al. [68], Yin et al. [65]	Autonomous robots	Embedded system	Good accuracy	No benchmarking

### III. WSN IN PRECISION AGRICULTURE

With the advent of the dominant adoption of sensors, current research work towards PA has been revolutionized more toward incorporating smart sensing. One of the prime motivations towards this research trend is the increasing awareness of Internet-of-Things (IoT), where sensors are integral. IoT is one dominant research topic for improving agricultural yields (Kour and Arora [69]). It has contributed towards opening avenues for smart farming and PA, although there is some dominant research gap (Kour and Arora [69]). In this aspect, various forms of sensors have also been investigated towards PA, where it is found that support vector machine and random forest are dominant classification approaches (Kamath et al. [70]). Apart from this, there is also dedicated research work being carried out where machine learning approaches are claimed to optimize IoT performance in PA to facilitate predictive operation for farming.

With the adoption of various sensors for capturing field information, the data are forwarded using various IEEE standards of the family (e.g., 802.15.4/11 as seen in the work of Kone et al. [71]), which further forwards it to the gateway node and then to cloud where the application of analytics resides (Ahmed et al. [72]). The study offers some specific information that was not found in conventional PA-based approaches, e.g., i) energy being one of the practical constraints of using sensors in PA, and ii) routing and topology is another essential operation, which is also challenged in adverse environmental condition. There are various MAC protocols in wireless sensor networks [72], but they do not combine to ensure downlink scheduling, multi-hop decisions, heterogeneous duty cycles, and traffic adaptive. To perform a full scenario to capture environment information of farming process, all this characteristic is demanded in IoT. The adoption of IoT technology in PA is depicted in Fig. 6. The figure shows how sensor devices, gateways, and WiFi technology integrated with cloud infrastructure enable IoT-PA ecosystems. There are basically several wireless sensor nodes deployed in the farm and agriculture fields in rural regions. The sensor nodes capture significant events related to agriculture and send them to the

cloud computing system via WiFi and gateway-based networking systems. The sensed data collected to the cloud is further stored and processed by an analytics engine and fog networking to enable framers managing farms to boost the quality and quantity of products and optimizes the cost associated with human labor required. However, in this scenario, the biggest impediment is a trade-off concerning supportability and efficiency between the protocols in IoT and Wireless Sensor Network (WSN).

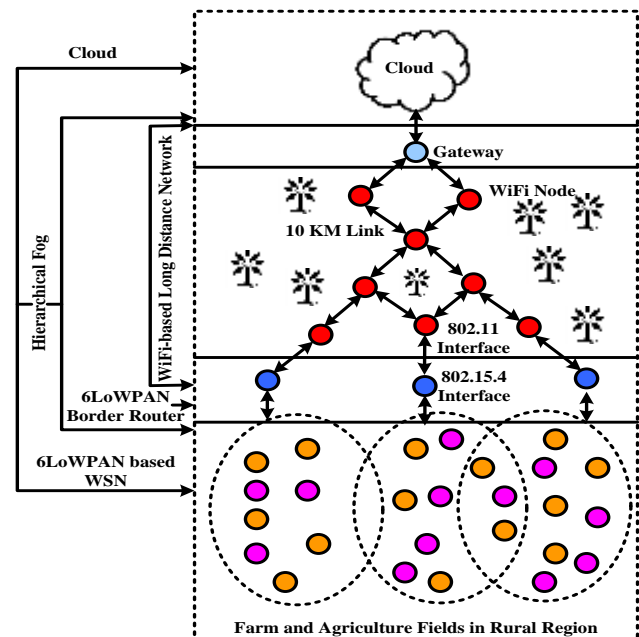


Fig. 6. Adoption of IoT in PA.

The most recent study carried out by Gulec et al. [73] has discussed improving the lifetime of WSN focusing on PA in a distributed environment. The study uses connected dominating sets as a backbone of communication in WSN considering harvester and regular sensors in farming. The study outcome is obtained from both experimental and simulated versions stating that the proposed system is energy efficient. Existing research

shows certain dedicated attempts to model WSN in PA with uniform sensory node distribution over the farming area. The work carried out by Bacco et al. [74] has developed a channel model that is used by the ground sensors to perform data transfer. However, the emphasis was more on the usage of IEEE standards and less on WSN. Adopting the heterogeneous sensor network is witnessed in Sylvian et al. [75] and Kaiwartya et al. [76]. In this work, prototyping is carried out using different sensors to capture different information associated with farm fields and crops.

Further, WSN also claims to offer a decision support system for facilitating water usage (Khan et al. [77]). A prototype is designed where the temperature is used for environmental monitoring in PA. The study analyzes the consumption of current while functioning over different degrees of temperatures. Importance over plant water is another investigation in the existing system, an essential part of the leaf sensing system in WSN with PA. The current study claims that the adoption of backscatter-based sensor nodes could enhance the PA performance from the perspective of power-saving (Daskalakis et al. [78]). The study has also used Morse code, which is computationally cost-effective for carrier signal modulation. Focus on power saving can also be implemented using non-orthonormal multiple access in WSN (Hu et al. [79]). The study outcome shows that this mechanism significantly controls outage probability and the rate of summed data.

The majority of the existing studies emphasize estimating soil parameters in PA; however, the modeling attributes are less emphasized towards power. A study on such issues is carried out by Estrada-Lopez et al. [80], where a WSN topology is constructed using both cloud and IoT considering soil parameters. The data analysis is carried out by an artificial neural network followed by using a unique power management scheme. Apart from the terrestrial application, the adoption of WSN is also carried out over the underground ecosystem. Salam et al. [81] have developed such a system to model channel impulse. The study has also analyzed various time-domain attributes, e.g., gain in multipath power, channel capacity, delay, etc. A study on a similar direction towards the underground ecosystem is also investigated by Castellanos et al. [82], where soil parameters are collected using a narrow-band communication scheme of Long Term Evolution (LTE). The study uses unmanned aerial vehicles to collect data from underground sensors over the potato crop field. Another study

of the underground ecosystem is carried out by Sambo et al. [83], where a path loss model is presented along with predictive framework development using a complex dielectric constant.

Deployment of WSN in PA was also claimed to enhance productivity by using dataloggers and actuators (Lozoya et al. [84]). The current study of WSN is also focused on incorporating intelligence in the process of irrigation in PA. The work carried out by Jamroen et al. [85] has developed an irrigation scheduling mechanism using fuzzy logic in WSN. The outcome witnessed an increase in crop yield. The current study also discusses the usage of WSN for assisting in localizing in PA. Sahota and Kumar [86] have implemented a model where the received signal strength has been used for distribution over WSN. The study develops a node localization model considering distance propagation invarious degrading effective over the signal considering fading and path loss model. The study contributes to predicting loss in nitrogen. A similar received signal strength-based approach for assisting in localization has also been carried out by Abouzar et al. [87]. This study has used a spanning tree for developing belief propagation.

A unique concept towards promoting energy harvesting in PA is discussed by Konstantopoulos et al. [88]. According to this study, the electric potential produced within a plant is used as a power source for WSN. The study uses nonnegative matrix factorization to process this electric potential signal. From the viewpoint of power saving, it is also found that data registers' frequency plays a crucial role. The energy-saving in WSN can be facilitated using this data register frequency variation to impact PA (Santos and Cugnasca [89]). Another essential factor to be considered is the presence of partitioned sensors in PA, which leads to disruption in the network. The work carried out by Maheswararajah et al. [90] hypothesizes that the presence of such nodes leads to noise in the measurement. A Kalman-filter-based optimization strategy is developed to restore such nodes. Existing literature further hypothesizes that monitoring environmental values is essential when deploying WSN in PA. The work of Kampianakis et al. [91] has presented a prototype that employs the networking principle of sensor nodes (especially modulation of analog frequency) along with software-defined radio.

The summary of the practical approaches in WSN in PA is tabulated in Table II.



TABLE II. SUMMARY OF WSN-BASED PA APPROACHES

Author	Problem	Methodology	Advantages	Limitation
Gulec et al. [73]	Network lifetime	Connected dominating sets, solar energy harvesting	Reduced energy consumption	Lacks considering different resource retention
Bacco et al. [74]	Coverage and Connectivity	Channel model	Simplified design	Only focus on IEEE 802.15.4 usage
Sylvian et al. [75], Kaiwartya et al. [76]	Health monitoring of crops	Multi-sensor prototype	Effective field measurement	Lacks benchmarking
Khan et al. [77]	Water utilization in the farming area	Decision support system	Higher accuracy	does not consider energy factor
Daskalakis et al. [78]	Plant water monitoring	Backscatter	Power saving	Cost is still incurred in the usage of multiple equipments
Hu et al. [79]	Enhancing Network lifetime	Non-Orthonormal Multiple Access	Reduces outage probability	Not applicable for the sparse network.
Estrada-Lopez et al. [80]	Power management, soil parameter estimation	Artificial neural network, cloud, IoT	Enhanced reliability and better system performance	The study uses a specific sensor node, which demands more training for accuracy.
Salam et al. [81]	Underground channel development in WSN for assessing soil health	Assessing impulse response	Approach with practical constraints, reduced energy depletion, reduced delay	The routing aspect is not considered in WSN
Castellanos et al. [82]	Computation of link quality	Narrow-band communication, path loss model	Applicable for both under and above ground operation	It does not ensure scalability owing to the defined range.
Sambo et al. [83]	Underground monitoring in PA	Path loss model, predictive	Higher accuracy	Performs a highly iterative operation
Jamroen et al. [85]	Irrigation scheduling	Fuzzy logic	Reduces energy consumption, increased crop yield	Increased dynamic attributes may cause an increase in fuzzy rules
Sahota and Kumar [86], Abouzar et al. [87]	A crop network architecture in PA	Received signal strength, maximum likelihood	Resistive against multipath fading	Cannot sustain over intermittent links in WSN
Konstantopoulos et al. [88]	Energy harvesting	Nonnegative matrix factorization	Highly cost useful energy source	Workability over extensive, dense, and uncertain network is not evaluated
Maheswararajah et al. [90]	The partitioned node in WSN	Kalman Filter	Reduced error rate	Error computation is resource-dependent and hence not scalable for large networks.
Kampianakis et al. [91]	Environmental monitoring	Prototyping, software-defined radio	Higher precision	It demands excessive power consumption

#### IV. REVIEWING RESEARCH TREND

From the perspective of the global trend, it is seen that IoT, along with the inclusion of software and different variants of sensing technology, is going to minimize the skilled labors in agriculture in the coming days. The global market is not consistently evolving with the rise of real-time kinetic technology, remote sensing technology, networking, variable rate technology, robotics, and fertilizers and sprayer controllers.

##### A. Trend in PA Research

The last decade has witnessed approximately 1710 research papers in PA approaches while only 230 are found to be journals in IEEE Xplore digital library. A nearly similar trend is found in other reputed publishers like ACM digital library, Springer, ScienceDirect, and Elsevier. There are very few studies towards automated steering systems, while more studies are populated in the adoption of satellite positioning systems (GPS, GNSS). Not much work is carried out towards variable rate technology. However, some potential work in a

large number has been carried out towards remote sensing and soil mapping. More inclination is seen towards remote sensing approaches using hyperspectral images or other equivalent forms of images from an unmanned flying object (drones). However, the trend is more on adopting a single crop field is extensively more investigated, and multi-crop land is less found in consideration, which could impede upcoming research work. Agriculture 4.0 is an upcoming standard for automating PA; however, studies show few implementations associated with such upcoming standard formulation. Image processing remains the dominant approach, and its adoption is consistently increasing; however, there is a shift of this approach with data-centric technologies in IoT.

##### B. Trend in Technological Adoption

The present scenario of implementation in PA is highly scattered. More work is carried out using prototyping, and less mathematical or computational modeling is noticed. Adoption of machine learning or artificial intelligence is also found to be less prominent in this aspect. Although machine learning has been used in existing studies, it is not evaluated from its

computational complexity. The engineering area, e.g., robotics, embedded system, machinery compilation, etc. is more focused, limiting investigation strength and giving less exposure to unknown challenges in PA. Adopting IoT and WSN has just started its research work, and it has more way to go to achieve its state of maturity as a research standard model. The development of a test-bed for analyzing farming data is another inclusive research trend in PA.

### C. Trend in Target Issues

The issues mainly considered in the existing system in PA are mainly associated with environmental monitoring. The existing research trend is also to consider a specific issue connected with a specific crop, making the model heavily case-specific and less applicable to different environments. Data acquisition is another target issue considered in the existing research trend in PA. Different techniques have been carried out towards acquiring data. However, less emphasis is offered to analyze this collected data. The trend towards analytics over multi-crop land is less found. Adopting sensors integrated with different networking principles also assists in data acquisition; however, there are various open-end challenges associated, e.g., non-inclusion of the energy model makes such a solution limited to theoretical concepts.

## V. DISCUSSION AND PERSPECTIVE

Based on the observation being carried out towards conventional approaches used in PA and the upcoming adoption of WSN in PA, it is noticed that there are various concluding remarks associated with the overall techniques used in PA. This section briefs about the learning outcomes of the proposed review work as follows:

- *A tradeoff between Demands and Available Technology:* A closer look into the available approaches shows that PA needs to consider multiple attributes simultaneously, e.g., soil health, plant-related features, surrounding environment, and weather. There are many more sub-attributes for this core attribute, which require equal attention for improved crop cultivation and environmental risk reduction. All the existing approaches using a conventional approach or WSN based approaches use only a limited number of such attributes in modeling its PA. On the other side, there has been an immense advancement in prototyping as well as computational modeling. However, prototyping is the most dominant approach in PA in existing studies. Hence, the demand to offer productive PA performance is immensely more which are not found to be considered while modeling with existing technological advancement.
- *Lack of Uncertainty-based Modelling:* There are various attributes like crop health, rainfall, temperature, soil health, etc. they are stochastic. Existing approaches focus on modeling predefined ecosystems, which is more or less impractical than real-world scenarios. There is a various uncertain scenario that could develop either using conventional or WSN based approaches, e.g. rate of energy depletion, incoming streamed data, mobile of machinery, occlusion in GPS-based data, etc. Until and unless such uncertainty conditions are not included in the modeling, the outcome may eventually result in outliers. Apart from this, various studies where machine learning has been used do not consider this, leading to its solution inapplicable to real-time application.
- *Use Case Specific Study:* Almost all the existing PA approaches have considered a specific use case of crop or study environment (e.g., soil health, water, temperature, etc.). On the other side, the conventional study approach has focused on the adoption of specific machinery. The modeling is carried out considering a specific form of crops using any of the approaches in PA. This means that there is no generalized algorithm to solve a similar problem when environmental variables change. It also incurs more cost when it comes to deploying commercial products and their adoption. It is only cost-effective of a simplified model (or product) that can address multiple PA problems altogether.
- *Less Emphasis over Routing:* Routing or deploying a communication protocol is significant using the larger farming area with challenging communication scenarios (e.g., forest, terrain, etc.). It is already observed that the adoption of the hybrid approach is the most effective one to mitigate the limitation of single-approach. For example, GPS integrated with sensor nodes or drones could offer more effective data capture than considering any of them. This also means that there is a good possibility of hybridizing different types of machinery and different nodes to facilitate an effective data transmission in PA. However, this challenge can be addressed if a unique routing protocol is designed and developed for such a scenario. No studies are being carried out in evolving a novel routing scheme in PA; instead, it reuses the adopted techniques' routing scheme. This also offers more impediments towards data transmission when the farm environment is subjected to priority-based data transmission or exercising specific time-critical applications.
- *IoT and WSN still in the Nascent Stage:* IoT is slowly making its entry from the roof of research and development to the commercial world. Apart from this, the study shows that most PA approaches have a deployment of sensor nodes for soil mapping, remote sensing, etc. (conventional approach in PA), but they do not have a deployment of WSN, which makes a network of sensors. With the inclusion of automation standard 4.0, there is a need for smart farming using IoT, which is still under development. Apart from this, WSN is an integral part of IoT. However, there has been immense work towards addressing multiple problems in WSN in past decades, and their solutions are not directly applicable in IoT. There is always a tradeoff between IoT and WSN with the inclusion of IoT based routing scheme and WSN based routing scheme that requires smooth integration. Hence,

current approaches in WSN on PA are significantly less and insignificant in contrast to conventional PA approaches.

- *Lack of inclusion of Resource:* Sensor nodes of any form are characterized by the limited capability of processing as well as they have limited availability of resources too (e.g., memory, channel capacity, energy, etc.). None of the existing studies where WSN is considered in PA has any inclusion of novel resource management model exclusively focusing on constraints associated with PA's farming environment. Without the inclusion of the resource factor, modeling any solution will be more impractical.
- *Few Studies towards Optimization:* By optimization, it can represent a technique that offers increased performance yield with low inclusion/dependencies of resources. Machine learning has been used for this purpose to some extent. At present, many optimization-based approaches fit on solving various problems associated with PA. A closer look into the existing system also shows that it does not ensure computational cost-effectiveness in its algorithm. Hence, the adoption of appropriate optimization techniques is highly demanded.

## VI. CONCLUSION

The manuscript discusses the PA approaches and techniques that are mainly associated with implementing a management scheme towards facilitating effective responses toward crops, measurement, and observation towards animals and fields. Adoption of PA leads to enhanced yields in the crop, cost reduction, and process input optimization. However, there are various challenges associated with it. There is an inclusion of higher initial capital to implement PA in real-time, and such investment is carried out for long-term plans. In order to reach the PA implementation maturity stage, several years may be consumed prior to even possessing adequate data to implement even the conventional approaches completely. The final challenge in PA implementation is its data aggregation followed by an analysis, which could be an extensively demanding task. Based on the presented findings of existing research work, it could be just said that effective implementation of PA demands i) precise management, ii) identification and adoption of appropriate technology, and iii) data.

1) *Overall summary:* The essential findings of the proposed study are summarized as follows: i) existing approaches of PA has an increasing concern over interoperability of different innovative systems and tools, ii) adoption of PA by ordinary farmers will be a big task as the technologies involved in it are highly advanced and require a thorough knowledge of it, iii) despite various studies using IoT, narrowband, GPS, WSN, etc., coverage and connectivity in rural areas will be a potentially tricky task, iv) An appropriate PA implementation leads to generate a massive score of big farming data which is impossible to analyze from a single data point in the crop field. With the increasing adoption of multi-crop land, there will be

massive growth of data and understanding the significance and priority of such data will be near to impossible for average farmers in existing times, v) IoT and WSN is the most promising technology in PA, but adoption of current schemes only induces scalability problems along with troublesome configuration issues, vi) there is a lack of mathematical modelling seen in the existing system using WSN, which has better future scope.

2) *Future work:* The future direction of work will consider adopting IoT and WSN, which is the most demanding upcoming technology for reshaping the existing system to Farming 4.0. In this context, the next work is to design and develop an IoT scenario with multi-crop land powered by heterogeneous WSN. The focus will be first to include all real-time constraints, e.g., energy, coverage and connectivity, resource management of the sensors. The secondary focus is to formulate a novel routing scheme that offers flexibility, scalability, and resource efficiency. It is also necessary to perform the complete modeling using the computational model, considering its applicability to practical world scenarios. The inclusion of multiple challenging test-bed and an effective validation technique could further offer more reliability to PA's upcoming solution.

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