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GIS Systems for Precision Agriculture and Site-Specific Farming

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5.1 Introduction

Precision agriculture (PA) is a way to control farms that use statistical analysis to ensure that vegetation and soil receive the right nutrients needed for maximum fitness and productivity. The goal of PA is to make sure profitability, sustainability, and environmental concerns are satisfied. Satellite TV for farming, or web-based concrete crop control, is a farming control concept based on detecting, quantifying, and responding to differences in vegetation between fields (Alahi et al., 2018).

PA is a current and sustainable technology that offers possibilities to optimize productivity and decrease natural resource strain. This generation primarily focuses on integrating the unique agricultural understanding of farmers with features of geographical information system (GIS), global positioning system (GPS), remote sensing (RS), and statistics generation (Akkaş & Sokullu, 2017). The use of PA is revolutionizing farm management and

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reducing agriculture's dependence on harmful chemicals. It is changing people's perspectives on how to farm. Currently, transparency is increasing to reduce harmful chemical use. The use of diversified methods and approaches in agricultural production is allowing it to be more sustainable and safer while causing less harm to the environment. PA is essential for achieving a good result. The control of variability rests at the core of Precision Farming (PF). The generation might be new in India, but the notion of precision control is not. In Indian agriculture, soil conditions, fertility, moisture levels, and so on differ tremendously between fields. Various factors within fields are responsive to unique types of inputs and cultural practices in their respective regions. It is likely that the PF generation that has been thoroughly adopted by developed nations will not be followed in Indian farming structures because of Indian socioeconomic circumstances differing from those of developed nations. India's agriculture continues to face challenges in relevance and adaptability (Bhanumathi & Kalaivanan, 2019b). An important use of geospatial technology could be in PA, according to a recent literature review.

5.2 Literature Survey

5.2.1 Geographic Information System Role

GIS is a machine-based framework for gathering, preserving, interpreting, analyzing, planning, and visualizing spatial data. GIS portrays a closer perception of information for identifying collaborations, designs, and situations that help individuals make more informed decisions in their daily lives (Adeyemi et al., 2017). A GIS software program is largely used to maintain datasets and integrate PA information via remote sensing, as well as to provide many options for analyzing geospatial information. There are numerous modern GIS programming languages combining raw materials, such as maps, base maps, imagery, spreadsheets, and features, freely standardized by many standards like GeoMedia, OpenStreetMap, ArcGIS, GRASS GIS, and QGIS. In addition, it is embedded with publicly available tools for tackling difficult situations (Barik et al., 2018). Rather than providing the user's location, the GPS displays the user's altitude, longitude, and latitude, making it ineffective for finding a place. GIS, on the other hand, uses a computerized tracking process to provide information about where you are on a map. Moreover, the topography surface can be viewed in two-dimensional and three-dimensional modes. In the process, a GIS method is combined with GPS, producing important information about data transmission locations and satellite imagery mapping to the associated farmer's enrolled cropland.

5.2.2 Geospatial Technologies for Precision Farming

The common geospatial technologies are (i) remote sensing, which is the collection of images from space or from camera and sensor systems in an aircraft (Bhanumathi & Kalaivanan, 2019a). There are several satellite communication picture suppliers that develop images with one meter or key characteristics. (ii) The GPS, a satellite network operated by the United States Department of Defense. It provides a precise unit vector to military users and civilians with the appropriate receiving devices. In a few years, a parallel European program known as Galileo will be active, and a Russian network is operating, but it is limited (Bhardwaj et al., 2016). (iii) GIS stands for Geographic Information

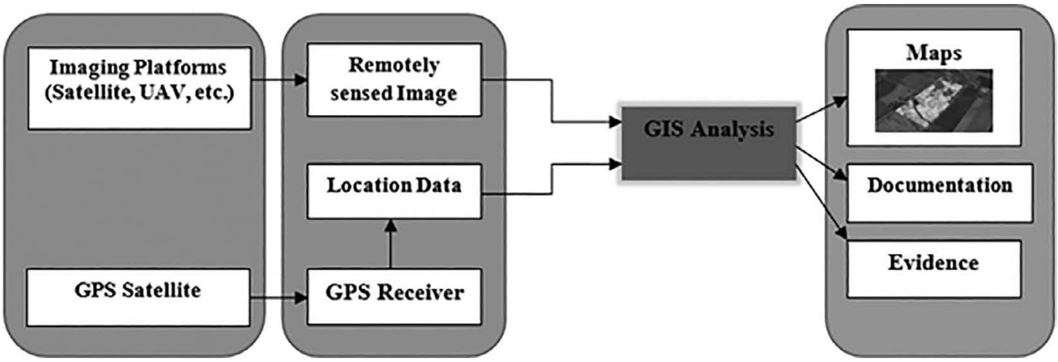

FIGURE 5.1
Geospatial technologies.

System, which is a structure for capturing, analyzing, storing, organizing, and presenting various forms of geographical and spatial data. For any other type of information, GIS uses space and time as the important variables. Figure 5.1 explains the geospatial technologies.

5.2.3 Remote Sensing for PA

Remote sensing can be defined as the process of gathering data from non-contact measurements of scattered or generated radiation from a particular substance (Campos et al., 2019). Reflection and radiation are two properties of the item that are commonly used for remote sensing. In addition to the physical and chemical characteristics of the specific object, the geographical environment, such as leaf moisture, chlorophyll content, and temperature, influences signal reflection or emission from the object. Chlorophyll, which is a chemical substance found in plants, releases radiation that is inversely proportional to the absorption of infrared radiation (Fang et al., 2018). Multispectral images are used to measure emitted signals at various levels including Green Blue Red (GBR), Near InfraRed (NIR), and Short-wave Infrared (SWIR). The infrared, green, and red indices are frequently used to determine estimation methods in agriculture. The Normalized Difference Vegetation Index (NDVI) Index is a standardized method for calculating vegetation index (Foughali et al., 2018). These indicators are used to analyze specific properties such as organic manure, LAI, crop count, moisture content, staple crops, and water level. Chlorophyll content in agriculture is very sensitive to changes in the red and green spectrum (Hammoudi et al., 2018).

For example, plants that produce high amounts of chlorophyll reflect more blue and red spectrum light than ultraviolet or green spectrum light. On the other hand, the high red frequency reflects less chlorophyll. The study of optical to infrared signal transduction can provide information on the cellular architecture of plants and can therefore be used to measure stress and production. This spectral range has a better response to stress due to changes in chlorophyll concentrations, and it also calculates the LAI more accurately than the red and green ranges (Im et al., 2016). Satellite-based platforms and ground-based platforms can both be used for satellite data.

The ability to determine spatial patterns of crop yield, N stress, salinity, soil temperature, potassium, calcium, phosphorous, carbon, moisture, soil pH, water stress, and soil organic matter (Srinivasan et al., 2019) is essential with earth remote observation, also known as local satellite data, which is when IoT devices are mounted to a tractor, sprayer, or other pieces of farm equipment. Sensors are used to control the agricultural production process, such as irrigation, fertilizer, and insecticide. Remote earth observation is less impacted by weather and is a better option than cloud satellite data because of its less weather-dependent characteristics. López-Martínez et al. (2018) reported a method for analyzing earth's spatial data that used a linear motion irrigation system with six thermal cameras and a rolling radar station to detect aerial temperature and agricultural dryness. With the data gathered, the grower was able to open the irrigation actuator.

The following are some examples of surveillance applications in agriculture: (i) analysis of the cropping (Mulla, 2013) method; (ii) agriculture dryness evaluation and tracking; (iii) soil analysis and tracking; (iv) controlling water management; (v) assessment and controlling the agricultural area; (vi) frequency prediction; and (vii) pest and diseases diagnosis The following are the constraints of remote sensing in agricultural production:

1. The sensor's simultaneous monitoring of the crop's reflection radiation generates different spectral confusion. Figure 5.2 shows the remote sensing process in PA.
2. Scaling concerns arise as a result of the inadequacy of the relationship between the real consideration and distant sensing data, and it also provides insufficient information for analyzing past data.
3. Low precision in images obtained from soil and water because of organic matter, microstructure, and wetness. Describing soil and water properties is extremely difficult.

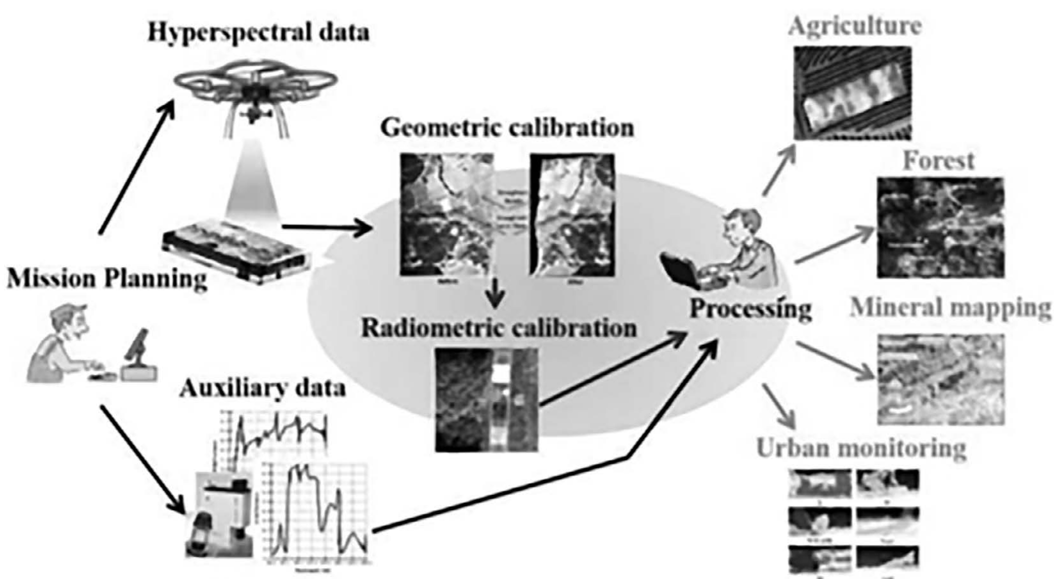

FIGURE 5.2
Architecture for the ground, remote, and aircraft sensing methods organized for PA.

4. Crop varieties are difficult to classify.
5. Weather conditions have a significant impact on the use of passive sensors in remote sensing.

5.2.3.1 Satellite Remote Sensing

Satellites have been used for remote sensing data in agriculture since the 1970s. They are specifically designed for large-scale crop classifications. Remote sensing programs in traditional agriculture quickly led to PA initiatives. Satellite imagery was used to measure physical geographical styles in soil natural organic matter, which was used in combination with floor-based total measurements (Nagarajan & Minu, 2018) to measure geographic styles in plant nutrients and flour grain yield. This was the first remote sensing application in Pennsylvania. Modern PA operations rely on GPS satellites, Landsat, and SPOT for their geographical planning (45–55 m). Eventually, satellite television began to be developed for computer imaging structures that would have better spatial decision-making and faster revisit periods. As new spectral and spatial sensors have become available, higher correlations have been discovered. Images from the IKONOS satellite have been used to detect nitrogen deficiencies in sugar beet, pesticide performance (Pajares, 2015) in wheat, and insufficient synthetic flow in wheat subject web pages. QuickBird images of olive fields in Spain were used to estimate olive crop areas, tree counts, geographic distributions of tree canopies, and olive yields. These satellites have steadily gained a large base of commercial subscribers interested in PA programs, compared to older satellites such as SPOT or Landsat.

5.3 Proposed Framework

5.3.1 Precision Agriculture Using Geospatial Information

PA was described as an agricultural control system that collects real-time data, processes and analyses it, and then provides farmers with options to minimize resources and increase crop yield throughout the decision-making process. Innovations in technology paved the ground for its implementation in a variety of industries (Pradhan et al., 2018). With the use of IoT and reliable software, the agriculture sector and automation vendors are attempting to identify and utilize prospects for boosting productivity, efficiency, and agricultural practices. Figure 5.3 indicates the typical design for integrating geospatial data with IoT to achieve PA. As can be seen in the diagram, the detectors in the farm and farm machinery give actual information and alarms over the Internet for additional processing.

After the information is gathered, it is processed with big data and analytics and saved on a cloud server for use in decision-making. Decisions are made after gathering geospatial data. Sensor data is typically exchanged to and from users in sensor-based PA via a database machine or the cloud. The stability of the transmission network and the Internet play an important role in sharing information among users (Sahani et al., 2018). Using mobile devices and consumer applications, the generated information can be accessed in a timely and effective manner. According to the research, geospatial data affects crop productivity,

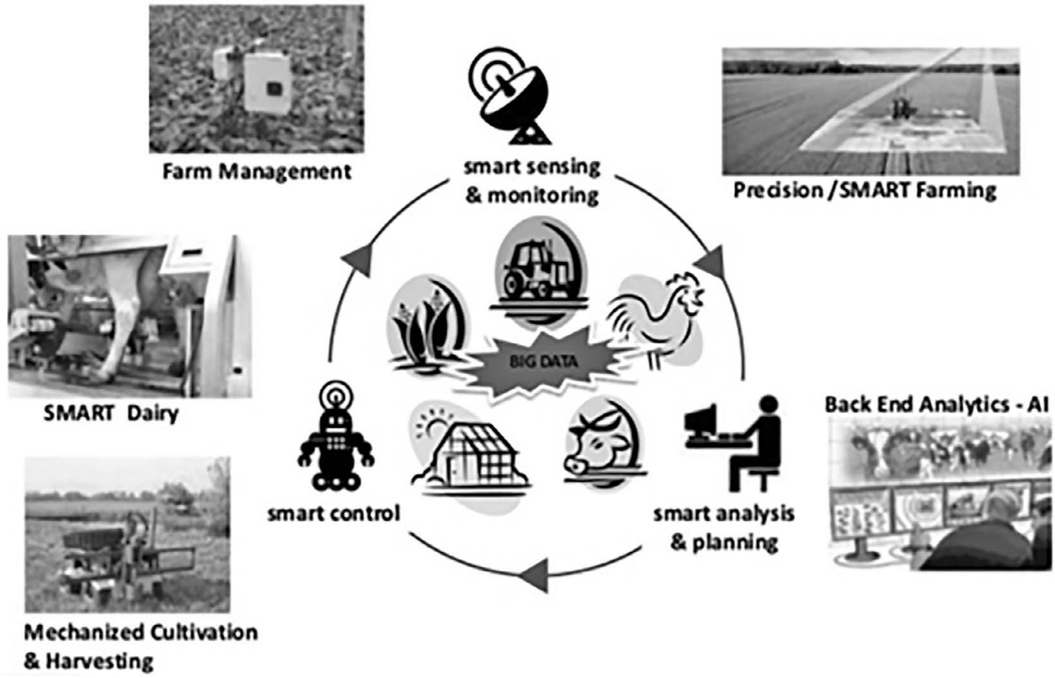

FIGURE 5.3
Concept of IoT.

watering, and soil quality. As a result, IoT-based PA aims to simplify remedial and preventive activity. A better understanding of accessible and needed water, nutrients, and pest control is possible. Due to advances in technology, PF has been gaining popularity among farmers worldwide. Farmers need this to generate maximum yield with limited resources (Sarkar et al., 2016). In this climate change era of extreme weather, it is impossible to anticipate efficient agricultural production without these smart technologies.

5.3.2 Precision Agriculture Using Remote Sensing

5.3.2.1 Data Gathering

The great degree of variability in agricultural-based conditions within fields prompted the adoption of PF technologies. Establishing an agricultural credit data system that provides information on plant status, crop field cultivation, soils, and other factors is one of the criteria for introducing PA technologies. Data from this source can be a starting point for growth and yield estimation. It is crucial to use advanced data collection and processing tools to establish such an information system. Monitoring the earth's crust and its changes was done with the most effective technology.

5.3.2.2 Yield Monitoring

Information about crop production fluctuations within a field is becoming more relevant for crop management as more PA techniques are used. Yield maps incorporate a variety of geographical variables, including soil conditions, elevation, growing conditions, nutrient

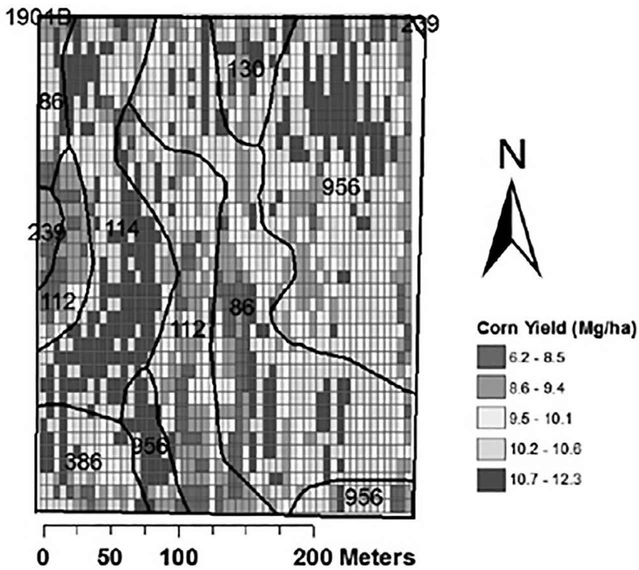

FIGURE 5.4
The effect of the direction of harvest on the quantity of crop measured.

replacement techniques, and applied agriculture technology. Thus, a production map, alone or in combination with other spatial data, can be an important input for site-specific activities. By mounting yield monitors on the harvester, yield data can be obtained at harvest time. A yield measuring device was first applied in the early 1980s, and it has now become standard equipment on most combines. In the near future, farmers will have access to detailed and reliable yield data due to technology improvements like GPS and harvester-mounted production sensors. The construction of productivity maps may be carried out immediately following the collection of data in order to identify trends in productivity across specific areas (Thorp et al., 2015). Based on the results of the analysis, after-season management can be implemented. A yield monitor's accuracy is determined by the brand and type of yield monitor, as well as harvest conditions, validation regime, and flow rate. In order to achieve the highest level of accuracy from the yield sensor, the yield monitor needs to be validated. Figure 5.4 presents the yield monitoring process for crop production measurement.

Although yield monitors are commercially available, many agricultural harvesters lack them. To analyze the map effectively, additional information is needed, such as information on plant stress during the growing season. Within a season, yield monitor data cannot be used to detect problems and generate maps. The use of remote sensing can be beneficial for estimating crop yield fluctuation and identifying stress within seasons. Spatial data may be used to produce productivity maps for both after-season and within-season crops during the growing season (Figure 5.5).

5.3.2.3 Indicators of Vegetation

By measuring the reflectivity of the plants at different frequencies, it is possible to gather more information about their condition. Light spectrum transmittance is influenced by tissue water content, plant type, and other intrinsic variables (Ayaz et al., 2019). Because chlorophyll absorbs light for photosynthesis, vegetation has short wavelengths in the blue

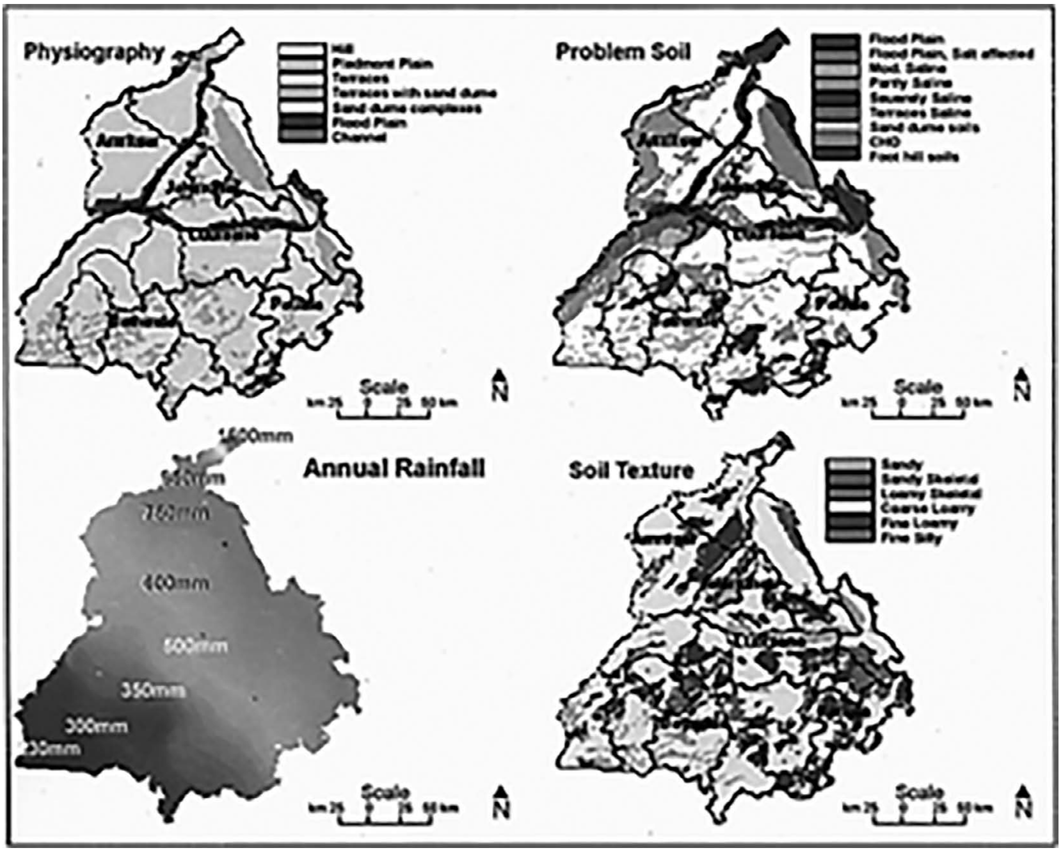

FIGURE 5.5
Cell yield of maize created from Sentinel data: Input data and output.

and red range of perceptible light. It reaches its peak in the green zone when vegetation takes on a green hue. Because of the cellular structure in the leaves, there is a much greater NIR area than there is in the wavelength spectrum. There is higher moisture content in the mid-infrared region of the spectrum (Figure 5.6).

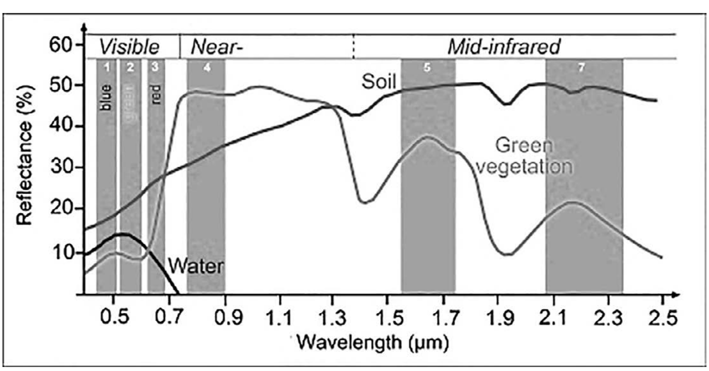

FIGURE 5.6
Spectral curve of the light reflected from the plant.

As part of the statistical analysis of spatial data obtained from vegetation, individual light spectrum bands or a collection of bands can be used to extract vegetation data for information analysis. A useful tool for determining the state of the vegetation is the construction of value iteration (VI) algorithms. The derivation of vegetation data from remotely sensed pictures is based on differences and disparities in plant vegetative leaves as well as canopy spectral features. As required, near-infrared (1–2.0 m) and red (1.1–1.3 m) or other bands are blended using a variety of methods. The amount of organically produced by an increasing plant population causes a decrease in red reflectance and an increase in total near-infrared reflection. According to earlier studies, there is a correlation between the indices using those two parts of the spectrum and the amount of vegetation. These estimates can be used to infer the data population provided by the detectors, which can also be used to predict future crop yields. We can calculate the NDVI to determine the crop's health when its plant cover is poor. A low index value indicates that there is little healthy vegetation, while a high index value indicates that there is a lot of healthy vegetation. Several indices have been developed to better represent the actual amount of vegetation on the ground. A number of studies have been conducted to determine the correlation between a crop's vegetation index assessed at a specific time and its yield. The study was conducted by Tzounis et al. (2017). Numerous indices have been developed to better design the total amount of plants on the ground. The study of land cover change often makes use of spectral indices derived from satellite data. The landscape index produces individual images by displaying vegetation quantity, or vegetation strength, using various multispectral remote sensing methods. This may reduce the amount of data needed for analysis and provide a more comprehensive picture of changes than any single band.

The number of bands acquired by satellite data was increasing as high-resolution spectroscopic equipment was developed. Numerous studies have addressed the relationship between vegetation indices and yields. The relationship between yield and index depends not only on the type of index but also on the time of data collection and the stage of the plant. Long-term yield estimation requires multiple time points during vegetation. NDVI is one of the most widely used indices. It is typically used to assess canopy vigor or development. It has been compared to the LAI, which is defined as the surface area of a leaf per square meter of ground. Figure 5.7 shows the change of vegetation index (NDVI) depending on vegetation growing.

5.4 Result and Discussion

5.4.1 Classification

Different methodologies and statistical approaches have been used to separate different types of habitats. A pixel-based and object-based approach was used in this study to map the spatial variability within a field. The researcher does not specify the natural vegetation or ecosystem types in an uncontrolled categorization (Figure 5.8). In an image analysis program, the data from the spectral analysis is separated into several groups without awareness of the image's spectral response. Spectral variance within each class and the number of data classes can both be limited by the user. An analyst must then assign labels to these groups based on their understanding of these photos and what the different

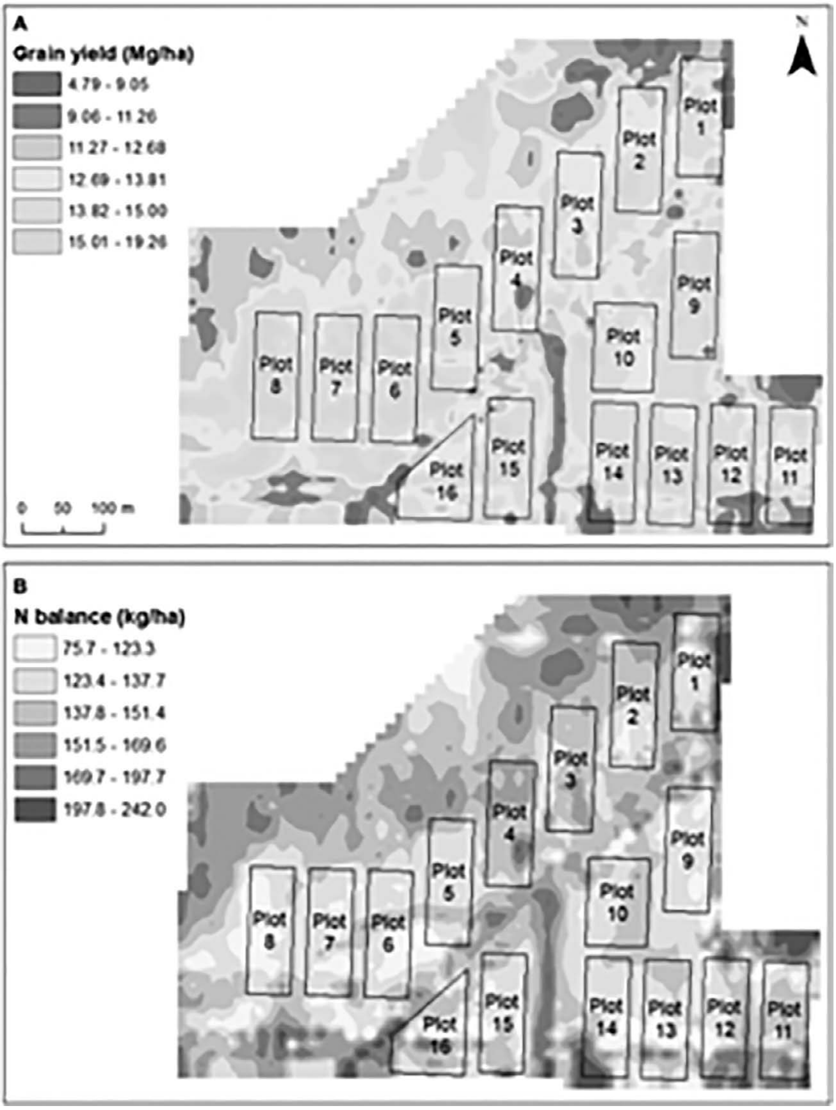

FIGURE 5.7
The change of vegetation index (NDVI) depending on vegetation growing.

habitats should look like as well as their knowledge and understanding of how different habitats should look in these photos. The purpose of this study was to develop a method for mapping fluctuations in field conditions using high-resolution remote sensing photos and image classification. Using OBIA, it was possible to identify no vegetation and monitor its condition in an agricultural field.

The data collection phase includes multi-scale picture segmentation, ruleset development, data pre-processing, the definition of features used to describe land use, classification based on the ruleset, and reliability evaluation. E-cognition software can retrieve information based not only on transmitted signals but also on size, density, and other factors. Figure 5.9 shows the workflow of mapping spatial variability by OBIA.

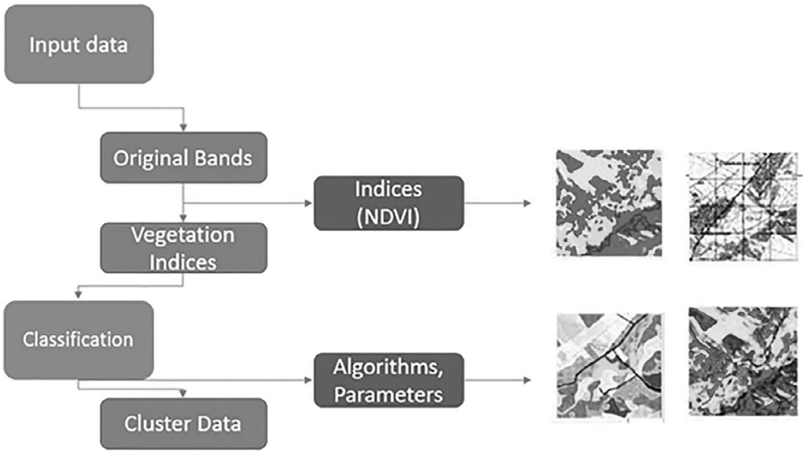

FIGURE 5.8
Workflow of mapping spatial variability by unsupervised classification methods.

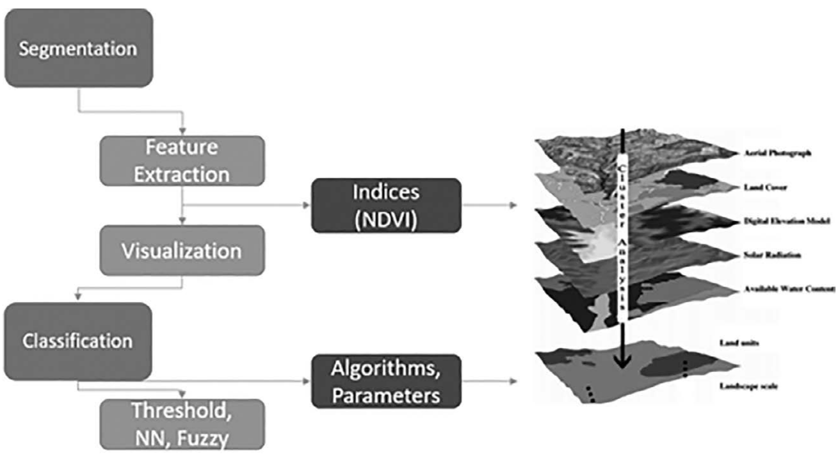

FIGURE 5.9
Workflow of mapping spatial variability by OBIA.

5.5 Conclusion

A remote monitoring system is useful for tracking and calculating the fluctuations in agricultural production. During the vegetative stage, images can be used to monitor crop growth and identify any issues that need to be addressed. Multi-temporal imaging can also be used to create production maps. These maps can be used to track yield fluctuation over time. Vegetation indices are useful in crop monitoring and crop estimation: Problems are identified; stressed plants are detected; irrigation requirements within a field change and fertilizer and pesticide requirements are identified, and prospective control zones are noted. This analysis should take into account that the reliability of such surveys depends on many factors, such as the type of index, the time of data gathering, and the stage of the plant. With the increasing availability of satellite and airborne imagery, more research is required to create the most appropriate algorithms for spatial prediction and other smart farming activities. Geospatial data is highlighted as an important component of the IoT. It uncovers critical tactics for dealing with environmental catastrophes such as floods, droughts, cyclones, pollution, climate change, and blights, among others, using geospatial data, as well as raising awareness about the use of PA. The proposal's goal is to raise awareness of PF and available control application software tools on the market and to encourage people to use them. A farmer can now immediately contact the area management office to update crop information and receive awareness and regulation data like crop diseases, soil nutrition, and soil irrigation. The agricultural sector would surely undergo major changes if the proposed model were developed as a prototype and executed in reality.

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6

Machine Learning Approaches for Agro-IoT Systems

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6.1 Introduction

Technological advancement sees no limits. One of the leading technologies Internet of Things (IoT) has made lots of advancements in making the environment around us smart, like smart homes, smart office, smart factory, and smart farming. Agriculture IoT and precision farming are some of the booming topics that inculcate the responsiveness of smart farming. The IoT has overpowered challenges like irrigation, scarcity, soil quality, weather issues, and recurrent infection to plants due to pests and diseases. Machine learning (ML)

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is a technique of statistics scrutiny that automates investigative replica structure. It is a branch of artificial intelligence (AI) based on the initiative that systems can learn from statistics, classify patterns and formulate decisions with a nominal human intrusion. Whereas AI is the wide knowledge of mimicking human beings' abilities, ML is a precise detachment of AI that trains an apparatus how to be taught. Arthus Samuel masters in the field of AI invented ML in 1959 and quoted that "it gives computers the ability to learn without being explicitly programmed" (Lee et al., 2017).

6.2 IoT for Agriculture

The IoT platform is a collection of software tools that facilitates the systematic storage and process of raw data received from sensors and actuators. Cloud computing is one the most popular technologies used from the last decade for speedy and skillful delivery of processed data to end-users and to manage centralized storage of massive data. Data analytics is performed on the cloud to predict output for decision-making. IoT sensors connected or mounted on agricultural land will provide a wide variety of data based on which analysis is done. Thus integration of cloud computing and IoT is the most used pattern for problem-solving and application development. But recent trend shows lots of research has been done using the combination of IoT with ML. Figure 6.1 shows the timeline of various revolutions that took place and clearly indicates the difference between then and now.

6.2.1 Role of IoT Data in ML-Based Agro-IoT System

Data, whether it is raw or processed, labeled or unlabeled, is the most vital element for solving any ML problem. It can be in images, videos, audio, or even text files. Not only for ML or AI but data is needed for most of the technologies such as big data, analytics in IoT, blockchain, and edge computing. IoT sensors are a rich source of generating data that can be later used by various technologies for analysis. The result of any application or

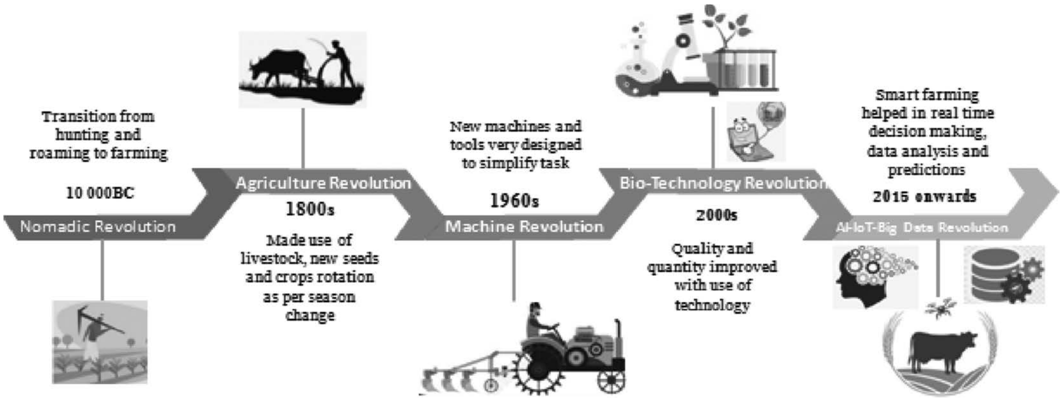

FIGURE 6.1
Timeline of agriculture and technology advancements.

problem-solving technique relies on the correctness of data because wrong data will give the wrong output. Cloud offers scalable on-demand services to the IoT devices for effective communication and knowledge sharing (Saravanan and Srinivasan, 2018).

IoT enables communication between the real and virtual worlds. Objects with virtual IDs known as sensors or actuators have the ability to collect the data from the real-time environment and the smart interfaces help in connectivity and communication. The collected data is then stored, analyzed, and viewed on a computer or mobile device. When it comes to the agriculture domain most used sensors are for quantifying environmental parameters like temperature, humidity, soil salinity, water turbidity, water level, etc.

ML also relies on lots of data for data analysis. Many research authors (Wang et al., 2021; Hasan et al., 2021; Yashodha et al., 2021) have proved that ML accuracy and performance are less for most problems if dataset size is small. Similarly, the author (Laure et al., 2018) tried to explain why massive data is needed for ML and techniques to manage the same. Based on the application requirement data is split into "training data, validation data, and test data." Whenever we prepare an ML model for some application it is trained first using training data and the learning process is initiated. Validating the data set is optional but recommended as it helps in the evaluation of the model during the training phase. Test data is used for real-time evaluation purposes, where input value from the user is fed to the model to predict the results, and later that result is compared with authentic output in testing data. Figure 6.2 shows how data is processed in ML for the prediction of output value.

6.2.1.1 Data Collected by Smart Agriculture Sensors

Data is gathered using mobile phones or stationary equipment like sensors, robotics, bots, autonomous vehicles, automated hardware, camera, and wearable devices. The wireless sensor network is used for connecting the initially low level; here raw data is collected from various sensors and passed to the next connected intermediate level sensor, and so on. The end layer is generally the decision layer and is deployed using cloud computing. The collected data is stored centrally over the cloud and used for analysis and decision-making. Prediction of certain decisions is also made possible by technology like ML and deep learning.

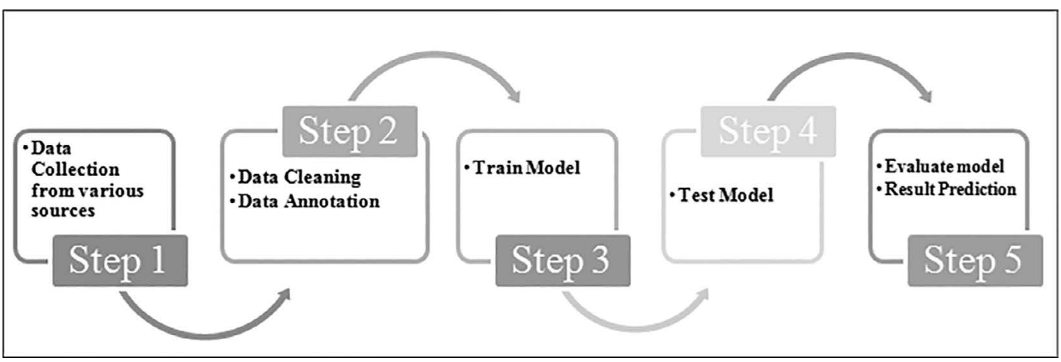

FIGURE 6.2
Machine learning process (Wood et al., 2020).

6.2.1.2 Data Collection by Agricultural Drones

Surface-station and aerial station drones have been utilized in the cultivation domain. Crop health monitoring, spraying of fertilizers and pesticides, water management, and soil analysis are a few of the common tasks performed by drones. Drones efficiently collect data in the form of images and transfer it to the server connected.

6.2.1.3 Predictions by Processing Raw Data

To forecast the prediction results artificial networks utilize data or information obtained by sensors from the cultivation land. This includes parameters such as soil, water, warmth, precipitation, moisture, etc. Using all these parameters and efficient algorithms early detection of anomalies and prediction of crop yield is possible.

6.2.2 Need of ML in IoT

Initially, ML was assumed to be a powerful tool for designing prediction models only, but with advancements in research, and it has been proved that ML is more beneficial in combination with wireless sensor networks (WSNs) and IoT. ML models have several advantages in solving IoT challenges (Akpakwu et al., 2017) like quality of service (White et al., 2017), network congestion and overload (Haroon et al., 2016), interoperability and heterogeneity, security and privacy (Sicari et al., 2015), and network mobility and coverage (Kishore Ramakrishnan et al., 2014). Table 6.1 contains the information of few notable research papers where researchers have works covering various agriculture issues and providing a solution using IoT and ML (see also Figure 6.3).

6.2.3 Assimilate ML with IoT

It is known that IoT is a layered framework, where data flows from one layer to another layer to pass the information, which helps in solving prediction problems. Research is being performed for placing ML algorithms at different layers of the IoT frameworks. Here the decision of placement totally depends on application/business requirement. Three choices can be given to integrating ML in IoT as shown in Figure 6.4.

- Choice 1: ML at IoT edge/endpoint, i.e., physical layer
  The foremost paradigm about IoT devices is that sensors are dumb and all the intelligence resides inside the cloud, but contradictory to this author (Gopinath et al., 2019) proved the accuracy of running ML algorithms locally on small, resource-constrained devices. The task of classification, regression, etc., for the prediction can be done on the microcontroller itself, so no need for connection to the cloud.
- Choice 2: ML at IoT gateway, i.e., network layer
  A gateway is a unit where IoT endpoints are connected and the data collected from these devices are transferred to the cloud. ML can be easily deployed on the local server or gateway where ML algorithms for classification, regression, or clustering can be computed. The basic idea behind this is to reduce the computation cost of transferring data to the cloud, bandwidth, processing power and reduce execution time too. If deployed at this layer it can control or give the command to all the end devices connected to the gateway.

TABLE 6.1

Research Paper on IoT and ML Algorithm in Agriculture Domain

Area	Model/Algorithm	Reference
Yield prediction	Sugarcane yield prediction using multilayer perceptron (MLP) in IoT agriculture. Accuracy – 99%, Precision – 95%, Recall – 96% Minimum mean absolute error (MAE) – 0.04% Root mean square error (RMSE) – 0.006%	Wang et al. (2021)
Pest management	Identifying tea leaf disease using neural network	Yashodha et al. (2021)
Crop, soil, water, and pest management	Survey on how IoT technology, UAV systems, and machine learning algorithms will benefit the agriculture domain	Hasan et al. (2021)
Crop management	Using deep neural network model in hydroponics system to monitor plant growth	Vanipriya et al. (2021)
Soil management	Soil moisture forecasts for potato crop using SVM, random forest, and neural network	Dubois et al. (2021)
Soil and water management	K-means and support vector regression (SVR) for forecasting droughts	Kaur et al. (2021)
Water management	Designed smart irrigation system, digital soil assessment (DSA), sustainable intensification (SI), and smart earth technologies using IoT and machine learning	Goel et al. (2021)
Crop, soil, water, and pest management	Survey on 5G technology in the agricultural using IoT and machine learning	Tang et al. (2021)
Water management	Predict irrigation patterns using support vector regression and random forest regression	Vij et al. (2020)
Water management	Using logistic regression, SVM, averaged perceptron, and fast forest for smart water management system	Singh et al., 2020
Crop, soil, water, and pest management	Reveal responsibility of machine learning in the WSN and IoT technology	Messaoud et al. (2020)
Livestock management	Early-stage lameness detection using random forest with accuracy of 91% and K-nearest neighbors (KNN) with 87% accuracy	Byabazaire et al. (2019)
Faulty sensor detection	Using ML models like KNN, isolation forest for detecting abnormal sensors	Rossi et al. (2020)
Water management	Deep reinforcement learning for smart irrigation system	Bu et al. (2019)
Livestock management	IoT framework for disease detection in cows using neural network	Vyas et al. (2019)

(Continued)

TABLE 6.1 ***(Continued)***

Research Paper on IoT and ML Algorithm in Agriculture Domain

Area	Model/Algorithm	Reference
Crop management	Crop quality improvement using IoT drones and SVM	Saha et al. (2018)
Water management	Smart irrigation using SVR and K-means Accuracy – 96%	Goap et al. (2018)
Water management	IoT-based hydroponics system using deep neural networks	Mehra et al. (2018)
Livestock management	Cloud IoT-based Livestock Management System for animal health monitoring	Saravanan and Saraniya (2018)
Crop management	Monitoring and data prediction in rose greenhouse farm using linear regression, neuronal networks, and SVM	Rodríguez et al. (2017)
Robotic grander	Autonomous gardening robotic vehicle which identifies and classifies the plant variety using neural network	Kumar et al. (2016)
Pest management	Early Detection of grape diseases using machine learning and IoT	Patil et al. (2016)

- Choice 3: ML on IoT cloud, i.e., application layer
  The most common and popular place where machine algorithms can be executed is on a cloud-based platform. Generally, data storage and analysis take place cloud-only. If an ML model is deployed at this layer it can control and pass commands to all the endpoints and gateways.

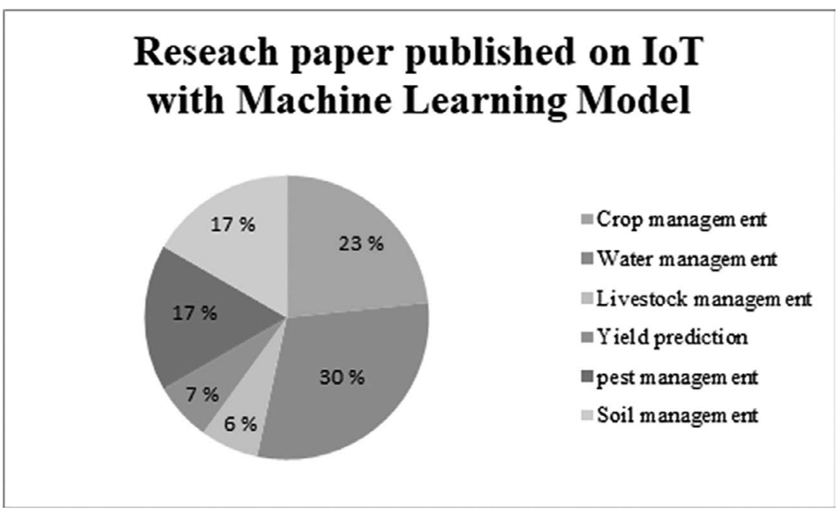

FIGURE 6.3
Recent research paper published on ML with IoT.

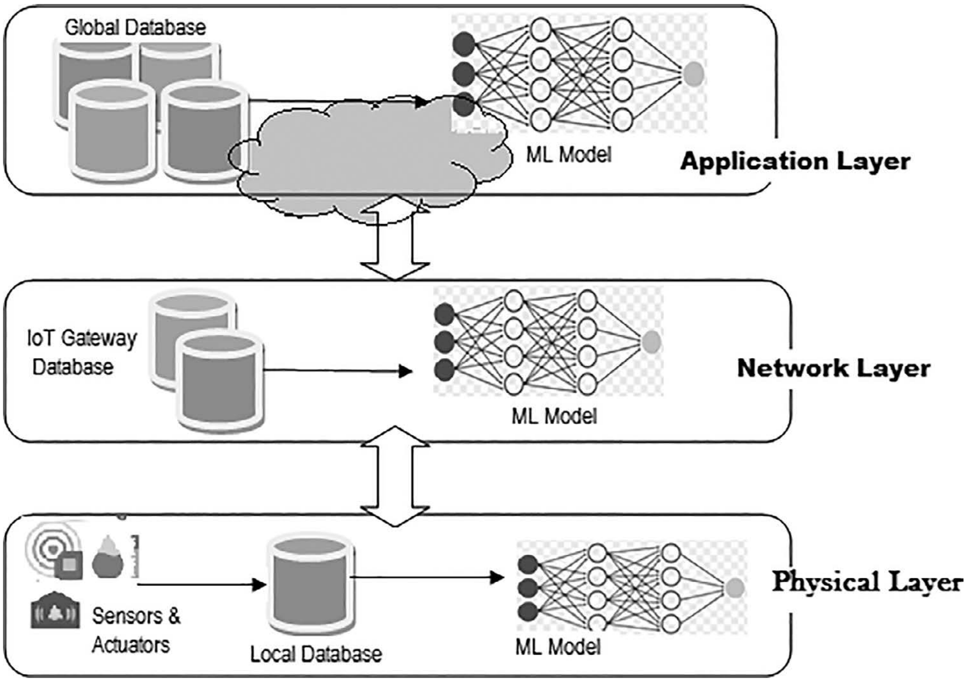

FIGURE 6.4
Integrating ML in IoT layers.

6.3 ML in Agriculture

ML models can be used for thing identification, review, prediction, categorization, and grouping of objects. Numerous models have been invented and a lot of research is present for various reasons in the agriculture domain nowadays. Figure 6.5 shows the list of models popularly used.

6.3.1 ML Learning Types and Models

The learning task can be ML categorized into "supervised," "unsupervised," and "semi-supervised." Depending upon the problem statement different models are used. The problem can be broadly divided in terms of identification, classification, quantification, and prediction.

6.3.1.1 Supervised Learning

If a model is trained using some labels for classification or prediction purposes it is termed supervised learning. It travels around classification and regression algorithms and learns about techniques for feature selection, feature transformation, and hyper-parameter tuning.

Regression is an arithmetical method to decide the relationship between one dependent variable and a chain of other variables or independent variables. In ML, we allow

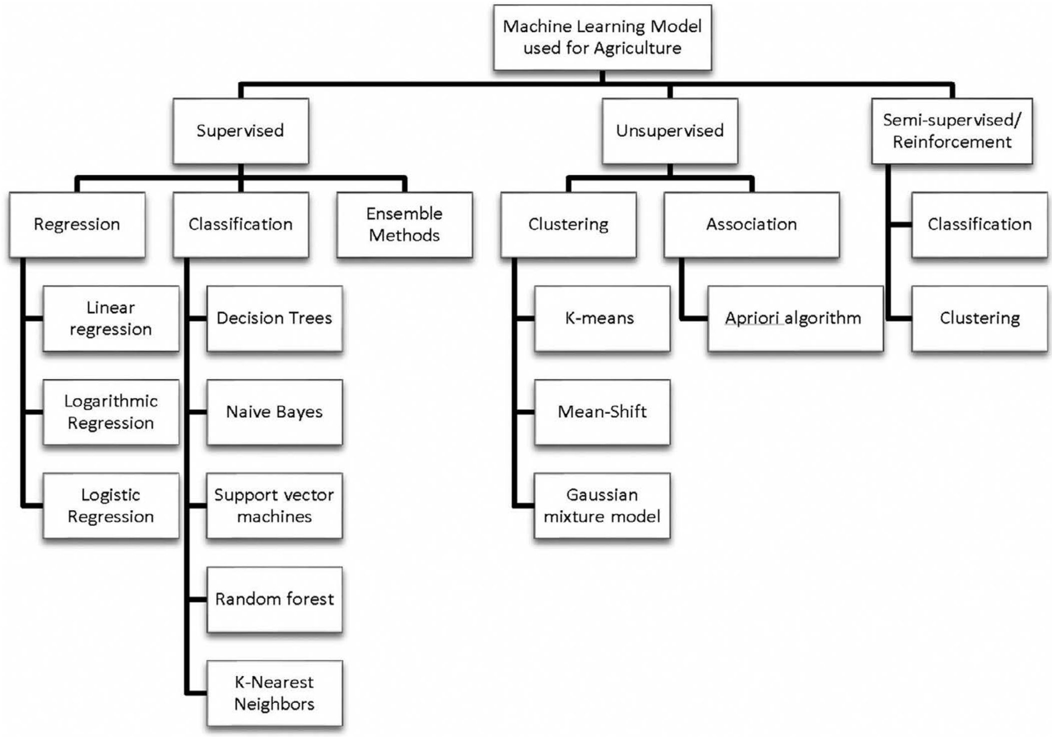

FIGURE 6.5
Machine learning models used in agriculture application.

machines to learn the relationships from the raw data provided and predict the output value. Regression techniques are not very popular in the agriculture domain but are used in solving resource management problems. Soil moisture quantity prediction system based on hybrid regression model was designed by author (Chatterjee et al., 2019), who did better than other models. Soil moisture and soil temperature will provide real-time values based on which the ML model can predict and decide if more watering is needed, thus improving the soil quality and having proper water management. Regression models are suitable for solving prediction problems.

Classification is a method to decide to which class a given object will belong. "Support vector machines" (SVMs) were pioneered in the work of numerical learn assumption. SVM is mainly a dual classifier for linear unraveling hyper-plane to categorize data instances and has been utilizing for categorization, "regression," and "clustering." SVM is one of the most popular models among all the others because of its capability of solving various issues including identification, classification, quantification, and prediction. This model is best suitable for any IoT-designed agriculture smart system, for example, in resource management, capitulate forecast, tidy discovery, ailment recognition, harvest superiority analysis, and farm animals management.

Bayesian models (BM) can be utilized for "classification" or "regression problems." Naive Bayes and Gaussian naive Bayes is the most well-known algorithms in the literature. For IoT smart agriculture systems this model can be used in the identification and classification of crop disease and its type. Also, it is suited for yield prediction where the author (Amatya et al., 2016) designed computerize quivering and grabbing cherries system during harvest, where the sensor provides information regarding color and quantity of fruits on trees and are based on ML decision system action is taken to shake the tree or not. Here too mechanical sensors are used for shaking. Livestock management can also take advantage of the Bayesian model for animal tracking and behavior explanation.

Most of the time a single learning algorithm cannot give expected accurate results, so multiple learning algorithms can be combined for the best prediction results. Thus ensemble learning (EL) focuses on such a combination of learning algorithms to train and test the ML models. Supervised machine learning algorithms used in agricultural applications are shown in the Table 6.2.

TABLE 6.2

Supervised ML Algorithm Used in Agricultural Applications

Application	Type	Results/Finding	Article
Water management	Multivariate adaptive regression spline (MARS)	Assessment of the amount of water evaporation and transpiration on a monthly basis	Mehdizadeh et al. (2017)
Plant-stress prediction	Dirichlet aggregation regression	Abiotic stress, namely drought, was predicted on barley crops well in advance before it became visible to human eyes	Kersting et al. (2012)
Plant-stress prediction	Multiple regression	Rice blast disease was predicted on rice crop	Kaundal et al. (2006)
Counting fruits	Linear regression	Based on RGB images apples and oranges were tallied	Chen et al. (2014)
Mapping crop and soil	Logistic regression	Soil typology and land distribution	Piccini et al. (2019)
Soil salinity prediction	Random forest regression (RFR) and support vector regression (SVR)	Accuracy: RFR 93.4–94.2% SVR 85.2–89.4% "Normalized root mean square error" (NRMSE): RFR 6.10–7.69% SVR 10.29–10.52%	Wu et al. (2018)
Plants water stress detection and drought conditions analysis	Linear and exponential regression	Skeleton for understanding and prediction of plant mechanisms under drought conditions	Sun et al. (2020)
Weed detection	Logistic regression	Accurately differentiated between crop and weed	Potena et.al. (2016)
Greenhouse monitoring	Linear and exponential regression	Framework designed for early fault detection and diagnosis	Lakhiar et al. (2018)
Stress	SVM variant	Nitrogen, phosphorus, and potassium (NPK) stress was identified for rice crop	Chen et al. (2014)
Plant disease	SVM	*Cercospora* leaf spot, sugar beet rust, and powdery mildew disease identified and classified for beetroot plant	Rumpf et al. (2010)
Water stress detection	Decision tree	Multiple trained decision trees are combined to provide an improved prediction performance	Castillo-Guevara et al. (2020)
Packaged food products	Decision tree	Identification of contaminants, diseases or defects or bruise detection	Lu et al. (2011)

(Continued)

TABLE 6.2 ***(Continued)***

Supervised ML Algorithm Used in Agricultural Applications

Application	Type	Results/Finding	Article
Plant disease	Bayesian classifier	Identification and classification of powdery mildew disease in tomato plants	Hernández-Rabadán et al. (2014)
Plant disease	Naïve Bayes	Recognition and categorization of *Alternaria alternata*, *A. brassicae*, *A. brassicicola*, and *A. dauci* diseases in rapeseed-mustard oilseed plant	Baranowski et al. (2015)
Plant disease	Bayesian classifier	Classification of beetroot plant disease like Uromycesbetae, Cercosporabeticola	Bauer et al. (2011)
Weed detection	Naïve Bayes	Accurate detection, location, and classification of weeds	Hasan et al. (2021)
Plant disease classification	Bayesian classifier	With no overfitting problem achieved an accuracy rate of 98.9%	Sachdeva et al. (2021)
Livestock management	Bayesian	Modeling cattle movements	Lindström et al. (2013)
Plant disease	KNN	Identification of Huanglongbing disease in citrus plant	Sankaran et al. (2011)
Yield prediction	SVM	Successfully detected coffee beans and their count from a particular branch. Also predicted their ripeness	Ramos et al. (2017)
Fruit counting	SVM	Identified the ripeness of citrus fruit Accuracy 80%	Amatya et al. (2016)
Livestock management	SVM	Early detection and warning of problems related to the production curve for hens with 98% accuracy	Morales et al. (2016)
Yield prediction	Ensemble model	Identified number of tomatoes with Recall: 0.6066 Precision: 0.9191 F-Measure: 0.7308	Senthilnath et al. (2016)
Quality management	Ensemble model	Prediction and classification of geographical origin of a rice sample with 93.83% accuracy	Maione et al. (2016)
Livestock management	Ensemble model	Classification of cattle behavior with an accuracy of 96%	Dutta et al. (2015)

6.3.1.2 Unsupervised Learning

In this type of learning, the model learns patterns without any supervision. It is generally used when the input data is not labeled. This type of algorithm learns patterns from untagged data. Here no supervision is needed by the uses or any expert person and permits the algorithm to follow its own way to predict patterns. These models are the most popular for clustering problems. This type of model is mostly needed in situations where it is difficult to translate domain knowledge into feature crafting; this may be useful for high-dimensional data.

K means clustering is a form of unsupervised learning which forms “k” clusters of data. It is a form of top-down clustering algorithm and follows centroid-based clustering. The data in a cluster are more similar to each other than the other clusters. The measure of similarity can be calculated using the Silhouette coefficient. Distance between data points can be calculated using distances such as Manhattan and Euclidean.

TABLE 6.3

Unsupervised ML Algorithm Used in Agriculture Application

Application	Type	Results/Finding	Article
Plant disease	K-means	3D to distinguish between *Cercospora beticola* and *Uromyces betae* disease in beetroot crop	Bauer et al. (2011)
Plant disease	K-means	Classified into "healthy" and "injured" classes of clover plants	Atas et al. (2012)
Weed detection	K-means	Accuracy: 92.89% Designed weed identification model for soybean crop	Tang et al. (2017)
Image background preprocessing	Principal component analysis (PCA)	Image cropping, contrast enhancement, and removal of background was done efficiently using PCA	Atas et al. (2012)
Plant fungus	PCA	Identified the presence of aflatoxins which is a harmful substance produced by fungus in chilli pepper plant	Atas et al. (2012)
Yield prediction	Clustering	Identified number of tomatoes with Recall: 0.6066 Precision: 0.9191 F-Measure: 0.7308	Senthilnath et al. (2016)
Disease detection	Self-organizing map (SOM)	Accuracy 99.27% in the detection of yellow rust in wheat crop	Moshou et al. (2005)
Weed detection	SOM	Recognition and discrimination of *Zea mays* and weed species with an accuracy of 100%	Pantazi et al. (2016)

Association rules are the next category under unsupervised learning, which helps to find relationships between variables. A priori algorithm is used to find rules which are satisfied in a particular dataset. Based on how frequently the number of items occurs and their correlation, this algorithm uses a bottom-up approach to get the desired rules. This algorithm makes use of "support" and "confidence" to figure out which items to consider or eliminate. The Unsupervised machine learning algorithms used in agriculture applications are shown in Table 6.3.

6.3.1.3 Semi-Supervised Learning

It can be said as semi-supervised is a combination of both supervised and unsupervised techniques. It takes advantage of both the learning type for presenting accurate results. It makes use of the tiny quantity of labeled data along with the huge quantity of unlabeled data. This is basically done large size of the labeled dataset is not available for problem solving. It is popularly used in classification and clustering problems. Semi-supervised machine learning algorithms used in agriculture applications are shown in Table 6.4.

TABLE 6.4

Semi-Supervised and Reinforcement ML Algorithm Used in Agriculture application

Application	Type	Results/Finding	Article
Weed detection	Semi-supervised learning	Accuracy: 82.13%	Shorewala et al. (2021)
Soil spectroscopy	Laplacian support vector regression	A robust model for soil spectroscopy was developed and soil samples from five different countries were studied successfully	Tsimpouris et al. (2021)
Water management, plant growth	Reinforcement learning	Framework for smart agriculture is designed	Bu et al. (2019)
Yield prediction	Reinforcement learning	Efficiently predicts the crop yield with an accuracy of 93.7%.	Elavarasan et al. (2020)
Water management	Reinforcement learning	Framework for irrigation control technique is designed which is suitable for various geographical locations	Sun et al. (2017)

6.3.1.4 Reinforcement Learning

This type of ML represents the way humans learn, i.e., by action and reaction. Here a mediator gains knowledge of how to perform in the neighboring surroundings. Deploy this algorithm; the apparatus is skilled in formulating precise decisions. This mechanism, this technique the apparatus is uncovered to a situation where it trains itself incessantly by means of trial and error. This apparatus acquires from past occurrences and it tries to incarcerate the best probable comprehension to compose precise commerce decisions. The instance of Reinforcement Learning is Markov Decision Process. Reinforcement machine learning algorithm used in agriculture applications are shown in Table 6.4.

6.4 Applications on ML Agro-IoT System

6.4.1 Pest Control Management

With an increasing demand for organic food items, farmers are more focused on cultivating crops that are pesticide-free or with minimum use of fertilizers. With proper use of some gas sensors and image sensors farmers can remotely monitor pest population and, if the levels reach the desired threshold value, can remotely release chemicals to reduce or stop the multiplication of pests. Also if an anonymous pest is detected it can be given to the agriculture department for studies giving scope for research activities. Climate change can also give rise to pest occurrence; with data made available by the meteorological department as well as temperature sensors and humidity sensors installed in agricultural land, farmers can get alter notifications in the form of SMS on mobile devices. It will help to avoid future losses and taking necessary precautionary measures. Pest has the worst effects on production as well as on human health, so controlling it becomes a prime motive. IoT technology aids overcome food safety challenges. Image sensors can be used to detect pests in a real-time environment. An infra-red sensor can also be used to perceive body heat based on which pest can be spotted. A four-layer IoT framework is used to build a pest monitoring system, whereas ML will be used for identification, classification, or prediction of type/class of pests. Ramalingam et al. (2020) designed a distant entrap supervision framework using IoT and the "Faster RCNN (Region-based Convolutional Neural Networks)" and "Residual neural Networks 50 (ResNet50)" for object recognition with an average of 94% accuracy. Identification and detection of plant diseases are some of the most important factors for agriculture. Crops can be monitored throughout the lifecycle with the help of IoT technology. Image sensors can be used to closely observe coloring patterns. Based on color values diseases can be detected easily. It can also facilitate understanding fruiting and flowering patterns. Image sensors can also be used to keep a watch on any pest or bug infecting the crop. Early detection can help in early prevention. Soil moisture sensors and water level sensors can help to calculate salinity and water need. The author (Yahata et al., 2017) suggested using ML models for plant breeding using biological features as well as environmental stress (Garg et al. 2020).

6.4.2 Resource Management

The scarcity of various natural resources, mainly water and soil, makes it important to wisely utilize these resources. The smart irrigation system is the best example for this where sensors can sense the water level and moisture level and accordingly supply water to crop, thus reducing water wastage and also preserving the soil nutrition level. Overwatering and under-watering both will have ad worse effect on plants and crops so have to use it properly. Water pumps and pipes can be remotely controlled by farmers giving them the freedom from manual efforts needed for watering the huge land. Sensors like pH (potential of hydrogen or "power of hydrogen"), ORP (oxidation–reduction potential), EC (electrical conductivity), and turbidity have demonstrated precise water quality status. The quality of soil will decide the types of crop cultivated and also the quantity of yield. Every time farmers make an additional effort during the land preparation phase to ensure and increase the quality of the soil. Land preparation includes different stages like clearing weeds, plowing, harrowing, flooding, and leveling. The traditional method for testing soil quality was to send samples of soil to the geological department and wait for results. Most accurate results were provided by this technique but the disadvantage were that it was time-consuming, required more testing equipment, was not economical for poor farmers, and fewer laboratories were set up, making it difficult for every farmer to connect to it. IoT provides an easy solution to this problem too. Soil sensors like NPK sensors, pH sensors, EC sensors, moisture sensors, etc., will provide information of soil nutrition level and quality to farmers on mobile phones through SMS or by some mobile designed application. The image sensor can also be used to detecting weeds and uneven leveling of land. Similarly, water level senor will be useful to maintain intensity during the flooding stage, especially for paddy land.

6.4.3 Safeguarding Crops from Animals, Birds, and Human Attack

Once the crop starts to give a good yield the next danger the farmers have to face is various types of attacks. It is a very common practice to stay awake day and night to look after crops till they are harvested. Famers have to protect their crops from various animals and birds; furthermore, humans are also harmful as they can destroy the crops by burring out the land out of any personal rivalry or by stealing the crops. Traditionally farmers used electric fencing for preventing animal attach but it was made illegal as it had a high risk of animal or human death. Image sensor along with proximity sensor is the best to answer for this, were the proximity sensor can detect the presence of any object within marked area and image sensor will help to identify that object, thus making farmer attentive and ready to take quick action. A flame detector, a type of fire sensor, is moreover accurate and responds faster, making it more reliable to identify a fire in the field.

6.4.4 Livestock Management

Raising livestock is not an economic chore. It mainly involves two tasks, firstly monitoring the health of their livestock and tracking their location. Health supervision is performed by placing appropriate wearable on livestock and evaluating body temperature, heat, pressure, heart rate, respiratory rate, digestive level, etc. It will avoid illness and lend a hand for early diagnose of diseases. It is an ordinary behavior of livestock to roam anywhere and get separated from the group. IoT wearable can track the livestock if lost in minimum time and also provides information about livestock movement patterns. Depending on the type of livestock different IoT-based applications can be designed, for example, monitoring cattle behavior as food consumed and steps walked for analyzing health as well as quantity of milk it may produce. An electronic shepherd guides and allows sheep to feed unwanted weeds only, thus safeguarding the vegetation and help to eliminate the weed. Many such applications based on needs are designed and deployed with IoT as a support system. The amalgamation skeleton of IoT and ML for livestock behavior and disease prediction was designed by the author (Lee 2018).

6.4.5 Yield Management

Predicting the crop capitulates to be healthy ahead of the yield time would help the strategists and farmers to captivate appropriate procedures for selling and storeroom. Precise forecast of crop expansion stages plays a pivotal position in a crop manufacturing organization. Such predictions will also sustain the allied industries for the device the strategy of logistics of their business. The crop yield forecast is a vital agricultural crisis. Each and every cultivator has forever tried to recognize how much he will get from his anticipation. In the precedent, capitulate forecast was intended by analyzing farmer's preceding occurrence on a meticulous crop. The Agricultural capitulate is mainly relies on climate circumstances, vermin, and preparation of harvest maneuver. The precise figure about the history of crop capitulation is a significant thing for conception decisions associated with agricultural hazard organization. A greenhouse is constructed with walls and roofs made mostly of see-through material like glass, in which plants that want regulated climatic conditions are developed. Skilled laborers are needed to work in such an environment, but with IoT technology, manual work is eliminated as most tasks are automated. Smart greenhouses deployed with the support of IoT will intelligently monitor and control the inside climate.

6.4.6 Quantifying the Emission of Greenhouse Gases

Climate change has affected the agriculture domain badly, and rises in the atmospheric concentration of greenhouse gas (GHG) is the main factor for this which future influences Global warming. Last three decades the warming effect has increased by 37%, which is highly alarming. "Water vapor, carbon dioxide (CO_2), methane (CH_4), ozone and nitrous oxide (N_2O)" are the five most important GHG. Care must be taken to control the increase in the amount of emission of these gases. Industrial and metropolitan pollution is the foremost reason for the increase in the level of GHG but also agriculture is one of the reasons. Paddy lands reveal the fact that they are also one of the sources for the release of greenhouse gases such as methane (CH_4) and nitrous oxide (N_2O), which are caused due to excessive use of fertilizer and poor climate conditions. GHG affects not only the crop's growth but also affect the health of farmers. Most farmers work in paddy land where the concentration of GHG s high is suffering from lung diseases. Author (Jadhav et al., 2019) IoT can give the solution by finding harmful gases by deploying various gas sensors like CO_2 sensor, MQ-2, MQ-4 or MQ-5 for methane gas, MQ-7 or MQ-9 for Carbon Monoxide (CO), MQ-135 for ammonia, etc., at different locations to monitor, detect and prevent GHG emission.

6.5 Conclusion

Affluent insight for decision making and improving action in order to protect the crops or to increase yield can be facilitated by integrating ML to sensor data. Most research shows that IoT challenges like Quality of Service, Network congestion and Overload, Interoperability and heterogeneity, Security and privacy, and Network Mobility and Coverage can be easily addressed by ML techniques. ML models facilitate inaccurate classification, regression, or clustering for predicting output values. Thus knowledge-based agriculture systems can be designed by incorporating ML models into the IoT framework. Figure 6.3 shows a count of research papers published based on the integration of these two massive technologies in the agriculture domain. The numbers are not huge and thus encourage us to explore more in all the directions for finding solutions to numerous problems.

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7

A Survey on Internet of Things (IoT)-Based Precision Agriculture

Aspects and Technologies

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CONTENTS

7.1 Internet of Things

Figure 7.1 depicts the IoT concept's sensing, monitoring, planning, analysis, and control. The Internet of Things (IoT) is an electronics-oriented integrated system in which sensors, controllers, various forms of software, and network interconnectivity are used to

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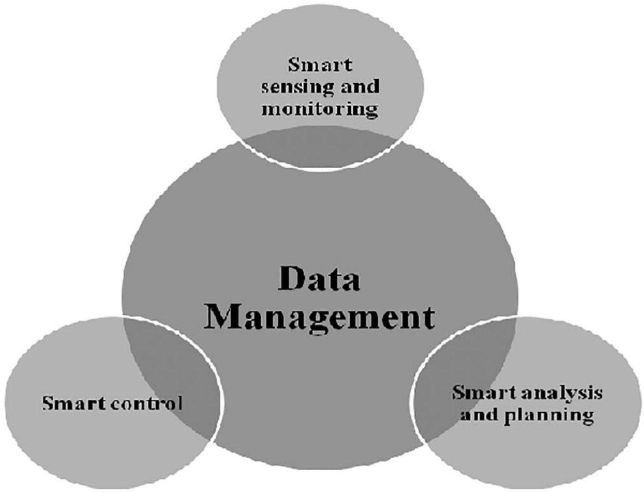

FIGURE 7.1
Concept of IoT.

acquire and exchange data between actual electronics circuits and devices. IoT's accuracy and efficiency are the major benefits for real-time applications to handle a variety of problems. Agriculture is a major manufacturing application of IoT to use the accelerated growth of IoT controllers for the overall rate, and subsistence is solely based on agricultural goods.

IoT concepts are enhanced by the huge number of electronic devices connected through the Internet. With it, we can look, at any time, anyone or any connection paradigm [1], with applications for different fields of work, such as travel, intellectual property, education, marketing, logistics, transformation, industrial and environmental production, and smart agriculture [2].

Figure 7.2 and 7.3 depicts the various states and applications of the Internet of Things in the field of agriculture.

7.2 Introduction

Table 7.1 depicts the many types of agricultural expansion. To maintain economic development and stability, agriculture plays a vital role in countries' production [3, 4]. Overcoming the gap between population growth and grain yield is a big challenge for agriculture.

Figure 7.4 shows how sensors work in the field. The main objective of precision agriculture (PA) is to increase the production of the crops, decrease labor time, proper irrigation processes, and effective consumption of fertilizer and provide higher productivity and use of resources when compared with traditional methods. PA is used for efficient use of various inputs like the efficient use of seeds; pesticide; fertilizer; and water, fuel, land, and soil.

IoT offers suitable solutions for several applications such as agriculture, security, traffic congestion, smart cities, and industrial control. Wireless sensor networks (WSNs), along

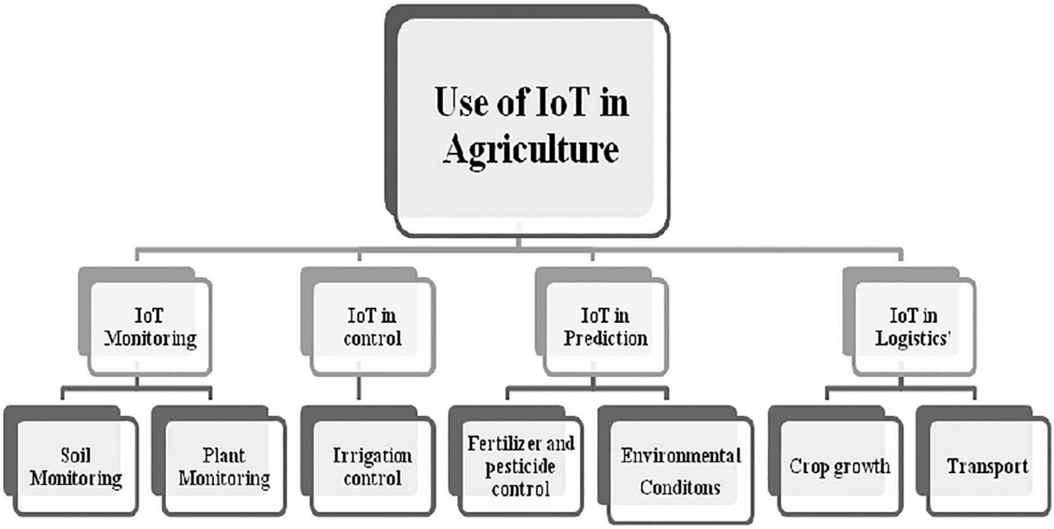

FIGURE 7.2
Hierarchical structure of usage of IoT in precision agriculture.

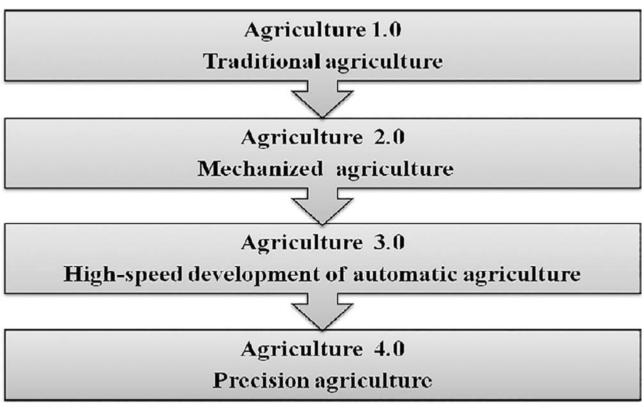

FIGURE 7.3
Characteristics of agriculture growth and how to deal with it (Agriculture 1.0 to Agriculture 4.0).

TABLE 7.1
Different Types Agricultural Growth with Issues and Periods of Time

Agriculture Growth			
Agriculture 1.0	Traditional agriculture	From 1784 to 1870	Operation efficiency is low
Agriculture 2.0	Mechanized agriculture	In the 20th century	Inefficient use of resources
Agriculture 3.0	High-speed development of automatic agriculture	From 1992 to 2017	Intelligence accuracy is low
Agriculture 4.0	Precision agriculture	From 2017	Security issues

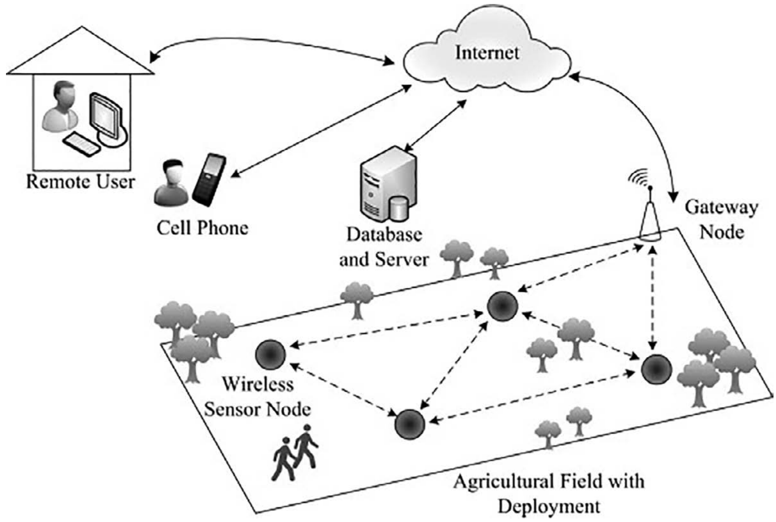

FIGURE 7.4
Wireless sensor node with agriculture field.

with IoT-based automation of PA measures, can modify the agriculture sector. Present IoT trends are security, development of network technologies, minimizing energy use, efficiency of devices, device integration, and user-friendly solutions for IoT controls. IoT is used for multiple-device communication and sharing and understanding their internal and external contexts with embedded technology. IoT technology can detect all of these problems and provide solutions to increase productivity. WSN efforts enable data collecting from sensory devices and transmission to larger servers. The data collected by the sensors will provide details about the unique environment: monitoring of environmental conditions or crop production such as field conditions and monitoring of soil and vegetation, movement of unwanted material, wildlife attacks, etc. IoT-based farming has major features: (1) physical architecture, (2) data acquisition, (3) data processing, and (4) data statistics (Figure 7.5). The whole system is built in a way that controls sensors, actuators, and devices.

Data can be collected from sensory devices and transmitted to larger servers thanks to WSN initiatives and obtain exactly what they require to optimize production and

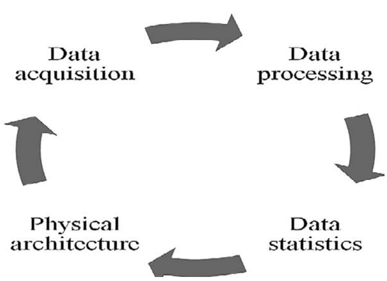

FIGURE 7.5
Major features of IoT-based PA.

sustainability. Actual information regarding the environment like weather changes, crop, and soil parameters can be retrieved from the sensor devices, which will be deployed in the yield. Many aspects and technologies of WSNs with IoT are being used presently in the PA for effective irrigation, fertilization, and pest control. PA manages the production of each crop, herbicide, seed, insecticide, effort fertilizer, etc. PA involves five stages: (1) collecting the data, (2) diagnosis, (3) analyzing the data, (4) precision field operation, and (5) evaluation. PA is mainly used for supervision plans to utilize information knowledge to improve quality and manufacture. PA systems aim to (1) reduce the cost, (2) decrease the time and effort, (3) save water and energy, and (4) provide a user-friendly interface for farmers. Some of the challenges in the technology implementation are a high investment, inexpert labor, fear of new technology, coverage and connectivity, split market, etc.

7.2.1 Types of Sensors in PA

To measure the different types of crops, PA plays an important role in segregating it [5], as shown in Table 7.2.

7.2.2 Layers Design for IoT in PA

IoT's core architecture is segregated into the perception layer, transmission layer, and application layer.

7.2.2.1 The Perception Layer

The perception layer is a top layer used to build the environment for various sensors, which collect data from various environments. This helps brief the current state of the environments [6].

7.2.2.2 The Transmission Layer

The transmission layer includes all types of network communication protocols. It will collect data from the perception layer and transmits it to the application layer based on network protocols [7].

TABLE 7.2

Different Types of Precision Agriculture Sensors

Agriculture Sensors	Functional Description
Location sensors	Location sensors are used to sense the latitudinal and longitudinal position of the area. To improve the accuracy of the sensing position, sensors use GPS satellite technology.
Optical sensors	Optical sensors are used to measure the structure of the soil. These sensors are mounted on robots, drones, and satellites to detect the organic matter and soil moisture content.
Electro-chemical sensors	Electro-chemical sensors help collect chemical data from the soil by detecting certain ions in the soil. They provide information on the pH status and nutrient levels of the soil.
Mechanical sensors	To analyze the soil compaction or mechanical resistance.
Dielectric soil moisture sensors	To measure the humidity levels with the electrolytic instability of the soil.
Airflow sensors	To analyze the air inflow from mobile mode or fixed mode.

TABLE 7.3

Specifications for Energy and Power for Wireless Communication in PA

Type of Data Communication	Application Possibilities	Size of Data	Depletion of Energy
The size of the data is minimal, and it consumes lesser energy	• Air temperature/direction/humidity speed • Humidity and temperature of soil • Color and thickness of leaf • Thickness of trunk • Size of fruit	100 bytes	Less than an mA
The size of data was medium, and the energy consumption also medium	• Still camera • Multiple cameras • Sensors that detect sound	13 mega bytes	13 mA
The size of data was large and high energy consumption	Video camera streaming	Ten seconds of Mb and a minute	50 A

7.2.2.3 The Application Layer

The application layer plays a major role in IoT architecture. It may be a cloud-based or local system–based function.

- Data storage – e.g., cloud-based platform and Hadoop Distributed File System for quick and secure access to data [8];
- Data management – e.g., Supervisory Control And Data Acquisition (SCADA) for real-time data monitoring [7];
- Data statistics – e.g., decision-making process, production modes, and crop controls for automatic control in agricultural production [9]; and
- Data marketing – e.g., data detection, tracking capabilities of agricultural products for new business models, ownership, and privacy [10].

7.2.3 Specifications for Energy and Power in PA

The energy and power in PA play a major role in processing data and analysis. Table 7.3 shows the various specification of energy and power level for communication.

7.3 Precision Agriculture Requirement

In PA a set of rules must be followed to attain better yield. Related activities to agriculture are:

1. Before going to yield the crop in the field, a field survey is important. Soil sample as well as study of soil conductivity, soil moisture, and pH according to the soil for the chosen agricultural plant are done using sensors.

2. Remove unnecessary plants growing with crops and avoid unnecessary competition between them.
3. Monitor the plant growth and health, periodically examining nutrient status for phosphorous, potassium, nitrogen, etc.
4. An important factor to be considered after crops are planted is detecting diseases in the crops.
5. In the time of growth of crops, check the water level and soil moisture of the yield.
6. The finding of lodging is also a vital part of PA.

7.4 Multispectral Remote Sensing in Precision Agriculture

Remote hearing is vital to the PA component. It uses multispectral satellites to collect high-resolution images for agriculture practices. The multispectral imaging camera sensors mounted on agricultural drones allow farmers to monitor crops, soil, parasites, fertilizers, and water, the data that they need more accurately. Consequently, such drones have proven to be helpful in terms of increased yield and other benefits. Multispectral sensors use four bands, namely red, green, red-edge, and near-infrared (NIR) bands, to capture images of crops and vegetation in the visible and invisible regions (Figure 7.6) [1].

Modern PA is designed to increase yields and resources such as reducing environmental impacts such as over-fertilization and the use of pesticides. Many benefits of using more images or data include higher accuracy, simplicity, and lower costs. This helps to balance yield, crop growth, and soil quality [11, 12]. A wide variety of multispectral camera sensors are used in agricultural practices such as [13, 14].

Different types of sensors used in multispectral remote sensing are

- Sentera Quad
- Parrot Sequoia

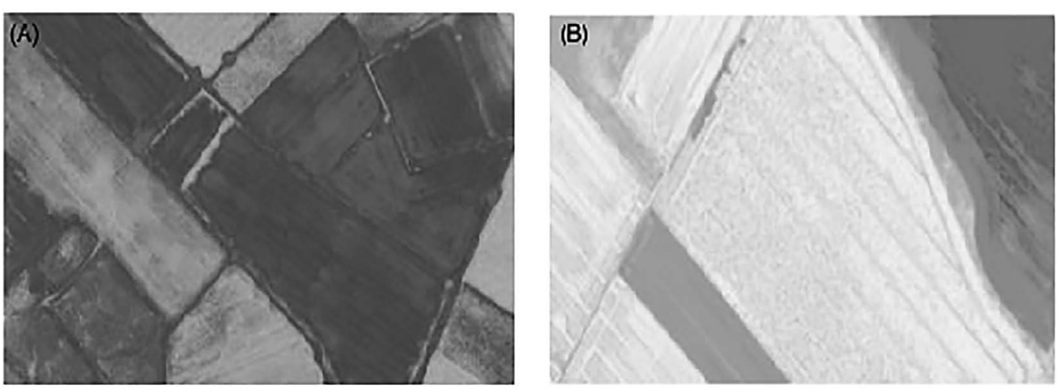

FIGURE 7.6
(A) Image of the field in multispectral images; (B) image of the field from unmanned aerial vehicles.

- ACD light sensor – Tetracam
- MicaSense Rededge Sensor
- Airinov multiSPEC 4C Agronomic Sensor

7.4.1 Hyperspectral Remote Sensing

Hyperspectral imaging sensors have more advantages than multispectral sensors for classification and discrimination. They provide detailed information on any item due to the availability of band information. Hyperspectral sensors have good spectral correction. High-resolution spectral processing of hyperspectral data has the advantage of PA capture and monitoring, but it also includes unwanted data, which affects the level of accuracy [15].

7.4.2 Hyperspectral Data in Agriculture

Hyperspectral data involves the acquirement of images in hundreds of narrow adjoining spectral bands to get high-resolution information for each pixel of an exact scene. Extracted spectral signatures from hyperspectral images are used to recognize and categorize the characteristics of objects. Several applications of hyperspectral and multispectral imaging are being confirmed in different types of agriculture techniques, together with excellence in organizing, classifying, and categorizing farming products and in the classifying insect and contaminants as well as in food protection [16].

7.5 Global Positioning System

GPS technology is used to monitor the growing situation. It takes in parameters such as air, water, soil, pesticides, and fertilizers. The GPS structure is used to locate the exact place in a farming field and check a range of farming parameters by using wireless communication networks. It interfaces with Acorn RISC Machine (ARM) like an intelligent monitoring system to attain functions like SMS or MMS to make an alarm to the farm manager when unwanted changes occur. It is also used for the maintenance and monitoring of the crop for agriculture [17].

7.6 Technologies for IoT-Based PA

Protocols play a vital role in enabling network connectivity in IoT devices. Combining applications and protocols allows devices to exchange data over the network, define the data exchange format, encode data, address schemes for devices, and route packets from sources to destination, and protocols include functions like flow control, sequence control, and retransmission of lost packets. Agri-IoT data gaining component consists of several protocols such as Hypertext Transfer Protocol (HTTP), Message Queuing Telemetry

TABLE 7.4

Wireless Communication Technologies with Their Standards

Parameters	**Zigbee**	**LoRa**
Standard	IEEE 802.15.4	IEEE 802.15.4g
Channel bandwidth	2 MHz	<100 Hz
Data rate	20, 40, and 250 kbps	100 Mbps
Network size	65,000	1,000,000
Application	WPANs agriculture	Agriculture Environment

Transport (MQTT), Data Distribution Service (DDS), and Advanced Message Queuing Protocol (AMQP) and also communication wireless protocols such as IEEE 802.11 Wi-Fi, LoRaWAN, WiMax, Bluetooth, Zigbee, and 2G/3G/4G Mobile Communications Standards.

Table 7.4 depicts the many types of wireless communications technologies and standards.

Table 7.5 depicts the many forms of precision agricultural routing protocols.

7.7 Challenges of IoT in PA in India

- Lack of knowledge among farmers about the advantages of PA
- Extra manual work
- Frequent changing of weather
- Expensive for machinery work
- No interest in PA among young and educated professionals
- More expensive
- Difficulty in understanding the technology among farmers
- IoT devices and smart farming require breakage-free Internet connectivity. It creates challenges in developing countries.

TABLE 7.5

Routing Protocol Schemes in PA

Parameters	**Sink Mobility**	**Multipath**	**Cluster Head**	**Routing Metric**
Wireless protocols/devices	Simulation	Zigbee	Zigbee/simulation	Zigbee/IEEE 802.15.4
Power savings/battery lifetime	High power	1825 min	20 times established without cluster heads	28.4 days
Application	Forest area	Irrigation system	Crop farming	Precision agriculture
Limitations	Packet losses lead to more energy consumption	Consumes a lot of power at low communication distance	Unreliable communication beyond 80 m	Short battery life

7.8 Conclusions

PA and agricultural systems based on IoT have proven to be incredibly beneficial to farmers, as less irrigation is beneficial to agriculture. Sensor coefficients like temperature, data collecting through sensors, humidity, and wetness could be set dependent on the state of the agriculture field. The proposed approach will create optimal resource usage and solve the problem of irrigation scarcity. An important ability of wireless networks was better represented graphically than prior technologies that could be recovered and statistically analyzed. Using IoT technology, real-time field monitoring is conceivable. The presented method closely monitors the waste of agricultural resources. PA is the science of art to improve crop yield and to support management via high technology sensors and analysis tools [18]. PA is the application of technology to manage spatial and temporal unpredictability of inputs to improve productivity and environmental quality. PA is a practical approach that reduces the risk and variables in agriculture. The growth of technologies in the 21st century led to the development of the PA concept [19]. PA is used for the efficient use of various inputs like effective use of fertilizer, seed, pesticide, fuel, land, data, and water. Agriculture and the agricultural industry in a remote area can benefit from the WSNs and cloud server–based vast networks with IoT.

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