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2 Data science, computer vision and machine learning for agriculture and natural resource management: an overview

Abstract: The progress of humanity is dependent on agriculture and natural resources. A developed society with modern amenities and infrastructure will be useless without access to food or natural resources. As population and living standards rise, so is the demand for food. On the other hand, the Earth has finite natural resources. Therefore, researchers must develop innovative solutions to improve the yield and effectively manage natural resources. Data science, computer vision and machine learning are spearheading key innovations in agriculture in the present times. In the near future, the farms will be a great source of data. The data obtained from farms will drive digital agriculture. It will help farmers or customers to make optimal decisions in real time. The chapter shows how to best use available voluminous, dynamic and real-time data. In turn, it will drive the effective development of agriculture and proper utilization of natural resources.

Keywords: agriculture, computer vision, data science, machine learning, natural resource management, remote sensing

2.1 Introduction

The areas of concern for agricultural development are lack of natural resources, rise in population, urbanization, climate change, energy and food waste. The entire agriculture supply chain has to gear up for the challenges as the food consumption pattern changes. One of the crucial questions arising is: "Who will farm?" [1]. Urbanization is

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spreading rapidly with a shrinking rural population. The spiraling population growth and the rise in living standards have placed unprecedented pressure on agriculture and natural resources. Agriculture is a domain with many uncertainties aggravated by climate change, land pollution, water pollution and modifications in demands due to socioeconomic upliftment [2].

These challenges demand improvement in productivity from agriculture while reducing the overuse/misuse of natural resources. The traditional approach of farming has benefited from technology interventions [3]. It has to accelerate further using science and technology-driven agriculture 4.0. Precision agriculture (PA) is turning out to be the fulcrum of agriculture 4.0 [1]. The PA or intelligent agriculture domain has shown promise to handle uncertainties in agriculture and natural resource management (NRM). Emerging technologies like remote sensing – satellites and unmanned aerial vehicles (UAVs), Internet of things (IoT), global positioning system (GPS) and cloud computing are driving onfield and off-field activities in PA. The information and communication (ICT) technology helps at every stage of the typical crop cycle – soil preparation, sowing, growth management, irrigation, harvesting and storage.

IoT combines physical objects or "things" and creates their network. Each of these objects is equipped with sensors, and they connect to exchange information. As more advanced machines and sensors are involved in farming, the knowledge builds in amount and breadth. This enables penetration of digital technologies in the farms. The digital technologies monitor and measure various in-field parameters, for example, weather and off-field parameters producing "big data" quickly. The sensor produces data with massive *volume*, *variety* and *velocity*. It necessitates large-scale data collection from hybrid sources, preprocessing, storage, modeling, and analysis. The agri-data needs real-time processing and integration to extract economic benefits. Mark [144] shows five major "V" dimensions of big data as follows:

1. Volume: It shows the amount of data available for processing and analysis.
2. Velocity: The rate at which data arrives and its processing for deriving timely and relevant outcomes.
3. Variety: The data arrives from heterogeneous sources with different dimensions, formats, resolutions and applications.
4. Veracity: It deals with data accuracy, reliability, and confidence in the data.
5. Value: It is about extracting a value from the data after all the data processing.

Later, many other V's have been added [2]; for example, the veracity dealing with the reliability of data, valorization for knowledge propagation and visualization for presenting the information. The typical applications, which handle the prominent "5 V's," are shown in Table 2.1.

Big data sets contain both structured and unstructured records. The survey paper [2] shows different data sources as follows: ground sensors – chemical sensors, biological sensors, weather devices; governmental records – statistics handbooks, reports, regulatory body reports; remote sensors – UAVs, satellites, robotic vehicles; online

Table 2.1: Agriculture applications using big data.

V's	Sample agriculture application
Volume	Earth observation, yield estimation, land use/land cover, weather forecasting
Velocity	Pest and disease identification, weed identification, financial transactions in agri domain, weather forecasting
Variety	Crop estimation, quality monitoring, plant phenotyping, plant species identification
Veracity	Yield estimation, agriculture econometrics, weather forecasting
Value	Crop prediction, plant phenotyping, land use/land cover, disease identification

web services, public repositories, archives, live feeds; crowdsourcing – images, social media mining and cell phone data. The sources are heterogeneous and generate data at a different rate and in various formats. The dataset is also governed by the application for which it is used, for example, plant phenotyping would often use ground sensors or platforms. At the same time, remote sensing is required for applications related to land mapping and monitoring. Kamilaris et al. [2] also suggested that images and videos are popular sensing modalities that computer vision (CV) algorithms can process. The output by CV is most often used with machine Learning (ML) for prediction, clustering, and classification problems. The importance and integration of CV and ML in solving problems in agriculture are described in the next section.

2.2 Vision and machine learning in agriculture

Technology-driven PA is dependent on sensors, signal-processing devices, computation and ICT. PA is expected to balance the supply and demand side of the equation, making the agriculture cycle more efficient, safe and green. It is expected that PA will penetrate and increase the connectivity among the farms. The growing number of devices based on vision will bring both challenges and opportunities. CV uses visual cues and helps the computer to understand the surrounding world. Broadly, it is an interdisciplinary domain that tries to mimic human visual systems to automate the understanding of the surrounding environment. A classical CV task has four main parts as follows:

1. Data acquisition through spatial or spatiotemporal sensors like cameras or radar.
2. Data preprocessing to improve the visual signal quality, for example, noise reduction and contrast enhancement.
3. Image analysis extracts practical information from the signal that breaks the given image or video into different segments.
4. Image understanding provides semantic meaning to the constituent parts and meaning to the surrounding world.

CV offers many advantages for agriculture domain processing. Some of them are summarized as follows:
- The high-resolution sensors with many modalities, for example, visible spectrum and near infrared (NIR) bands, are available at low cost.
- Present-day electronics allow high-performance computations. Cloud computing provides resources on an as-you-need basis.
- The CV, when combined with ML, creates a robust mechanism for nondestructive testing. It provides state-of-the-art accuracy with a very high repeatability rate.
- The sensing technology allows data capturing at multiple resolutions and distances.

It is vital to use technology that helps to interact with the environment (sensing and actuating), learn, reason and draw inferences. As a sample, this section shows ML and agro-vision to solve some of the agriculture problems [4–6]:
- Crop growth monitoring
- Weed pest and disease identification
- Product quality testing
- Yield estimation

Common to all of these tasks is to detect the objects of interest and classify them. It requires a robust pipeline with high-quality sensing, high-performance computing and a generalized data analysis framework.

2.2.1 Crop growth monitoring

Plant phenology study changes in the plant in reaction to the variations of environmental conditions – temperature, light and humidity. The automation in quantitative measurements (plant phenotyping) of plant properties offers an efficient and productive alternative. Seventeen micronutrients, macronutrients and secondary nutrient elements are essential for plant growth [7]. Crop growth monitoring is one of the essential aspects of PA, and it helps in understanding the growth environment. A minor adjustment in the environment can significantly increase production [8]. Faragó et al. [9] suggested a CV-based method to measure morphological and physiological parameters of in vitro plants. Using a Canon camera, the size, shape and color of the plants were repeatedly captured. The image analysis measured several parameters – rosette size, convex area and ratio, chlorophyll and anthocyanin. The imaging proof of concept revealed several significant differences between wild-type and transgenic *Arabidopsis* plants. Rico-Fernández et al. [10] performed a foliage segmentation for measuring plant growth. The paper presented an approach consistent across different crop species – tomato, maize and carrot. The approach is also robust to changes in environmental conditions. It contextualized the information and color space transformation to segment the foliage accurately using a support vector machine (SVM). On average, it achieved a segmentation quality of 0.9 which is showing very good accuracy.

Naik et al. [11] showed an end-to-end phenotyping pipeline for automated analysis of the iron-deficiency chlorosis (IDC) in soybean plants. The paper shows experiments with ten classifiers and selects the best for use in a smartphone. Several preprocessing steps were carried out for effective segmentation. Calculating the proportion of yellow regions (chlorosis) and brown regions (necrosis) is essential. The accuracy and interpretability – the ability to interpret data by the user – are chosen as metrics for evaluation. It was observed that the hierarchical model performed well.

It is essential to develop an automatic measurement system for grain [12]. The authors proposed an automated wheat-head growth monitoring system. The images are captured directly from the field under different light conditions. The two-stage detection mechanism has been employed to detect the spike – the wheat head. In the first step, wheat ear detection occurs, and in the second step, non-ear regions are eliminated. The sift-invariant feature transform forms a low-level visual descriptor encoded by the Fisher vector to form a mid-level feature. Then SVM is employed to classify the ear. The results match reasonably with the human observations. Table 2.2 summarizes the application of ML and CV to growth monitoring of the crop. It shows the successful use of conventional ML approaches on color images. Figure 2.1 shows a semantic segmentation for sample images in the GrassClover dataset [13], which contains images collected in outdoor agriculture scenarios.

Table 2.2: Summary of crop growth monitoring.

Author	Application	Sensor/ image size	Classifier/results
[9]	Measuring morphological and physiological parameters of in vitro *Arabidopsis* plants	RGB camera/ 3000 × 4000 pixels	Rosette size and plant size are highly correlated ($R^2 > 0.9$)
[10]	Foliage segmentation for growth monitoring – tomato, maize and carrot	Robot mounted RGB camera	SVM/segmentation accuracy – 0.9
[11]	IDC – soybean	RGB DSLR camera	10 classifiers – decision trees, random forest, naïve Bayes, SVM. Mean per class accuracy – 95.9%
[12]	Wheat development in the field	RGB camera	SVM/accuracy – 66.9%

Semantic segmentation is further helpful for growth monitoring. In one such challenge, wheat ear heads were counted using CV and ML. The global wheat head dataset (https://www.aicrowd.com/challenges/global-wheat-challenge-2021) contains 6000 images collected from 11 countries. It aims at finding the size and density of wheat ears from different wheat types. Sample images for successful detection is shown in

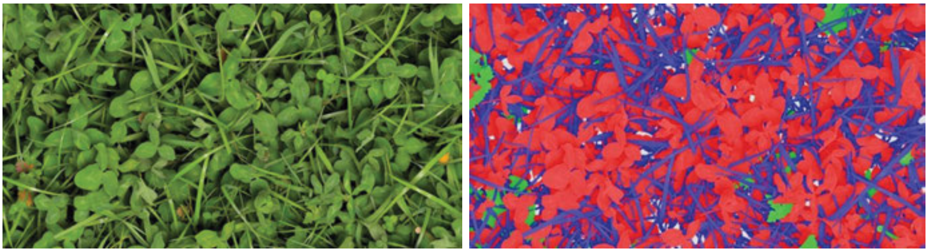

Figure 2.1: Semantic segmentation for yield estimation. Red is clover, blue is grass, green is weeds and light gray is soil [13]. Grassclover dataset: https://vision.eng.au.dk/grass-clover-dataset/.

Figure 2.2. It can be seen that the digital detection is challenging due to overlapping wheat heads, variation in wheat type, head orientation, presence of barbs and wind. Figure 2.3 shows the cases where CV and ML approaches fail to detect the wheat head.

Figure 2.2: Yellow bounding box shows detection of the wheat head. Top row – difficulty level of detection is easy. Bottom row – difficulty level of detection is hard (source: https://www.aicrowd.com/challenges/global-wheat-challenge-2021).

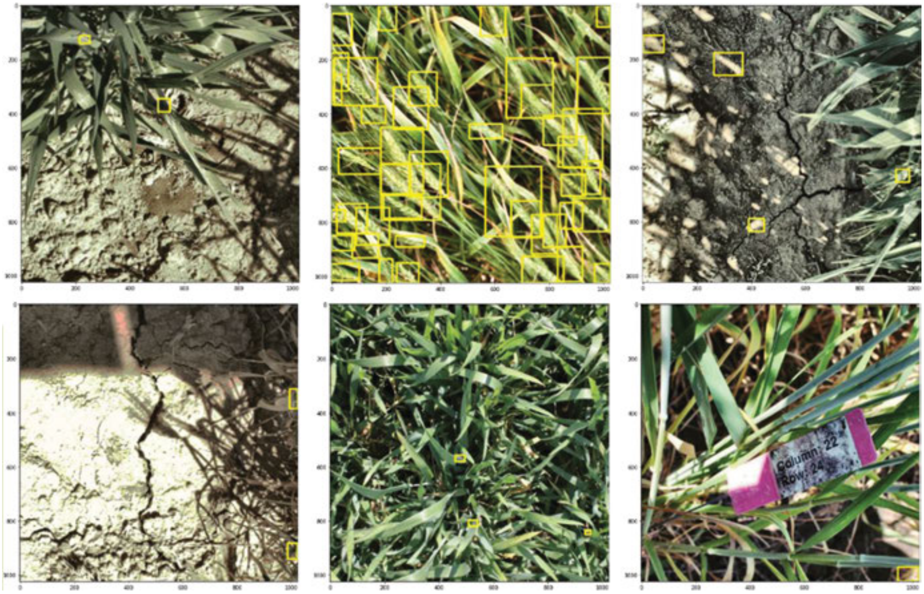

Figure 2.3: The cases of failure for wheat head detection (source: https://www.aicrowd.com/challenges/global-wheat-challenge-2021).

2.2.2 Weed, pest and disease identification

The crop quality is controlled by protecting against weed, pest attacks and disease. A quick and full diagnostic measure to automatically estimate the severity can limit the loss in the yield [14, 15]. Ma et al. [15] presented a segmentation of the foliar disease spots on images captured in the greenhouse using a color information and region growing method for segmentation. The method was evaluated on the cucumber downy mildew images captured under challenging conditions. The proposed algorithm achieved a good precision compared to the state-of-the-art method.

Ramcharan et al. [16] train a convolutional neural network (CNN) to detect disease symptoms appearing on the foliar of cassava plants. The CNN identified symptoms of three diseases (cassava mosaic disease, cassava brown streak disease and brown leaf spot), two types of pest damage (green mite damage and red mite damage) and nutrient deficiency. The model used single-shot multibox [142] model with the MobileNet classifier pretrained on the COCO dataset. The developed algorithm is deployed in the mobile app and tested in the fields of Tanzania. The model predicted two levels of severity of the disease – mild and heavy. It was observed that the performance of the trained model drops when tested on the images and videos captured in the open field.

Aphids are the pests that heavily impact the wheat crop [143]. The insects feed on the sap of the wheat, severely affecting its development. The paper proposed identifying the red and green species and monitoring the density of aphids in the field. Preprocessing is used for image enhancement and noise reduction on the image captured in the field. A histogram of oriented gradients (HoGs) and SVM were used for classification. The HoG feature is used to train a binary classifier that detects the presence or absence of the pest.

Sabzi et al. [17] proposed a neural network-based system for identifying three weeds and potato plant types. Weed removal is necessary as they compete with plants for nutrients, minerals and even water. It affects the growth and quality of the main crop. The paper used color features and texture features to classify three weeds and potato plants. The images are captured using a camera mounted on a moving platform, and 3459 objects were extracted for training. Table 2.3 summarizes ML and vision's application to detect weed, pest and disease in the crop. Figure 2.4 shows a sample weed image and its corresponding segmentation mask. The tuple trains the ML algorithm to perform semantic segmentation of the images.

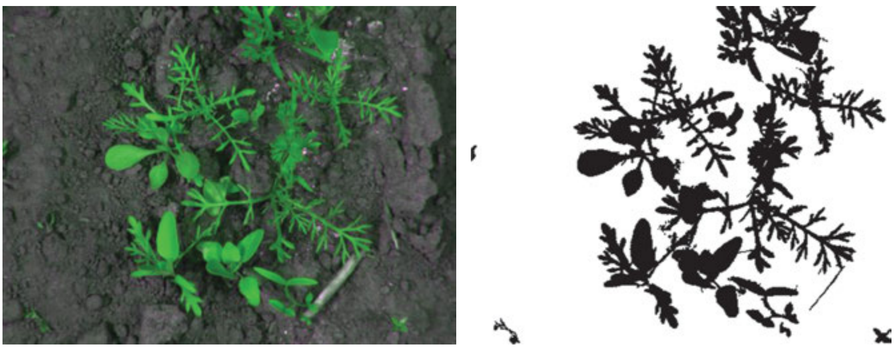

Figure 2.4: Weed and its corresponding mask [18]. CWFI dataset https://github.com/cwfid/dataset.

Table 2.3: Summary of weed, pest and disease identification.

Author	Application	Sensor/image size	Classifier/results
[15]	Detecting cucumber downy mildew	Color CCD camera/ 4320 × 3240 pixels	Region growing/precision – 97.2%
[16]	Disease, pest damage and nutrient deficiency in Casava	20 MP camera/2415 images	MobileNet/mean average precision 75% on image and 81.2% on video
[143]	Pest detection – aphids	Digital camera/ 1200 × 1800 pixels	SVM/average detection rate – 86.8% Error rate – 8.91%
[17]	Weed detection	Video camera on moving platform/	Neural network/accuracy – 98.3%

2.2.3 Product quality monitoring

The quality of the agricultural product is achieved by automatic grading and quality inspection. It helps promote commercialization and meet the standards required with product exports [19]. Quality testing has been automated to lower the cost of the traditional system [20]. The automation also overcomes the inconsistencies of manual quality checks and increases the satisfaction levels of the customers. Deng et al. [21] developed an automated carrot grading system. It improved the grading efficiency through the automated carrot sorting system using CV. The overall system has image acquisition, a conveyor belt to carry crops and a control system for sorting. The quality is determined by checking the surface defects. The system detects three types of defects such as unnatural shape, fibrous root and surface crack. After removing the carrots with defects, they are graded based on their length. A convex polygon is used to detect the shape of the carrot. The system achieved good accuracy in grading and sorting.

Nondestructive testing and measurements are the obvious mechanisms in post-harvesting for checking the damage to the crop. The mechanical damage to the citrus fruit is not easily detectable, specifically through deformation in appearance. The paper [22] proposes using image processing and UV radiation to detect the mechanical damage to sweet lemon. First, the fruits were dropped from the height (2–3 m) on the ground, and then UV light of different wavelength images are captured. The images are analyzed using the green spot index, which shows mechanical damage. It significantly increases the detection level, and all 135 fruits were classified as damaged and undamaged with 100% accuracy.

It is vital to classify fruits into different grades considering their popularity. Iraji et al. [23] proposed many methods to classify tomatoes in different grades. The paper proposes adaptive neuro-fuzzy inference system with input features, regression and an extreme learning machine. In another approach, deep-stacked sparse autoencoders on images are used for tomato classification. The method produces excellent accuracy in grading the tomatoes without extracting features.

Wang et al. [24] used hyperspectral imaging to measure the internal mechanical damage of the blueberries. The method uses two CNN architectures, ResNet and its newer variant, ResNeXt. The fine-tuned networks achieved the accuracy of 0.88 and 0.89, respectively. For comparison, the author also used five other ML algorithms with k-fold cross-validation. The accuracy for CNN is better than five classical ML techniques. Table 2.4 summarizes the use of machine learning for quality monitoring of agriculture products. The approaches show the successful use of deep learning to solve the problem.

Table 2.4: Summary of product quality monitoring.

Author	Application	Sensor	Classifier/best results
[21]	Carrot grading and sorting	Industrial-grade camera	Convex polygon for curvature – 95.5%, concave point method for fibrous root – 98%, Hough transform for surface crack – 88.3%
[22]	Sweet lemon mechanical damage	UV camera	Binary classifier, accuracy – 100%
[23]	Tomato-quality grading	RGB camera	Deep-stacked autoencoder/95.5%
[24]	Internal damage in blueberry	Hyperspectral camera	CNN ResNet Accuracy – 0.89

2.2.4 Yield prediction

Real-time information from farms can help estimate the yield in PA. It is one of the critical mechanisms in production planning. UAV provides a platform for acquiring images with low cost and high resolution for quick implementation [25]. The details in images can help with better planning in agriculture economics and production outputs. Maldonado et al. [26] proposed a method to estimate orange crop yield on three varieties. It exploits a known correlation between the number of fruits detected in an image and fruits present in an orange tree. All images are taken by a camera placed at a distance of 2 m from the tree canopy. The method uses series of image processing techniques to extract the green fruit feature. The fruits were classified using SVM, and a lower distance between plant canopy and camera resulted in significant false positives. The algorithm could not detect all the fruits in images. However, under good lighting conditions, it has a false-positive rate of less than 3%.

The quality of the field scanned has significantly improved with the use of UAVs. Drone technologies have grown in leaps and bounds, facilitating the treatment and analysis of sugarcane farms [27]. The paper evaluates the degree of canopy for different planting approaches and row spacing to assess the potential application in predicting the yield of the sugarcane field. The images are taken considering the biomass accumulation curve. The leaf area index (LAI) and green–red vegetation index (GRVI) are computed by field sensor and UAV. The use of GRVI resulted in an R^2 value of 0.69 between the onfield sensor and UAV image. When combined with LAI, the yield estimates improved to $R^2 = 0.79$. It shows that UAV is an effective mechanism in estimating the yield.

Han et al. [28] used UAVs to capture structural and spectral information and use ML algorithms to estimate the maize biomass. The feature elimination obtained essential features. Four ML regression algorithms were evaluated: multiple linear regression, SVM, artificial neural network (ANN) and random forest (RF) regressor. In this paper, the authors used three methods to estimate the height of the plants and compared them with the manual ground-based measurement. The results indicated that RFR produced the best results with the lowest estimation error. The proposed method increased the ratio of explained variance with the least error rates.

Multispectral and hyperspectral sensing also gain prominence in the PA for yield estimation [29]. The paper used an unmanned ground vehicle to capture line-scan hyperspectral images in a mango orchard. The best model was obtained after the preprocessing of tree delimitation and identifying pixels belonging to mango in the image. The count obtained through RGB techniques is compared with that obtained after manually counting fruits on the tree. The model was then mapped to find field count – number of trees and mango count per tree. The model achieved a high degree of determination coefficient value. Table 2.5 summarizes the approaches for yield prediction using ML and CV. Figure 2.5 shows the use of CV and ML for fruit detection and yield prediction. It shows the field image and corresponding

Table 2.5: Summary of yield prediction.

Author	Application	Sensor	Regression best results
[26]	Orange yield estimation	RGB – camera/ 2592 × 1944 pixels	Coefficient of determination (R^2) manual – automatic yield prediction – $R^2 = 0.48$ SVM for correct fruit identification. Accuracy – 49%
[29]	Sugarcane field yield estimation	Onfield and UAV images	Correlation GRVI – $R^2 = 0.69$
[28]	Maize biomass estimation	Digital camera, multispectral camera	RFR $R^2 = 0.944$
[27]	Mango yield estimation	Ground-based hyperspectral sensing	Field count $R^2 = 0.75$ (18 trees) Mango count $R^2 = 0.83$ (216 trees)

The section reviewed the applications of CV and ML in four essential areas of PA. It shows that how agriculture automation can be achieved with low cost and high efficiency. The penetration of technology will continue to grow in PA with the use of AI. It will improve the efficiency and quality of the agroproducts.

2.3 Data science and ML for natural resource management

With the advancements in remote sensing, GPS and real-time kinematics, it is easier to monitor crop health, identify nutrient deficiencies and reduce yield. Google Earth Engine (GEE) is an emerging big data platform. The United States Geological Survey,

Figure 2.5: Mango yield estimation with field image and corresponding ground truth image [30] (dataset: https://github.com/avadesh02/MangoNet-Semantic-Dataset).

in partnership with several US universities and international institutes, produced the world's first Landsat satellite-derived, global cropland extent product at 30 m resolution (GCEP30) for the nominal year 2015 by using the GEE platform [31]. The emerging Web-based geoportal platforms help visualize, access, query and disseminate the information to the users for efficient planning, monitoring and sustainable management of natural resources. The section shows the following application for DS and ML in NRM:
– Drought monitoring
– Land-use changes monitoring
– Crop types mapping and monitoring
– Prediction of soil properties
– Land degradation assessment
– Irrigation water management

2.3.1 Drought monitoring

Drought is considered one of the most widespread natural disasters in almost all ecosystems [32, 33]. It severely affects natural ecosystems, global food production and human livelihoods [34]. The period, frequency and degree of droughts varied from region to region [35]. Various input parameters are needed to analyze the nature, extent and severity of droughts, usually derived from climate, remote sensing, hydrological and atmospheric systems. The advance Earth Observation (EO) and climate detection systems provide massive EO data with high spatial, temporal and radiometric resolutions [36]. The probabilistic methods help predict drought due to quantifying uncertainties from drought-causing hydroclimatic variables [37].

ML algorithms like RF and decision tree (DT) were also used in drought monitoring. They increase the decision-making capacity and reduce the subjectivity in obtaining the results [38]. RF algorithm that works based on the combination of several classifications and regression tree (CART) models. Kuswanto and Naufal [39] used CART and RF algorithms to classify the droughts and reported that both methods had been proved to be computationally efficient in predicting droughts. Dimension reduction algorithms like principal component analysis eliminate redundancy by converting the original feature space axes. Drought information can be shown in a new model space without correlation [40]. Alizadeh and Nikoo [41] studied the drought events using new fusion approaches from high-resolution satellite data at the feature level. They reported that ML approaches of RF, support vector regressor (SVR) and ANN showed excellent performance in obtaining significant results.

In recent times, data mining techniques were also applied to build drought monitoring and forecasting models by using ML algorithms such as SVR and ANN [42]. Chiang and Tsai [43] found SVM superior in predicting hydrological drought compared to the classical model. ANN models were used to predict quantitative values of drought indices to measure the degree of dryness for any period [44]. The drought forecast model was proposed based on the RF method to predict the monthly standardized precipitation index (SPI) [45]. Park et al. [46] developed drought prediction models for a short period using remote-sensing data and climate variability indices over East Asia through the RF model. A regional-level seasonal drought analysis was carried out based on SPI and DT algorithm at watershed level in Turkey [47]. The hybrid models like ANN and RT with the fuzzy segmentation approach using satellite images were used to identify and predict the drought in Ethiopia [145].

2.3.2 Land-use changes monitoring

In recent years, the application of ML algorithms in the classification and analysis of remotely sensed imageries in land-use/land-cover (LULC) mapping has been increased considerably [146]. ML algorithms are popular in remote-sensing and EO studies, especially LULC classification and vegetation monitoring [48]. The information generated by time-series satellites data is widely used in various EO studies, including vegetation monitoring [49] and land-use changes [31]. Zhang et al. [50] used MODIS data to analyze the driving factors of space observations of plant greenness and phenology. RF is one of the most widely used machine learning algorithms [51]. It can be used for classification and regression purposes with categorical and continuous variables [52]. RF showed its potential in land-cover classification due to its straightforward and understandable decision-making process and excellent classification results [53] from geo-big data computations.

SVM, neural networks and classification and regression tree algorithms were performed in land-cover classification with limited training data. It was reported that SVM outperforms other classifiers due to its overall high capacity to generalize complex features [54]. DL algorithms were widely used in remote-sensing data analysis, including scene classification, LULC analysis and object detection [55, 56]. Srivastava et al. [57] compared the performance of the ANN and SVM as classification algorithms for LULC change studies. Based on the performance analysis, they reported that the ANN was better than the SVM. Keshtkar et al. [58] advocated that the SVM classifier was performed better than the RF to classify land-cover types of a heterogeneous landscape.

However, the selection of suitable algorithms in vegetation monitoring and assessment depends upon the study's objectives. Suitable ML algorithm, input datasets and parameters are needed to be considered to obtain accurate results. Noi and Kappas [59] compared the performances of RF, k-nearest neighbor (kNN) and SVM classifiers for LULC classification using Sentinel-2 image data of a river delta in Vietnam. They reported that all three classifications provided high overall accuracy (OA) ranged from 90% to 95%. However, SVM produced the highest accuracy among the three classifiers with the least sensitivity to the training sample sizes, followed by RF and kNN. However, few limitations are also associated with ML algorithms, as DT is too sensitive to small changes in the training dataset. It is occasionally unstable and tends to overfit in the model [60].

2.3.3 Crop-type mapping and monitoring

In PA, accurate and detailed mapping of crop types are crucial for crop monitoring and accurate crop yield estimations. Since there is limited scope for increasing agricultural land horizontally, more food is needed from the existing land and water resources [61, 62]. To ensure food and nutritional security, sustainable intensification in the crop fallow areas through cereal-based systems needs an hour [63]. Hence, crop-type mapping and monitoring at higher resolution assume greater importance in agriculture and ensure global food security. The spectral response of cropland areas varies significantly among the crop's phenological stage and the cropping calendars [64]. Remote sensing has been widely used for rice fallows mapping [65, 66] to provide policy inputs in decision-making.

Pelletier et al. [67] reported that the RF algorithm helps classify large datasets with high spatial and temporal resolutions for extensive area land-cover mapping. GEE platform is widely employed to analyze multitemporal satellite data in crop-type mapping using ML algorithms [68]. Landsat data on the GEE platform was used to produce cropland at 30-m resolution and reported that the RF algorithm could map croplands rapidly and accurately at various scales [69]. Gumma et al. [70] used Landsat 30-m TM (Thematic Mapper) data on the GEE platform by adopting the RF algorithm in cropland mapping in South Asia. They reported that the RF algorithm gives better OA in producing agricultural croplands. Moumni and Lahrouni [71] used high-resolution Sentinel-1 and Sentinel-2 fused satellite data by adopting ANN, SVM and maximum likelihood in mapping crop-type irrigated areas. They reported that fused images of optical and microwave improved the accuracy in crop-type classification compared to the classification results of optical or SAR data alone.

The SVM algorithm can classify high-dimensional data with small training samples [54]. Inglada et al. [72] applied RF and SVM on high-resolution multitemporal optical imagery of SPOT4 and Landsat 8 to produce crop-type maps at the global scale. SVM classifier using Gaussian kernel density function was superior in crop-type mapping [73]. In general, several studies reported that RF and SVM were more suitable for classification in agricultural regions using high-resolution satellite imageries [74, 75]. However, further research is to be carried out to develop hybrid algorithms to precisely analyze and discriminate crop types, especially in the small agriculture fields of heterogeneous landscapes.

2.3.4 Prediction of soil properties

Accurate prediction of soil properties immensely helps in the optimum management of soil resources. Digital soil mapping (DSM) technique showed its great potential in producing spatial information on soil resources [76]. In soil mapping, the information on environmental variables such as climate, lithology, vegetation and landforms play an essential role in soil properties mapping and soil landscape analysis [77]. DSM techniques offer to generate soil property distribution maps. It is done through numerical models that take soil environmental covariates into account in inferring spatial and temporal variations of soil properties [78]. Tree-based ML algorithms and the simplest version of regression tree and their variants have been used in the DSM [79].

RF algorithms were widely used in DSM [80, 81]. Vaysse and Lagacherie [82] introduced a quantile RF to map the uncertainty associated with predicting the soil properties. Forkuor et al. [83] used SVM to map soil properties. It can handle large datasets, learn complex data classes and make better decisions regarding the separation of classes. Soil organic carbon (SOC) plays a significant role in soil health management, water holding capacity, nutrient availability and plant growth. The spatial variability of SOC at the field to the regional scale is highly related to the soil-forming factors, including the climate, organisms, relief, parent materials and time [84]. In the context of the availability of huge remotely sensed imageries in the public domain and easy accessibility of climatic and digital elevation model data at different resolutions, the application of ML algorithms in the prediction of SOC is significantly increased [85].

Many ML algorithms have been successfully applied for quantitative mapping of various soil properties like the prediction of SOC [86], map soil textural classes like clay, silt and sand content [81, 87], soil pH [88] and cation exchange capacity [83]. ML algorithms were also applied to make maps of soil nutrients such as nitrogen [83], phosphorus [89], potassium, calcium or magnesium [90]. Emadi et al. [91] reported that the deep neural network (DNN) algorithm outperformed other ML algorithms regarding the power of the prediction uncertainty at the province scale. It demonstrated that DNN is suitable for use as a robust estimator for SOC mapping. In SOC assessment, ML algorithms were proven their merits than the geostatistical methods due to their higher ability to obtain more information for unsampled points by investigating nonlinear relationships between SOC and environmental auxiliary variables.

2.3.5 Land degradation assessment

On a global scale, soil erosion by water is recognized as one of the world's most serious environmental problems of the twenty-first century [92] and the leading cause of land degradation [93]. More than 83% of the global land degradation in all climatic regions is caused by soil erosion alone [94]. Using advanced tools assumed greater importance in the context of changing climate, land-use practices and meeting the global commitments in climate change and land degradation neutrality. Soil erosion caused by water is the major challenge of India, which is contributing to land degradation when it exceeds the natural soil formation rates [95–97]. By using the six parameters of the empirical universal soil loss equation model, that is, rainfall erosivity (R) factor, soil erodibility (K) factor, slope length (LS) factor, cover (C) factor and support practice (P) factor in GIS, estimated the extent and spatial distribution of soil erosion by many authors [77, 98–100].

Current trends in automating the identification and assessment of land degradation are based on vegetation indices [101, 102]. The analysis of time-series vegetation indices derived from satellite data can effectively distinguish and map soil degradation [103]. The selection of satellite images can be performed using deep ML algorithms [104] to perform the data mining procedures [105]. Yousefi et al. [106] analyzed 12 independent conditional factors for their relationships to range quality by applying RF, CART and SVM. They reported that RF was determined to be the most robust. Various ML algorithms were used in erosion susceptibility prediction on heterogeneous landscapes [107, 108] such as ANN [109], SVM [110], logistic regression [111] and RF [112, 113].

Haghighi et al. [114] employed SVM, multivariate adaptive regression splines (MARS), generalized linear model (GLM) and dragonfly algorithm (DA) ML algorithms to generate high-quality and accurate land degradation risk maps in a watershed of central Iran. They reported that DA had the highest accuracy and efficiency with the most outstanding learning and prediction power in land degradation risk mapping. Since the GEE platform offers time-series satellite data at various resolutions, ground observations can map more extensive areas in a short period, along with ground surveys.

2.3.6 Irrigation water management

As water resources are limited, smart irrigation is more important in PA and enhancing crop productivity. Big data coupled with sensor systems showing promising ways to plan water systems optimally, schedule irrigation plans, mitigate climate change and detect the water-induced changes in the ecosystem. ICT technologies facilitate disseminating extensive data analysis and modeling to the farmers to access weather forecasts and market information. It allows to make better decisions, improve the livelihoods, optimum utilization of water resources and ensure food security. Al-Ghobari and Mohammad [115] tested the evapotranspiration (ET), ICT and Internet Information Services (IIS)-based technologies in Saudi Arabia in wheat and tomato fields. They concluded that IIS was more feasible in water usage than ICT and ET-based systems.

Cai et al. [116] showed strategies for solving extensive nonlinear models for water resources management. They combine genetic algorithms (GAs) with linear programming. Hinnell et al. [117] developed neurodrip irrigation systems by using ANNs to predict the spatial distribution of water in the subsurface. Kim et al. [118] used a distributed wireless network for sensing and control of irrigation systems from a remote location. Wall and King [119] developed an intelligent system that controlled valves of sprinklers using temperature and moisture sensors deployed in the field. Wardlaw and Bhaktikul [120] developed GAs to solve irrigation water scheduling. They optimized the utilization of water resources in irrigation systems operating on a rotational basis and field soil moisture constraints. Twarakavi et al. [121] developed SVMs for estimating the hydraulic parameters describing the soil water retention and hydraulic conductivity. Cruz et al. [147] exploited the ANN feed-forward and back-propagation technologies to optimize the water resources in an innovative farm. Different ML algorithms are used for water needs estimations in automatic irrigation systems. Yamaç and Todorovic [122] compared kNN and adaptive boosting (AdaBoost) algorithms to estimate water needs for the potato crop.

Tang et al. [123] used AI models for actual crop ET modeling, and water needs estimation in maize croplands. Kisi [124] compared SVR with MARS and M5 model tree (M5Tree) in modeling reference ET. Davis et al. [125] conducted a study in Florida. They found that ET-based watering scheduling controllers are more useful in irrigation cost, size and labor requirement. Viani et al. [126] reported that fuzzy logic-based decision support system (DSS) provides more water-saving over single-threshold and multithreshold-based irrigation scheduling. Gutiérrez et al. [127] proposed an automated irrigation system using a wireless sensor network (WSN) and GPRS module to save water in irrigation through real-time monitoring and irrigation control. Roopaei et al. [128] developed an intelligent irrigation monitoring system using thermal imaging techniques to identify crop water requirements and irrigation monitoring.

Albeit tremendous progress using DS in agriculture and NRM, there are still many gaps and challenges to be addressed. The following section delves into some crucial issues.

2.4 Gaps and challenges

WSN, IoT and cloud computing are the primary driving forces in PA. The sensor measures the physical quantity and transmits the collected information to the cloud or the device. The physical layer contains all the sensory data. The network layer takes care of data transmission, and the application layer analyzes and processes the data. The sensing may retrieve real-time information about soil, crop, fertilizer, weather, water requirements, market and government policies. PA may use in-field or remote-sensing techniques to collect data at multiple stages. This needs collection of big data from various sources at different geographic locations. The collected information is processed and analyzed to generate agro-recommendations for enhancing the yields. Therefore, sensing, communication and computing combine to satisfy the precise needs of the crop. This also shows that the application of ML to PA involves a cross-domain paradigm and requires an interdisciplinary research. There are several challenges in implementing technology or data-driven PA, and issues are listed further and explained:
- Data acquisition for in-field and remote sensing
- Data transmission
- Data management
- Data security
- Nontechnical factors

2.4.1 Challenges in data acquisition for in-field and remote sensing

The use of the GPS for civilian use initiated the PA era. The next decade allowed yield monitoring and generate recommendations for soil reaction rectification or fertilizer. Typical sensors for in-field measurements are: the location sensors use GPS satellites to find latitude, longitude and altitude. An optical sensor measures the clay properties, organic matter, soil temperature and soil moisture. Electrochemical sensors sense pH and soil nutrients. A mechanical sensor measures soil compaction through a strain gauge, and an airflow sensor measures the soil permeability.

The above sensor types show the heterogeneity in captured data, their formats, the devices and specifications, the frequency of data collection, the distance between the sensor and the object, and the transmission protocol. The environment also impacts the accuracy of data collection by the sensor. The in-field sensors are susceptible to variations in environmental conditions – wind, temperature changes and rain.

A remotely placed sensor senses the data for PA. Remote sensing measures the physical phenomenon by looking at reflections from a distance. There are many types of cameras to capture images in its field of view. Imaging platforms are also a critical factor when capturing an image. RGB camera appears to be the most prevalent sensor for image acquisition [129] in PA. However, they are sensitive to illumination variations in the field impacting object detection. Integrating visible spectrum cameras with NIR modality can improve the performance against changes in illumination. The cameras are mounted on different airborne platforms – UAV, airplane or satellite [130]. Spectral-range remote sensing is mounted on airborne platforms, which has its characteristics. Table 2.6 shows the typical features of such platforms and sensors [131].

The collection and distribution of images in real time are also hindrances for open solutions. It can be seen that data acquisition is impacted by the spatial resolution, data collection frequency, the spectral range of the sensor and distance. The images captured by remote sensing, especially the airborne and satellite, are impacted by the cloud formation and haze formed due to aerosols. It needs the development of advanced techniques for atmospheric corrections, cloud detection and noise cancellation. The images should also target specific applications using appropriate imaging platforms [129]; for example, the ground-based platform with a top-down camera will be more appropriate than a UAV for capturing images of the weed and observing the dynamics of crop characteristics/traits. At the same time, UAVs are well suited for large field-of-view applications, for example, field scouting.

Table 2.6: Characteristics of platforms and sensors for remote sensing – multispectral (MS), hyperspectral (HS), panchromatic (PAN), synthetic aperture radar (SAR), short-wave infrared (SWIR), light detection and ranging (LiDAR).

Platform	Spatial resolution	Coverage	Difficulty in use	Sensor	Height
UAV	<1 m	Tens of meters	Easy	Camera, LiDAR	Few meters
Airborne	<1 m	Few km	Medium	Camera, LiDAR, SAR	Up to 10 km
Satellite	<1 m to km	Swath width – few tens of km	High	MS, HS, SWIR, PAN, X-band, C-band	Hundreds of km

The type of agricultural task governs the data acquisition in PA; for example, growth monitoring may span over a whole season as it would require image collection over multiple growth stages. On the other hand, some tasks can be completed quickly, for example, fruit picking within a week [129]. The existing datasets do not address the large-scale diversity in the species. It, in turn, limits the generalization ability of the machine learning algorithm.

2.4.2 Challenges in data transmission

The main challenge for any IoT-based sensing system is latency in data transfer, low power devices, low bandwidth availability, intermittent Internet connectivity, cloud congestion due to transmission by a large number of devices and line of sight. Many WSN protocols are cellular, 6LoWPAN, ZigBee, Bluetooth, RFID, LoRaWAN and WiFi. The protocols have their specifications, including bandwidth, the number of channels, power, price and availability; for example, the deployment of 4G technology provides high bandwidth with reliable connectivity but requires higher battery power consumption, infrastructure deployment and high operational costs.

Table 2.7 summarizes the technologies available in communication that differ highly in terms of power, data rate, range and cost. Environmental conditions can hinder communication between the in-field sensor and the central processing server; for example, noise in the wireless communication channel may increase during the rainy season due to disturbances. The development of new technology, for example, 5G, can provide better security at a higher speed.

Table 2.7: Summary of fundamental networking and communication technologies in PA.

Protocol	Power	Data rate	Range	Standard
ZigBee [132]	Low	Few hundreds of kbps	~100 m	IEEE 802.15.4
Bluetooth [133]	Low	Few Mbps	~ 30 m	IEEE 802.15.1
RFID [134]	Ultra low	Few tags per second	~ cm	RFID
LoRaWAN [135]	Very low	Tens of kbps	~10 km	IEEE 802.11ah
WiFi [136]	Medium	Tens of Mbps	~50 m	IEEE 802.11
4 G [137]	High	Tens of Mbps	~Tens of km	GSM

2.4.3 Challenges in data management

The in-field and/or remote sensor generate the data. The measurement from sensors has to be real time and precise for decision making. They would need continuous calibration for generating accurate data. In the PA domain, the information influx is heavy as the in-field sensors create a time series at different frequencies, and the airborne platforms generate high-resolution MS or HS images. It would need high-performance computing for subsequent data processing and analysis. It also increases the storage requirements. It demands newer scalable facilities in terms of software and hardware platforms for effective management of big data. The cloud computing platforms can facilitate software as a service, focusing on merging sensor data and data management functions.

The use of different digital standards in PA causes interoperability and better data/knowledge issues, severely limiting the adoption of the newer technologies in PA. It impacts the growth rate and efficiency of digital agriculture applications. Protocols for the machine-to-machine (M2M) communication and development of better data sharing protocols between machine and information management systems handle the interoperability issue.

2.4.4 Challenges in data security

Data-driven farming has raised privacy issues and rights to data usage. The information about farming activities can be used by rivals and create speculations in the commodity markets [2]. There are issues related to security and data access within the ambit of the law of the land. The development of technology in PA has facilitated autonomy and the fusion of intelligence [138]. It needs a peer-to-peer system that can securely verify, monitor and analyze agricultural data. The penetration of IoT devices into agriculture will bring in various IoT attacks by hackers. Due to a lack of standardization in IoT, security attackers can execute forgery routines, data blocks and encryption [138]. IoT also works with M2M communication. The attacker can use industrial control system to launch an attack and encrypt the data or launch ransomware across many operating systems [139]. Data security can be handled by creating blockchain-based information systems in PA. Blockchain will allow reliable sharing of data in a decentralized environment while transparently manipulating data.

2.4.5 Challenges due to non-technical factors

Big data analytics in agriculture demands vast investments required for data collection, storage and processing. There is a considerable gap in available hardware, software resources and even baseline Internet connectivity. There exists a digital divide between developed and developing countries. The lack of financial resources restricts technology implementation, resulting in lower use of PA in the present context of sustainable development and climate change aberrations. The real-time information availability demands high-quality sensing elements and sensor procurement, deployment and maintenance that involve substantial costs. Therefore, digitization seems to be benefiting technology-savvy and wealthy farmers. It concludes that PA was found to be cost-effective for sizeable arable land. However, low-cost solutions for small arable land are also emerging on the horizon [140]. Literacy also impacts the adoption of PA in developing countries [141]. Farmers use traditional practices for the crop cycle, which is based on intuition and experience. Many times, lack of education may limit the benefit arising out of using the technology. Technology concentration in the hands of few corporations may lead to farmers' monopolistic practices and dependence on these big corporations [2].

2.5 Discussions and summary

The content in Sections 2.2 and 2.3 highlighted applications in agriculture and NRM, handled using data science. The sections analyze images as they emerge from sensors on the ground or sensors placed on UAVs or satellites. The CV-based non-destructive approaches gain popularity as data can be systematically obtained over a desired geographic area – large or small. The coarse-resolution satellite images from popular sensors – AVHRR, Landsat and MODIS – have become a primary source for data analysis. The high spatial resolution from Landsat or SPOT satellites is used for decision-making and NRM.

The farmers can learn from cooperatives' success, for example, in India's dairy industry, and leverage their strength to create *the agri-data ecosystem*. It will bring in parity in data-driven agricultural practices. The government should promote and legislate laws for copyright protection and data ownership. A robust policy framework for data management and security is required to further adopt DS into agriculture and NRM.

It is essential to provide large-scale access to the hardware and software resources. It requires investments in cloud infrastructure for storage, analysis and data visualization. It is crucial to develop easy accessibility to the data through user-friendly online platforms [2]. The use of well-accepted open-source libraries could help develop tools added to existing platforms to support large-scale data analysis. The emergence of publicly available datasets is also a healthy sign for data-driven approaches [2]. The large-scale challenges using CV and ML provide complex and large annotated datasets.

With the increasing availability of big data, well-known data analytic techniques through open source have tremendous potential to adopt digital technologies in agriculture and NRM further. It will accelerate producing a large quantity of quality food while protecting the environment and existing natural resources. Government support in making open data policy and making data readily available and affordable will enhance the quality and productivity and, in turn, improve the data/informatics culture. Federated systems will augment the research capabilities and innovations, thereby having a social impact.

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