Machine learning techniques in the decision of the present and future of agriculture

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ABSTRACT

The objective of the research was to analyze the effectiveness of machine learning techniques in the decision of the present and future of agriculture. A literature search was conducted in English and Spanish in Science Direct and Scopus database in August-September 2021 and 37 original studies ranked by SC Imago Journal & Country Rank -SJR were reviewed. The results indicate that machine-learning techniques applied in smart agriculture, offer a cost-effective approach for the prediction of soil properties and crop yields, promoting improvements in the modernization of agricultural systems. Finally, the importance of machine learning techniques in agricultural production systems is discussed and it is recommended to highlight studies on the adverse effect on sustainable agriculture.

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Keywords: Smart agriculture; sustainable agriculture; machine learning; agricultural systems; machine learning techniques.

DOI Number: 10.14704/nq.2022.20.9.NQ44572 **Neuro Quantology 2022; 20(9):4943-4962**

Introduction

The development of computational technology has become a fundamental tool for agriculture in recent decades. This process configures machine learning, understood as the process of extracting useful information from various types of data (Jagtap et al., 2021) and have contributed to an explosive increase in the application of computing to complex scientific problems that were previously considered impossible (Katarya et al., 2020). The integration of remote sensing data and machine learning algorithms offers a cost-effective approach to predicting soil properties and crop yields compared to conventional approaches (Khanal et al., 2018). Machine learning techniques allow monitoring large areas of land cover and land use (Roy, 2021), monitoring the productivity and conservation of natural resources (Lampach et al., 2021).

The introduction of new and diverse machine-learning techniques seems to be a good predictor of the future of sustainable agriculture. Agriculture plays a vital role in the economic growth of any country; however, with increasing population, frequent changes in climatic conditions and limited resources, it becomes a challenging task for current and future agriculture (Priya et al., 2018). Therefore, many regions have economic losses in agricultural production due to environmental factors and inaccurate weather predictions (Zhang et al., 2021). On the other hand, fluctuations in climate parameters such as humidity, temperature, etc., result in a decrease in crop productivity (Shinde & Kulkarni, 2018). This has made the agricultural sector one of the most basic needs in developing countries (Semin et al., 2021); therefore, more scientific agriculture is one of the main requirements to achieve this goal.

In this regard, at the global level, they have paid special attention to smart agriculture, since it plans to take advantage of a variety of information and communication technologies (ICTs) to increase productivity that was once sustainable and economically viable (Gyarmati & Mizik, 2020; O'Grady et al., 2019). However, ICTs applied in agricultural systems can help farmers to take appropriate preventive and mitigation measures in case of crop diseases, adverse weather conditions or even soil health (Gyarmati & Mizik, 2020). In such a context, the knowledge that the farmer can acquire on effective techniques of autonomous learning, can help him to make timely decisions and significantly increase the density of production and reduce the possible damages (Semin et al., 2021).

In view of this, various studies have been carried out, the results of which indicate that machine learning has become an alternative solution for the new agricultural systems. In this regard, Pathan et al. (2020) indicate that these technologies can reduce costs, improve soil fertility and increase productivity. For their part, Wahabzada et al. (2016) applied machine learning techniques to hyperspectral imaging data and were able to reveal physiological and structural characteristics in plants, facilitating the monitoring of physiological dynamics and the prediction of diseases. Similarly, Pourghasemi et al. (2020) after the application of a neural network of quantification with learning vectors (LVQ) found that land use, average annual precipitation and slope angle were the most useful determinants of the Environmental Quality Standard (ECA).

In this sense, modern agriculture is highly productive and provides resources and services that are of critical importance to humanity. However, many current agricultural production techniques undermine the long-term viability of ecosystems and their services (Techen et al., 2020), therefore, it is necessary to reflect and systematize the positive of technological science applied to sustainable agriculture, to take advantage of the knowledge generated on the effectiveness of soil management, crop growth and sustainable agricultural production. Therefore, this research analyses information on the effectiveness of machine learning techniques and how they contribute to current and future decision-making in agriculture.

2. Methodology

The review was carried out in the months of August-September 2021 in the ScienceDirect and Scopus database; research articles were used as criteria for inclusion, published in high impact journals, classified by SCImago Journal & Country Rank -SJR and in accordance with its SJR considered at most the quartiles Q1-Q4 of the highest values.

The languages considered for revision were English and Spanish. The selected articles were from the last 6 years of publication until September 2021.

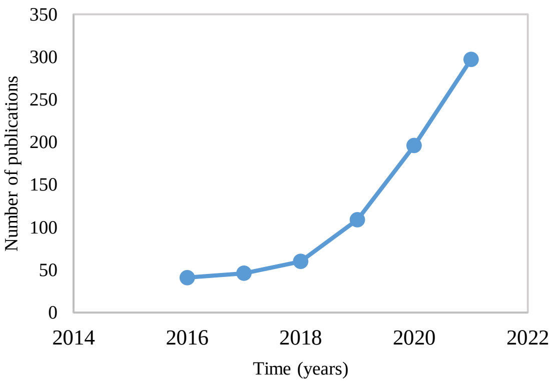

Figure 1. Publications retrieved from Science Direct and Scopus by year.

The methodology proposed by Sanders (2020), who outlines how to write a scientific review, was taken as the horizon. The methodology of Danet & Jimenez (2019) was considered as criteria for review and search. The search terms used were taken from The Thesaurus of the University of Barcelona (TH-UB).

The search took place in two moments. Initially, the search was conducted in English with the following complete terms: Effectiveness of machine learning techniques in the prediction of sustainable agriculture; from the base terms, combinations were made between words such as: "machine learning techniques" and "prediction" and " smart agriculture"; "machine learning techniques" and "sustainable agriculture". In the second stage, the search was conducted in Spanish with the complete terms: effectiveness of machine learning techniques in the prediction of sustainable agriculture; from the base terms the following combinations were made: "machine learning techniques" + "prediction" + "smart agriculture"; "machine learning techniques" + "sustainable agriculture" (see Fig. 2).

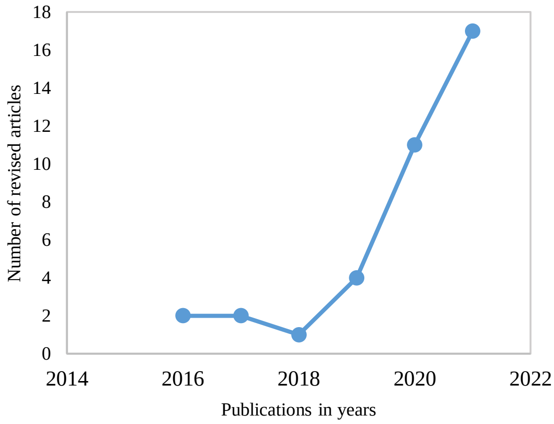

Figure 2. Articles reviewed with search criteria: "Machine learning techniques" and "Prediction" and "Sustainable agriculture" (English and Spanish)

In the initial search, a total of 1,850 studies were recovered; then it was filtered using the publication date, that is, it was considered research from 2016 to September 2021, reducing to a total of 1,174 studies between empirical and revisions. Then, it was filtered by type of research and considered only original research articles and a group of 749 studies was obtained. Finally, the summaries and key descriptors were revised, based on the study variables and resulted in 175 studies. Finally, our review consists of 37 articles that met the objectives that the research requires, as shown in Figure 3.

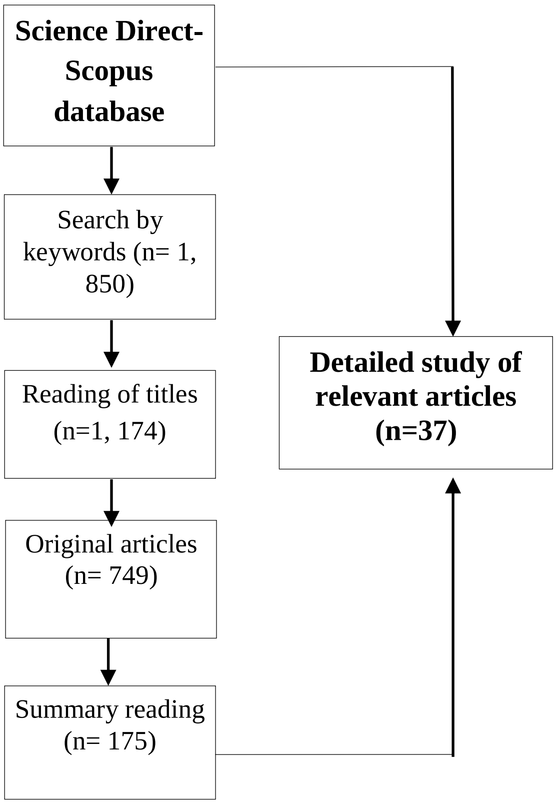

Figure 3. Review screening process

3. Results

Table 1 shows the description of empirical research on the effectiveness of machine learning techniques in the decision of the present and future of agriculture, carried out in different contexts, between the years 2016-2021. Data that are organized by author, research title, descriptors and geographical contexts.

In relation to the geographical context, a frequency of 17 countries has been identified, among which 22 investigations are from Asia, 08 from the Americas and 07 from Europe. Denoting that the Asian continent leads research in this area.

Agricultural activity is very broad and covers several directly and indirectly related factors, as shown in the present study. The evaluated research mainly develops 04 work descriptors; first, the smart agriculture indicator was identified, mostly denoted in 17 researches, which represents 46% of the publications. Second, machine learning was identified with 24 % of publications (09). This highlights the importance of the use of smart agriculture within current production systems and the direct relationship between the first two descriptors. Third, the sustainable agriculture indicator was identified with 16 per cent of publications (06 studies) and is related to the previous indicators, that is, with smart agriculture and machine learning; in this sense, sustainable agriculture provides basic resources, improves the environmental quality and living conditions of both the producer and the society.

Finally, without diminishing its importance, we find the precision agriculture indicator with 05 investigations, which represents 14%, asserting the importance of these tools within the understanding and development of sustainable agriculture.

Table 1

Review of empirical studies on machine learning techniques in the decision of the present and future of agriculture.

Author(s) and year	Title	Descriptors	Geographical context
Gardezi & Stock (2021)	Growing algorithmic governmentality: questioning the social construction of confidence in precision agriculture.	Trust, Social Identities, Governmentality, Precision Farming, Farmer	The U.S.A.
Jagtap et al. (2021)	Towards the application of various machine learning techniques in agriculture.	Precision Agriculture, Machine Learning, ICT Feature Extraction	Thailand India

Author(s) and year	Title	Descriptors	Geographical context
Jia et al. (2021)	Mapping soil pollution by using drone image recognition and machine learning in an agricultural field contaminated with arsenic.	Arsenic Pollution, Soil Pollution, HRAI, Remote Sensing, Machine Learning	China
Kong et al. (2021)	Multi-flow hybrid architecture based on a blending strategy for the recognition of fine grain crop species in precision agriculture.	Fine Grain Crop Classification Deep Learning, Internet of Things, Multi-flow Crosslevel Fusion, Precision Farming	Pekín (China)
Kumar et al., (2021)	SP2F: a secure framework that preserves privacy for smart agricultural unmanned aerial vehicles.	Blockchain Technology, Artificial Intelligence Deep Learning, Intruder Detection System, Privacy Preservation Smart Farming, Unmanned Aerial Vehicles (UAVs).	India
Lampach et al. (2021)	Technical efficiency and adoption of multiple agricultural technologies in the mountainous areas of northern Vietnam.	Agricultural Advice, Inverse Probability Weights, Machine Learning, Corn, Mountain Areas Soil Conservation Technologies Technical Efficiency	Vietnam
Maass & Piso (2021)	Pair conceptual modeling with machine learning.	Conceptual modeling, Machine learning, Methodologies and tools Database management, Artificial intelligence.	Germany The U.S.A.
Martín et al. (2021)	On the suitability of sets based in stacking in smart agriculture for the prediction of evapotranspiration.	Stacking, Sets, Data Processing Evapotranspiration, Sustainability, Smart Farming.	Spain
Peng & Wang (2021)	An industrial grade solution for agricultural image sorting tasks	Agricultural Image Classification, Deep Learning System, Inference Acceleration, Network Compression, Model Deployment.	China
Pylianidis et al. (2021)	Introducing digital twins into agriculture.	Digital Twins, Agriculture, Research Roadmap, Value Added.	Netherlands
Roy (2021)	A machine learning approach to monitor and forecast the space-time dynamics of land cover in Cox's Bazar district, Bangladesh, from 2001 to 2019.	Random Forest Algorithm, Remote Sensors, GIS, Machine Learning, Cox's Bazar.	Bangladesh
Saeed et al. (2021)	The deep neural network presents fusion and selection based on PLS regression with an application for classification of crop diseases.	Crop Diseases, CNN, Feature Extraction, Fusion Functions, PLS-Based Selection.	Pakistán

Author(s) and year	Title	Descriptors	Geographical context
Sengupta et al. (2021)	Deficit irrigation and organic amendments can reduce the risk of arsenic in the rice diet: introduction of prediction models based on machine learning from field data.	Rice Grain, Arsenic Concentration, Alternative Wetting and Drying, Vermicomposting, Dietary Risk Assessment, Random Forest.	India
Sujatha et al. (2021)	Performance of deep learning versus machine learning in the detection of plant leaf diseases.	Plant disease, ML, DL, SVM, RF, SGD, Inception-v3, VGG-16, VGG-19.	The U.S.A.
Velmurugan et al. (2021)	Superior crop prediction algorithm by diffuse enumeration for big data agricultural applications.	Diffuse Enumeration Crop Prediction Algorithm (FECPA) Preprocessing, Big Data, Sequential Direct Selection Algorithm (SFSA)	India
Zhang et al. (2021)	Meteorological radar echo prediction method based on a neural convolution network and short- and long-term memory networks for sustainable electronic agriculture.	Weather Forecast, Upsampling, Radar Echo Prediction, Convolutional Neural Network, Short-Term and Long-Term Memory Neural Network	China
Zhong et al. (2021)	Soil properties: its prediction and extraction of features from the LUCAS spectral library using deep convolutional neural networks.	Deep Learning, Deep Convolutional Neural Network, Characteristic Wavelengths, LUCAS Topsoil Data Set, Soil Spectral Library.	China
Dong et al. (2020)	Precision fertilization method of field crops based on the Wavelet-BP neural network in China.	Fertilization, Sustainable agriculture, Cleaner production, Wave analysis, Neural network BP.	China
Franczyk et al. (2020)	Deep learning for the recognition of grape varieties.	Deep Learning, Agricultural Management Computer Vision, Grape Variety Recognition.	Germany Poland
Kuchler et al. (2020)	Evaluation of the optimal preprocessing steps of the MODIS time series to map cultivation systems in Mato Grosso, Brazil.	Mato Grosso, Integrated systems Classification, Phonometry, Agricultural intensification, TIMESAT.	Brazil
Paul et al. (2020)	Mapping of organic carbon and soil clay using remote sensors to predict soil workability for better adaptation to climate change.	Clay Content, Landsat Indices Random Forest, Soil Organic Carbon, Soil Plasticity Limits.	Canada

Author(s) and year	Title	Descriptors	Geographical context
Paul et al. (2020)	Soil quality assessment of the Bansloi river basin in eastern India using soil quality indices (SQI) and Random Forest machine learning technique.	Soil quality indicators. Main component analysis (PCA) Soil quality index (SQI) Random forest (RF) Land quality and ecological variables • Validation of SOI	India
Priya & Ramesh (2020)	ML-based sustainable precision agriculture: a future.	Machine Learning, Big Data Agricultural Factors, Decision Making.	India
Rettore de Araujo et al. (2020)	Security challenges for smart agriculture.	Smart Farming, Security. Open Field Farming.	Brazil
Saikai et al. (2020)	Machine learning to optimize complex site-specific management.	Machine Learning, Bayesian Optimization, APSIM, Precision Agriculture Site Specific Management, On Farm Experiments.	The U.S.A.
Tetteh et al. (2020)	Optimal parameters to delimit agricultural plots from satellite images based on supervised Bayesian optimization.	Multiresolution segmentation Bayesian optimization, Land parcel identification system Empirical segmentation evaluation.	Germany
Wang et al. (2020)	Estimation of soil salt content using machine learning techniques based on fractional remote sensing derivatives, a case study in the Lake Ebinur National Wetland Nature Reserve, northwestern China.	Remote Sensors, Particle Swarm Optimization, Support Vector Machine (SVM)Fractional Derivative, Soil Salt Content, Hyperspectral Index.	China
Yamaç & Todorovic, (2020)	Estimation of daily potato crop evapotranspiration using three different machine learning algorithms and four available weather data scenarios.	Artificial neural networks, k-Nearest neighbor, Adaptive impulse, Mediterranean region, Penman-Monteith equation.	Italy
Hong et al. (2019)	Combination of learning algorithm derived from fractional order and memory based to improve the accuracy of soil organic matter estimation using near infrared and visible spectroscopy.	Near infrared and visible spectroscopy, Soil organic matter, Fractional order derivative, Local modeling Memory-based learning.	China

Author(s) and year	Title	Descriptors	Geographical context
Marinoudi et al. (2019)	Robotics and work in agriculture. A consideration of context.	Replacement of the work machine Complementarity Work-machine. Workforce in agriculture.	Greek
Xu et al., (2019)	Soil organic matter detection from laser induced degradation spectroscopy (LIBS) and medium infrared spectroscopy (FTIR-ATR) along with multivariate techniques.	Laser-induced breakdown. Spectroscopy. FTIR-ATR spectroscopy Spectral preprocessing. Data fusion.	China
Xu et al., (2019)	Abandoned rural residential land: use of machine learning techniques to identify rural residential land vulnerable to abandonment in mountainous areas.	Rural residential land. Land abandonment. Machine learning technique. Land use planning. Porcelain mountainous area.	China
Khanal et al. (2018)	Integration of high-resolution remote sensing data and machine learning techniques for spatial prediction of soil properties and corn yield.	Remote Sensors, Earth, DEM, Produce, Cartography.	The U.S.A.
Antle et al. (2017)	Towards a new generation of data, models and knowledge products of agricultural systems: design and improvement.	Agriculture, Systems, Models Data, Knowledge Products, Next Generation.	The U.S.A.
Jeong et al. (2017)	Spatial prediction of soil nutrients using three supervised learning methods to assess land potential in complex grounds.	Mountain Soil, Soil Nutrients, Digital Soil Mapping, Land Potential Assessment.	South Korea
Houborg & McCabe (2016)	Adaptation of a regularized canopy reflectance model (REGFLEC) to the recovery challenges of dryland agricultural systems.	LAI; Chlorophyll foliar REGFLEC Rapid Eye, Red border, Aerosols Foliar dust, Adjacency effects, Precision agriculture.	Saudi Arabia (Egypt)
Rose et al. (2016)	Decision support tools for agriculture: towards effective design and implementation.	Decision Support Systems, Evidence-Based Decision Making, Human-Computer Interactions.	United Kingdom

Table 2, presents the methods and techniques of machine learning applied in the decision of the present and future of agriculture and analyzes the results or conclusions reached by each of the researchers. With regard to methods and techniques used in the 37 researches studied, it was found that they are directly related to smart agriculture and machine learning. So for methods we can find automated systems, hardware and software, mathematical and algorithmic regressions as well as sustainability indicators. On the other hand, regarding the most operational and executive techniques of the methods, specific techniques were identified, whether validated or new, addressed from neural networks, remote sensing systems, ICTs and satellite monitoring, the Internet of things, among others, which allow to determine the use of innovative tools within a precision agriculture.

Table 2

Main results of empirical studies on machine learning techniques in the decision of the present and future of agriculture

Author (s) and years	Techniques / methods	Result
Gardezi & Stock (2021)	Focus Groups (FGD). Precision Agriculture Technology (AP)	Farmers place their own identity and knowledge against the algorithmic rationality of precision agriculture. Discursive power changes the social identities of farmers, which is essential for reproduction.
Jagtap et al. (2021)	Evolutionary algorithms. Neural networks.	Object classification is an important area within the data field and its application extends to the field of science or not. Although the nearest k-neighbor classification is a simple and effective technique, it slows down the classification of each object.
Jia et al. (2021)	Digital maps. Landsat satellite images. Topographic indices.	Four machine learning algorithms were developed to predict risk levels of As. The ERF algorithm worked better overall. The performance of the prediction was better than the traditional one. The heterogeneity of soil contamination poses challenges for mapping the risk of soil arsenic. The fertilizer factory was the main source of pollution in this area.
Kong et al. (2021)	Fusion strategy. Fine grain called MCF-Net. Internet of Things (IoT)	The large-scale data set collected by various IoT sensors provides a better benchmark for agricultural applications. The recognition accuracy and the score according to the fine-grained visual recognition model F1 of MCF-Net achieves competitive results of up to 90.6% and 0.962 separately, surpassing the contrasted models.
Kumar et al., (2021)	Dispersed Automatic Encoder (SAE), Long and Short Term Stacked Memory (SLSTM)	The results were evident that the SP2F framework proposed outperforms other techniques, and was efficient compared to various cutting-edge techniques.

Author (s) and years	Techniques / methods	Result
Lampach et al. (2021)	SPF analysis	The varied adoption of traditional seeds significantly improves the productivity of the land. The dissemination of pest management practices by extension agents decreases technical efficiency. The empirical results are largely robust against the hidden danger of unobserved confounder factors.
Maass & Piso (2021)	Internet of Things sensors (IoT). Data mining (CRISP-DM)	Machine learning techniques are very successful in obtaining or extracting large amounts of data, which can be used to identify concepts and patterns that could be useful for inclusion in conceptual models.
Martín et al. (2021)	Stacking for predicting evapotranspiration in smart agriculture.	The results show that stacking is the best approach in all data sets and each group of characteristics evaluated, running as a good alternative to predict evapotranspiration when using data of different nature and under different conditions.
Peng & Wang (2021)	Fine tuning. Neural network pruning. ONNX format.	Tests from three representative datasets using the most advanced networks shows that deep learning has broad application prospects in precision agriculture.
Pylianidis et al. (2021)	Mixed method DT	Given the potential for adoption and the benefits of applying DT in agriculture, we believe that they have the prospect of bringing technological advancement in the near future.
Roy (2021)	Landsat 4-5 TM and Landsat 8 OLI/TIRS satellite images. Random Forest (RF) classifier. LULC remote sensing techniques.	The LULC classification indicates a rapid increase in vegetation classes, while bodies of water and bare land decreased. The findings of the overall classification are consistent with the global results of increased vegetation in the larger region.
Saeed et al. (2021)	Automated crop disease recognition system with minimum partial squares regression (PLS).	The methods of selection and fusion based on the PLS proposed not only improve recognition accuracy, but also reduce calculation time. In addition, based on the results it is ensured that the proposed plan will work even with slight variations and texture limitations.
Sengupta et al. (2021)	Wetting. Alternative Drying.	Alternative wetting and drying and vermicomposting reduce the As in the grain of rice.

Author (s) and years	Techniques / methods	Result
	Vermicompost.	Treatments were effective in reducing the risk of As in the diet. Random Forest is an effective machine learning tool for predicting As grain. Paired samples, different soils and genotypes improve the robustness and predictability of the model.
Sujatha et al. (2021)	ML (Support Vector Machine (SVM), Random Forest (RF), Stochastic Gradient Descent (SGD) and DL Inception-v3, VGG-16, VGG-19)	AI is the area that makes the meeting between information and communication technologies (ICT) with various application sectors. Decision-making is provided by the algorithms that prevail in AI. ML and DL are the main players in the domain.
Velmurugan et al. (2021)	Diffuse Enumeration Crop Prediction Algorithm (FECPA)	The FECPA diffuse enumeration crop prediction algorithm requires an acceptable estimate and increased prognostic capacity through parameters such as this year's harvest, area, yield and alternative variables such as climate, agriculture and soil characteristics.
Zhang et al. (2021)	LSTM automatic encoders.	This research can predict the evolution of the shape of the echo in the next 1.5 h, which fully meets the needs of the meteorological warning of agricultural disasters.
Zhong et al. (2021)	LucasResNet-16 LucasVGGNet-16. DCNN modeling.	The study demonstrates the potential of deep learning modeling for soil properties based on spectral data, allowing timely adjustment of agricultural management. It also provides data for real-time quantitative monitoring of changes in soil properties, quality assessments and performance estimates.
Dong et al. (2020)	Wave analysis. Neural network wavelet-BP. Experiment 3414	The proposed method of wavelet-BP neural network provides a new technique for precision fertilization research and enriches the existing fertilization system. It also provides reference for research or related practical applications.
Franczyk et al. (2020)	Digitization of viticulture. Deep Learning. Recognition of images and residual network architectures.	The KSM classification (Keras Standard Model) achieved an accuracy of 47% and the Restnet classification (Resnet Classifier) achieved an accuracy of 89% of the correctly identified grape clusters. The combined methods exceeded the

Author (s) and years	Techniques / methods	Result
		previous one and reached the accuracy of 99% of the correct classified grape clusters.
Kuchler et al. (2020)	Satellite Imaging Time Series (SITS)	The potential of MODIS time series to map integrated cropping systems is evaluated. The best ranking results are obtained with unprocessed time series of vegetation indices.
Paul et al. (2020)	Soil and vegetation indices. Landsat satellite images, SOC and CL. Generalized reinforced regression model.	The production of spatially explicit information on soil workability is essential for effective management and adaptation to climate change on agricultural land.
Paul et al. (2020)	Soil quality indices (SQI). SQI weighted method. Random forest method (RF).	The overall results confirm the optimal RF performance for SQI prediction and it is found that PSQI r is the most competent tool for predicting soil quality in non-sampled locations. However, the authors recommend full validation of PSQIr in other regions and long-term field experiments.
Priya & Ramesh (2020)	Algorithms ML	Machine learning offers favorable computational and analytical solutions for integrated study of different types of data sets from various sources.
Rettore de Araujo et al. (2020)	Agriculture 4.0 Smart Agriculture. IoT. Internet of things.	Modernization of agricultural methods is essential to increase production rates and preserve natural resources.
Saikai et al. (2020)	Machine learning algorithm based on Bayesian optimization techniques. Complex site-specific management.	Site-specific management, learned from 5-year experiments generates $43/ha higher gains with 25 kg/ha less nitrogen fertilizer in the first scenario and $40/ha higher gains with 55 kg/ha less nitrogen fertilizer in the second scenario. Therefore, site-specific complex management can be learned efficiently and be more cost-effective and environmentally sustainable.
Tetteh et al. (2020)	The multiresolution segmentation algorithm (MRS). Remote sensing (RS). Sequential models (SMBO)	The investigation showed that the structural composition of agricultural parcels in a particular area influences the quality of segmentation. The larger the size of agricultural parcels, the higher the quality of segmentation.

Author (s) and years	Techniques / methods	Result
Wang et al. (2020)	Method of fractional derivatives.	This technique highlights spectral detail information and enriches the methods of preprocessing hyperspectral images, resulting in the mapping of the spatial distribution of the degree of soil salinization. This is of practical importance for the prevention and control of soil salinization in arid and semi-arid regions.
Yamaç & Todorovic, (2020)	kNN, ANN and Ada Boost machine learning	The ANN model produced slightly better statistical indicators. Therefore, the kNN model could be recommended for estimating ET when limited meteorological data are available. Otherwise, the ANN model must be applied.
Hong et al. (2019)	The fractional order derivative (FOD). Memory-based learning (MBL).	The correlation coefficient of soil organic matter (SOM) with FOD-processed spectra at some specific wavelengths was higher than with the original reflectance. MBL worked better than PLS and RF, regardless of the FOD transformation. Calibration with reflectance in the order of 0.25 and MBL provided the most accurate estimate of SOM, with an RPD of 2.23.
Marinoudi et al. (2019)	Robotic application to agriculture. Automation. Systems engineering.	The approach makes it possible to accurately compare different levels of technology in terms of workforce replacement.
Xu et al., (2019)	Laser-induced degradation spectroscopy (LIBS). Medium infrared spectroscopy (FTIR-ATR).	The use of LIBS and FTIR-ATR spectra in combination with multivariate calibration is a simple, rapid and non-destructive approach to monitoring soil organic matter. Strategy of great importance in the assessment of soil fertility, nutrient management and in the orientation of agricultural production of precision agriculture.
Xu et al., (2019)	Random forest. Vector machine supported Naive Bayes Ground Analysis	Quantitative assessment of factors influencing residential land use can also provide alternative knowledge for the development of planning protocols in order to ultimately improve the quality of life and living environments in rural areas.
Khanal et al. (2018)	Random Forest (RF) Neural Network (NN) Support Vector Machine (SVM)	High-resolution maps of soil properties and crop yields help farmers identify areas of potential concerns before planting and manage them to improve crop productivity.

Author (s) and years	Techniques / methods	Result
	Gradient Boosting Model Cubist (CU)	
Antle et al. (2017)	Next Gen. Precompetitive space. Competitive space	We envision new models and knowledge products that could accelerate the innovation process needed to achieve sustainable local, regional and global food security.
Jeong et al. (2017)	Digital soil maps Generalized additive model (GAM) Support vector regression (SVR). Recursive feature elimination (RFE)	The results suggested that vegetation indices have powerful abilities to predict soil nutrients. The use of predictors selected through RFE improved prediction results. RF showed the best performance. Cluster analysis identified four kinds of land potential: fertile, medium and low fertile with an additional class dominated by a high phosphorus content and low carbon and nitrogen content due to human impact.
Houborg & McCabe (2016)	Regularized Canopy Reflectance Model (REGFLEC) Rapid Eye Multispectral Images.	The leaf area index (LAI) and leaf chlorophyll content (Chl l) were recovered with average absolute errors of 12% and 16%, respectively. Correction of adjacency effects reduced reflectance by up to 60%. Taking into account adjacency effects and leaf dust, negative biases in LAI were reduced.
Rose et al. (2016)	Defra Sustainable Intensification Platform (SIP). Mixed method. R 3.0.0	Fifteen factors play a role in convincing farmers and advisors to use decision support tools. Including usability, cost-effectiveness, performance, user relevance and compatibility with compliance demands.

4. **Discussion**

In reviewing the literature on the effectiveness of machine learning techniques in deciding the present and future of agriculture, it was found that research and development projects carried out over the last 6 years, have been very interested in the agricultural sector. We reviewed 37 investigations in the modality of original scientific articles, published between 2016 and 2021 in the Science Direct database. In recent years, it seems that concern for agricultural systems has increased exponentially worldwide; thus, 46% of publications were made in 2021, 30% in 2020, 11% in 2019 and only 13% in the 2016–2018-time interval. It should be noted that the largest production of research in this sector is registered in Asia with 59% (22 publications in 17 countries); followed by America 22% (8) and Europe 19% (7). This shows that the greater scope and development achieved in the agricultural sector is reflected in the Asian continent. The revised studies demonstrate the application of a wide variety of machine learning techniques and methods aimed at optimizing sustainable agricultural production systems. For example, methods applied in smart agriculture improve agricultural processes in a more productive, efficient and sustainable way (Kumar et al., 2021; Martín et al., 2021; Rettore et al., 2020) Technologies such as the Internet of Things (IoT) are being regularly used in agricultural systems, allowing agriculture to be data based, leading to more timely and cost-effective production and management, while reducing environmental impact (Maass & Flat, 2021; Villa-Henriksen et al., 2020). The large-scale data set collected by various Internet of Things sensors provides a better benchmark for agricultural applications

(Kong et al., 2021). Similarly, remote sensing systems (RS) as identified in the research review are being used more widely in building decision support tools for contemporary agricultural systems (Chlingaryan et al., 2018; Gutiérrez et al., 2018; Wang et al., 2020). Likewise, machine learning techniques, such as neural networks, can also be used for the automated extraction of relevant data characteristics (You et al., 2017). Machine learning-based calibration models are used to interpret spectral data and predict soil contamination levels (Jia et al., 2021). Remote sensing, such as multi-spectral scanning by satellite and in the air, photography and video, enables precise weed management by generating accurate and timely weed maps (Lamb & Brown, 2001). Thermal remote sensing through airborne thermal imaging has the potential to identify spatial variations in crop water status (Tilling et al., 2007). Remote sensing systems (RS) approaches require the processing of huge amounts of remote sensing data, from different platforms and therefore more attention is currently being paid to machine learning methods (Chlingaryan et al., 2018; Tetteh et al., 2020).

Detection technologies and machine learning techniques provide cost-effective and comprehensive solutions for better estimation and decision-making of crop status and the environment (Chlingaryan et al., 2018), can also solve problems such as resource scarcity and manpower (Pathan et al., 2020), interpret spectral data and predict soil contamination levels (Jia et al., 2021), raise productivity and improve quality (Talaviya et al., 2020). They can also begin the journey towards reducing food waste and provide more information within the agricultural system to researchers (Farooq et al., 2019).

Similarly, the findings of the review identified that, in agricultural activity under machine learning techniques, 04 key descriptors are directly and indirectly related; among them, the smart agriculture indicator is directly associated with machine learning in the highest proportion of research through specific techniques; that is, it provides a set of tools in the strengthening of current productive systems. So too, sustainable agriculture and precision agriculture are linked to smart agriculture and machine learning; that is, they highlight their importance and provide effective tools for understanding and developing sustainable agriculture. In this context, machine learning techniques prove to be effective in the decision of the present and future of agriculture, promoting improvements in the modernization of the various agricultural systems. Modern agriculture makes use of technological advances and provides resources and services that are of critical importance to humanity (Techen et al., 2020).

5. Future prospects

While it is true, the importance of machine learning techniques in agricultural production systems has been discussed so far, it is also necessary to highlight the adverse effect on sustainable agriculture. Because many current agricultural production techniques undermine the long-term viability of ecosystems and their services (Techen et al., 2020). Other authors have discussed the lack of adequate detection of climatic conditions (Kamilaris & Prenafeta-Boldú, 2018), or the integration of knowledge as a constantly changing domain problem for environmental modeling and the development of associated software systems (Dutta et al., 2014). On the other hand, services provided under the umbrella of smart agriculture almost invariably depend on continuous access to the Internet; such access is first and foremost a social problem; farmers are particularly vulnerable because of their rural and often remote situation. In general, the problem is double; some do not have access to the Internet, while others have access to a poor quality intermittent connection (O'Grady et al., 2019). Consequently, there are gaps that modern science has to address and shorten the gap between the confluence of technological, social and economic factors, promoting social development with equal opportunities.

6. Conclusions

Machine learning techniques used in the prediction of sustainable agriculture, allow accurate estimations and at the same time make timely decisions regarding the state of crops and the environment in a cost-effective way; in other words, they minimize inputs and maximize productivity, making it economically viable to meet food demand in a large proportion in the global context. In recent decades, the agricultural sector has benefited directly from technological advances, by incorporating sustainable agricultural production systems based on new learning models, transforming agriculture into a viable activity. In summary, machine learning techniques are proving effective in predicting sustainable agriculture, promoting improvements in the modernization of various agricultural systems. It is specified that, machine learning requires solving some restrictions and closing the gaps present in each productive unit to obtain better results.

References

Antle, J. M., Basso, B., Conant, R. T., Godfray, H. C. J., Jones, J. W., Herrero, M., Howitt, R. E., Keating, B. A., Munoz-Carpena, R., Rosenzweig, C., Tittonell, P., & Wheeler, T. R. (2017). Towards a new generation of agricultural system data, models and knowledge products: Design and improvement. *Agricultural Systems*, *155*, 255–268. https://doi.org/10.1016/j.agsy.2016.10.002

Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, *151*, 61–69. https://doi.org/10.1016/j.compag.2018.05.012

Danet, A., & Jimenez, P. M. (2019). Professional experiences and emotions in the process of organs donation and transplantation. A systematic review. Spanish Surgery,*97*(7), 364–376. https://doi.org/10.1016/J.CIRESP.2019.01.015

Dong, Y., Fu, Z., Peng, Y., Zheng, Y., Yan, H., & Li, X. (2020). Precision fertilization method of field crops based on the Wavelet-BP neural network in China. *Journal of Cleaner Production*, *246*, 118735. https://doi.org/10.1016/j.jclepro.2019.118735

Dutta, R., Morshed, A., Aryal, J., D'Este, C., & Das, A. (2014). Development of an intelligent environmental knowledge system for sustainable agricultural decision support. *Environmental Modelling and Software*, *52*, 264–272. https://doi.org/10.1016/j.envsoft.2013.10.004

Farooq, M. S., Riaz, S., Abid, A., Abid, K., & Naeem, M. A. (2019). A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming. *IEEE Access*, *7*, 156237–156271. https://doi.org/10.1109/ACCESS.2019.2949703

Franczyk, B., Hernes, M., Kozierkiewicz, A., Kozina, A., Pietranik, M., Roemer, I., & Schieck, M. (2020). Deep learning for grape variety recognition. *Procedia Computer Science*, *176*, 1211–1220. https://doi.org/10.1016/j.procs.2020.09.117

Gardezi, M., & Stock, R. (2021). Growing algorithmic governmentality: Interrogating the social construction of trust in precision agriculture. *Journal of Rural Studies*, *84*(March), 1–11. https://doi.org/10.1016/j.jrurstud.2021.03.004

Gutiérrez, S., Diago, M. P., Fernández-Novales, J., & Tardaguila, J. (2018). Vineyard water status assessment using on-the-go thermal imaging and machine learning. *PLoS ONE*, *13*(2), 1–18. https://doi.org/10.1371/journal.pone.0192037

Gyarmati, G., & Mizik, T. (2020). The present and future of the precision agriculture. *SOSE 2020 - IEEE 15th International Conference of System of Systems Engineering, Proceedings*, 593–596. https://doi.org/10.1109/SoSE50414.2020.9130481

Hong, Y., Chen, S., Liu, Y., Zhang, Y., Yu, L., Chen, Y., Liu, Y., Cheng, H., & Liu, Y. (2019). Combination of fractional order derivative and memory-based learning algorithm to improve the estimation accuracy of soil organic matter by visible and near-infrared spectroscopy. *Catena*, *174*(June 2018), 104–116. https://doi.org/10.1016/j.catena.2018.10.051

Houborg, R., & McCabe, M. F. (2016). Adapting a regularized canopy reflectance model (REGFLEC) for the retrieval challenges of dryland agricultural systems. *Remote Sensing of Environment*, *186*, 105–120. https://doi.org/10.1016/j.rse.2016.08.017

Jagtap, S. T., Phasinam, K., Kassanuk, T., Jha, S. S., Ghosh, T., & Thakar, C. M. (2021). Towards application of various machine learning techniques in agriculture. *Materials Today: Proceedings*. https://doi.org/10.1016/J.MATPR.2021.06.236

Jeong, G., Oeverdieck, H., Park, S. J., Huwe, B., & Ließ, M. (2017). Spatial soil nutrients prediction using three supervised learning methods for assessment of land potentials in complex terrain. *CATENA*, *154*, 73–84. https://doi.org/10.1016/J.CATENA.2017.02.006

Jia, X., O'Connor, D., Shi, Z., & Hou, D. (2021). VIRS based detection in combination with machine learning for mapping soil pollution. *Environmental Pollution*, *268*, 115845. https://doi.org/10.1016/j.envpol.2020.115845

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*(July 2017), 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Katarya, R., Raturi, A., Mehndiratta, A., & Thapper, A. (2020). Impact of Machine Learning Techniques in Precision Agriculture. *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)*, 1–6. https://doi.org/10.1109 / ICETCE48199.2020.9091741

Khanal, S., Fulton, J., Klopfenstein, A., Douridas, N., & Shearer, S. (2018). Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield. *Computers and Electronics in Agriculture*, *153*, 213–225. https://doi.org/10.1016/J.COMPAG.2018.07.016

Kong, J., Wang, H., Wang, X., Jin, X., Fang, X., & Lin, S. (2021). Multi-stream hybrid architecture based on cross-level fusion strategy for fine-grained crop species recognition in precision agriculture. *Computers and Electronics in Agriculture*, *185*(April), 106134. https://doi.org/10.1016/j.compag.2021.106134

Kuchler, P. C., Bégué, A., Simões, M., Gaetano, R., Arvor, D., & Ferraz, R. P. D. (2020). Assessing the optimal preprocessing steps of MODIS time series to map cropping systems in Mato Grosso, Brazil. *International Journal of Applied Earth Observation and Geoinformation*, *92*(June), 102150. https://doi.org/10.1016/j.jag.2020.102150

Kumar, R., Kumar, P., Tripathi, R., Gupta, G. P., Gadekallu, T. R., & Srivastava, G. (2021). SP2F: A secured privacy-preserving framework for smart agricultural Unmanned Aerial Vehicles. *Computer Networks*, *187*(January), 107819. https://doi.org/10.1016/j.comnet.2021.107819

Lamb, D. W., & Brown, R. B. (2001). Remote-sensing and mapping of weeds in crops. In *Journal of Agricultural and Engineering Research* (Vol. 78, Issue 2). https://doi.org/10.1006/jaer.2000.0630

Lampach, N., To-The, N., & Nguyen-Anh, T. (2021). Technical efficiency and the adoption of multiple agricultural technologies in the mountainous areas of Northern Vietnam. *Land Use Policy*, *103*, 105289. https://doi.org/10.1016/J.LANDUSEPOL.2021.105289

Maass, W., & Piso, V. C. (2021). Pair conceptual modeling with machine learning.

Marinoudi, V., Sørensen, C. G., Pearson, S., &

Bochtis, D. (2019). Robotics and labour in agriculture. A context consideration. *Biosystems Engineering*, *184*, 111–121. https://doi.org/10.1016/j.biosystemseng.2019.06.013

Martín, J., Sáez, J. A., & Corchado, E. (2021). On the suitability of stacking-based ensembles in smart agriculture for evapotranspiration prediction. *Applied Soft Computing*, *108*, 107509. https://doi.org/10.1016/j.asoc.2021.107509

O'Grady, M. J., Langton, D., & O'Hare, G. M. P. (2019). Edge computing: A tractable model for smart agriculture? *Artificial Intelligence in Agriculture*, *3*, 42–51. https://doi.org/10.1016/j.aiia.2019.12.001

Pathan, M., Patel, N., Yagnik, H., & Shah, M. (2020). Artificial cognition for applications in smart agriculture: A comprehensive review. *Artificial Intelligence in Agriculture*, *4*, 81–95. https://doi.org/10.1016/j.aiia.2020.06.001

Paul, G. C., Saha, S., & Ghosh, K. G. (2020). Assessing the soil quality of Bansloi river basin, eastern India using soil-quality indices (SQIs) and Random Forest machine learning technique. *Ecological Indicators*, *118*(July), 106804. https://doi.org/10.1016/j.ecolind.2020.106804

Paul, S. S., Coops, N. C., Johnson, M. S., Krzic, M., Chandna, A., & Smukler, S. M. (2020). Mapping soil organic carbon and clay using remote sensing to predict soil workability for enhanced climate change adaptation. *Geoderma*, *363*(January), 114177. https://doi.org/10.1016/j.geoderma.2020.114177

Peng, Y., & Wang, Y. (2021). An industrial-grade solution for agricultural image classification tasks. *Computers and Electronics in Agriculture*, *187*(June), 106253. https://doi.org/10.1016/j.compag.2021.106253

Pourghasemi, H. R., Gayen, A., Lasaponara, R., & Tiefenbacher, J. P. (2020). Application of learning vector quantization and different machine learning techniques to assessing forest fire influence factors and spatial modelling. *Environmental Research*, *184*(September 2019), 109321. https://doi.org/10.1016/j.envres.2020.109321

Priya, R., & Ramesh, D. (2020). ML based sustainable precision agriculture: A future generation perspective. *Sustainable Computing: Informatics and Systems*, *28*(July), 100439. https://doi.org/10.1016/j.suscom.2020.100439

Priya, R., Ramesh, D., & Khosla, E. (2018). Crop prediction on the region belts of India: a naïve bayes mapreduce recision agricultural model. *2018 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2018*, 99–104. https://doi.org/10.1109/ICACCI.2018.8554948

Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. *Computers and Electronics in Agriculture*, *184*(October 2020), 105942. https://doi.org/10.1016/j.compag.2020.105942

Rettore, A., Da Silva, E., & Pessoa, L. C. (2020). Security challenges to smart agriculture: Current state, key issues, and future directions. *Array*, *8*(July), 100048. https://doi.org/10.1016/j.array.2020.100048

Rettore de Araujo, A., Da Silva, E., & Pessoa, L. C. (2020). Security challenges to smart agriculture: Current state, key issues, and future directions. *Array*, *8*(October), 100048. https://doi.org/10.1016/j.array.2020.100048

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., & Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural Systems*, *149*, 165–174. https://doi.org/10.1016/j.agsy.2016.09.009

Roy, B. (2021). A machine learning approach to monitoring and forecasting spatio-temporal dynamics of land cover in Cox's Bazar district, Bangladesh from 2001 to 2019.

Environmental Challenges, *5*, 100237. https://doi.org/10.1016/J.ENVC.2021.100237

Saeed, F., Khan, M. A., Sharif, M., Mittal, M., Goyal, L. M., & Roy, S. (2021). Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification. *Applied Soft Computing*, *103*, 107164. https://doi.org/10.1016/j.asoc.2021.107164

Saikai, Y., Patel, V., & Mitchell, P. D. (2020). Machine learning for optimizing complex site-specific management. *Computers and Electronics in Agriculture*, *174*(March), 105381. https://doi.org/10.1016/j.compag.2020.105381

Sanders, D. A. (2020). “How to write (and how not to write) a scientific review article.” *Clinical Biochemistry*, *86*, 67. https://doi.org/10.1016/J.CLINBIOCHEM.2020.10.001

Semin, A., Betin, O., Namyatova, L., Kireeva, E., Vatutina, L., Vorontcov, A., & Bagaeva, N. (2021). Sustainable condition of the agricultural sector’s environmental, economic, and social components from the perspective of open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 1–25. https://doi.org/10.3390/joitmc7010074

Sengupta, S., Bhattacharyya, K., Mandal, J., Bhattacharya, P., Halder, S., & Pari, A. (2021). Deficit irrigation and organic amendments can reduce dietary arsenic risk from rice: Introducing machine learning-based prediction models from field data. *Agriculture, Ecosystems and Environment*, *319*(March), 107516. https://doi.org/10.1016/j.agee.2021.107516

Shinde, S. S., & Kulkarni, M. (2018). Review paper on prediction of crop disease using IoT and machine learning. *International Conference on Transforming Engineering Education, ICTEE 2017*, 5–8. https://doi.org/10.1109/ICTEED.2017.8586207

Sujatha, R., Chatterjee, J. M., Jhanjhi, N. Z., & Brohi, S. N. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*, *80*(October 2020), 103615. https://doi.org/10.1016/j.micpro.2020.103615

Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Techen, A. K., Helming, K., Brüggemann, N., Veldkamp, E., Reinhold-Hurek, B., Lorenz, M., Bartke, S., Heinrich, U., Amelung, W., Augustin, K., Boy, J., Corre, M., Duttman, R., Gebbers, R., Gentsch, N., Grosch, R., Guggenberger, G., Kern, J., Kiese, R., … Vogel, H. J. (2020). Soil research challenges in response to emerging agricultural soil management practices. In *Advances in Agronomy* (Vol. 161). https://doi.org/10.1016/bs.agron.2020.01.002

Tetteh, G. O., Gocht, A., & Conrad, C. (2020). Optimal parameters for delineating agricultural parcels from satellite images based on supervised Bayesian optimization. *Computers and Electronics in Agriculture*, *178*(July), 105696. https://doi.org/10.1016/j.compag.2020.105696

Tilling, A. K., O’Leary, G. J., Ferwerda, J. G., Jones, S. D., Fitzgerald, G. J., Rodriguez, D., & Belford, R. (2007). Remote sensing of nitrogen and water stress in wheat. *Field Crops Research*, *104*(1–3), 77–85. https://doi.org/10.1016/j.fcr.2007.03.023

Velmurugan, P., Kannagi, A., & Varsha, M. (2021). *Superior crop prediction algorithm by diffuse enumeration for big data agricultural applications.*1–17.

Villa-Henriksen, A., Edwards, G. T. C., Pesonen, L. A., Green, O., & Sørensen, C. A. G. (2020). Internet of Things in arable farming: Implementation, applications, challenges and potential. *Biosystems Engineering*, *191*, 60–84. https://doi.org/10.1016/j.biosystemseng.2019.12.013

Wahabzada, M., Mahlein, A. K., Bauckhage, C., Steiner, U., Oerke, E. C., & Kersting, K. (2016). Plant phenotyping using probabilistic topic models: uncovering the hyperspectral language of plants. *Scientific Reports*, *6*(March), 1–11. https://doi.org/10.1038/srep22482

Wang, Z., Zhang, X., Zhang, F., Chan, N. weng, Kung, H. te, Liu, S., & Deng, L. (2020). Estimation of soil salt content using machine learning techniques based on remote-sensing fractional derivatives, a case study in the Ebinur Lake Wetland National Nature Reserve, Northwest China. *Ecological Indicators*, *119*(September), 106869. https://doi.org/10.1016/j.ecolind.2020.106869

Xu, F., Ho, H. C., Chi, G., & Wang, Z. (2019). Abandoned rural residential land: Using machine learning techniques to identify rural residential land vulnerable to be abandoned in mountainous areas. *Habitat International*, *84*(October 2018), 43–56. https://doi.org/10.1016/j.habitatint.2018.12.006

Xu, X., Du, C., Ma, F., Shen, Y., Wu, K., Liang, D., & Zhou, J. (2019). Detection of soil organic matter from laser-induced breakdown spectroscopy (LIBS) and mid-infrared spectroscopy (FTIR-ATR) coupled with multivariate techniques. *Geoderma*, *355*(January). https://doi.org/10.1016/j.geoderma.2019.113905

Yamaç, S. S., & Todorovic, M. (2020). Estimation of daily potato crop evapotranspiration using three different machine learning algorithms and four scenarios of available meteorological data. *Agricultural Water Management*, *228*(October 2019), 105875. https://doi.org/10.1016/j.agwat.2019.105875

You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017). Deep gaussian process for crop yield prediction based on remote sensing data. *31st AAAI Conference on Artificial Intelligence, AAAI 2017*, 4559–4565.

Zhang, L., Huang, Z., Liu, W., Guo, Z., & Zhang, Z. (2021). Weather radar echo prediction method based on convolution neural network and Long Short-Term memory networks for sustainable e- agriculture. *Journal of Cleaner Production*, *298*, 126776. https://doi.org/10.1016/j.jclepro.2021.126776

Zhong, L., Guo, X., Xu, Z., & Ding, M. (2021). Soil properties: Their prediction and feature extraction from the LUCAS spectral library using deep convolutional neural networks. *Geoderma*, *402*(July), 115366. https://doi.org/10.1016/j.geoderma.2021.115366