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Review

Integration of Remote Sensing and Machine Learning for Precision Agriculture: A Comprehensive Perspective on Applications

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Abstract: Due to current global population growth, resource shortages, and climate change, traditional agricultural models face major challenges. Precision agriculture (PA), as a way to realize the accurate management and decision support of agricultural production processes using modern information technology, is becoming an effective method of solving these challenges. In particular, the combination of remote sensing technology and machine learning algorithms brings new possibilities for PA. However, there are relatively few comprehensive and systematic reviews on the integrated application of these two technologies. For this reason, this study conducts a systematic literature search using the Web of Science, Scopus, Google Scholar, and PubMed databases and analyzes the integrated application of remote sensing technology and machine learning algorithms in PA over the last 10 years. The study found that: (1) because of their varied characteristics, different types of remote sensing data exhibit significant differences in meeting the needs of PA, in which hyperspectral remote sensing is the most widely used method, accounting for more than 30% of the results. The application of UAV remote sensing offers the greatest potential, accounting for about 24% of data, and showing an upward trend. (2) Machine learning algorithms displays obvious advantages in promoting the development of PA, in which the support vector machine algorithm is the most widely used method, accounting for more than 20%, followed by random forest algorithm, accounting for about 18% of the methods used. In addition, this study also discusses the main challenges faced currently, such as the difficult problems regarding the acquisition and processing of high-quality remote sensing data, model interpretation, and generalization ability, and considers future development trends, such as promoting agricultural intelligence and automation, strengthening international cooperation and sharing, and the sustainable transformation of achievements. In summary, this study can provide new ideas and references for remote sensing combined with machine learning to promote the development of PA.

Keywords: agricultural monitoring; disease and pest detection; land use and management; yield prediction; agricultural sustainable development

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1. Introduction

In the context of rapid global climate change, agricultural practices are facing unprecedented uncertainties and challenges, such as climate warming, sea-level rise, drought and flooding, and other extreme hydroclimatic frequent occurrence [1–4]. At the same time, the global population is expected to reach 8.7 billion by 2030 and climb to 9.7 billion by 2050, which undoubtedly puts tremendous pressure on global food production [5]. However, it is gratifying that in recent years, with the increase in investment in science, technology, and agricultural research, the development of PA has achieved specific results [6,7]. This progress not only changes the traditional mode of agricultural production, but also aims to optimize agricultural inputs (seeds, water resources, chemicals) through the application of advanced technologies (such as remote sensing, machine learning algorithms, agricultural robots, etc.), to effectively manage crop variability, to maintain or even increase yields, and to cleverly avoid potential losses, thereby improving the efficiency and profitability of agricultural systems [8]. For example, in 2023, Yomo et al. used the maximum likelihood algorithm, based on Landsat-8 remote sensing images, to classify land use and land cover, and by using the multi-layer perceptron–Markov chain modeling method, the results show that the overall accuracy (Kappa coefficient) is as high as 92% [9]. This study shows that the accuracy of agricultural monitoring and recognition can be significantly improved by integrating advanced remote sensing technology and machine learning algorithms. In addition, in another study, the integrated learning random forest classifier is used to study the progressive lodging-sensitive characteristics of rice types based on multi-spectral (444–842 nm) fusion unmanned aerial vehicle technology, with an overall accuracy of 96.1% [10]. These examples prove the effective application of advanced technologies and algorithms in PA. Although PA offers many advantages, limitations such as information accuracy, large data requirements, operational complexity, and high initial cost cannot be ignored [11]. Therefore, for most countries in the world, it is necessary to actively promote the coordinated development of PA, remote sensing (RS), and machine learning (ML); to ensure agricultural production safety; and strictly abide by the food safety red line.

In recent years, researchers have engaged in multi-dimensional, deep exploration and have exerted extensive efforts in the development of PA, which is mainly reflected in the research and application of new technologies, covering many key links such as personnel training, policy support, etc. [12,13]. The aim is to overcome the shortcomings of traditional agriculture, such as time-consuming and strenuous labor requirements, improper use of resources, unstable crop yield, and environmental pollution [14,15]. In this context, it is actually a complex and critical challenge to accurately monitor crop growth and conditions at multiple scales in different locations and environments in real time and to use data with different time resolutions to meet a variety of purposes. In fact, it is a complex and critical challenge to respond quickly to extreme events according to changing climate conditions [16,17]. Fortunately, RS technology has developed rapidly in agriculture, forestry, hydrology, environmental protection, and other fields because of its unique advantages (such as synchronization, timeliness, spatiotemporal continuity, and large-scale observation ability) [18–22]. RS is a technology that can obtain information regarding the earth's surface without physical contact. It uses sensors to capture and record electromagnetic radiation signals reflected, emitted, or scattered from the earth's surface via a long distance, and then to continuously identify, measure, and evaluate the characteristics of target objects located on, above, or even below the earth's surface by analyzing these signals [23]. This not only greatly improves the efficiency of agricultural information acquisition, but also provides strong support for dealing with agriculture in extreme weather, allowing crop managers to implement timely measures to reduce the impact of disasters and to ensure the safety and stability of agricultural production [24,25]. In addition, with the maturity of RS inversion algorithms (linear regression, the PROSAIL physical model, neural networks), inversion datasets based on RS images have also appeared, including inversion product datasets based on MODIS, Landsat-8, and Sentinel-2 images, e.g., water quality and water environment elements inversion, vegetation parameter inversion, land surface temperature inversion, and soil parameter inversion products. These provide reliable and rich data sources for agricultural RS-related research [26–28].

It is well known that most agricultural RS data comprise information provided by visible light and near infrared radiation reflected (or transmitted) by plants, measured according to wavelength, e.g., spectral reflectance [29]. According to the change in vegetation, the spectral data commonly used in PA include visible (400 nm), near infrared (700 nm), and short-wave infrared (1300 nm) light [30,31]. In addition, multi-spectral remote sensing and hyperspectral remote sensing have also been proven to be effective means of plant phenotypic analysis, crop index acquisition, and stress monitoring [32]. For example, European Sentinel-2, ENVISAT MERIS, French SPOT satellite, NOAA AVHRR satellite, India's Hyperion, China's GF series, and HJ remote sensing data have been widely used [33–35].

It is worth mentioning that the emergence of unmanned aerial vehicles (UAVs) marks a new era of RS. UAVs are a type of unmanned small aircraft which are often used to carry remote sensing equipment for aerial data acquisition. They can provide more abundant and comprehensive spectral, spatial, and temporal resolution data, vegetation height data, and multi-angle observation, and exhibit high efficiency, convenience, low cost, and strong adaptability [36]. There have been many successful cases of their use in crop classification, weed detection, and vegetation monitoring, which prove the feasibility of the use of UAVs in PA [37]. For example, in 2024, Marques et al. overcame the limitation of limited spectral coverage based on UAVs, especially under low light, fog, or smoke conditions, to achieve real-time, efficient, and distributed accurate monitoring [38]. Bah et al. used UAV images to detect weeds in the field in 2017, with an accuracy of more than 90% [39]. Yang et al. used UAV image information to identify rice lodging, based on a decision tree (DT) algorithm, in 2017, with an overall accuracy of 96.17% [40].

As the core means of dealing with agricultural remote sensing information, the ML model has been widely used and deeply studied in recent years. ML is a data analysis method that allows computer systems to automatically learn patterns and rules from data without explicit programming [41]. Researchers tend to use ML as an integrated framework for feature collection and classification, prediction, or decision support [42]. With the improvement in big data's computing power, many classical algorithms have been optimized and improved, and new models and methods continue to emerge [43]. Common ML methods include DT, support vector machine (SVM), and logical regression (LR). The core of these methods is to identify optimized methods of obtaining statistical information in order to automatically and efficiently solve practical problems such as classification and regression [44]. In addition, the convolution neural network (CNN) method, based on ML, offers unique advantages in the field of image processing. It can automatically extract deep features from images and achieve accurate classification or recognition tasks [45]. Because of their unique data expression abilities, these technologies can learn and extract valuable information automatically, thus effectively avoiding the complexity and subjectivity inherent in traditional methods, significantly improving the efficiency and generalization regarding processing multi-platform RS data [46]. It is these advantages of ML that have attracted more attention from agricultural researchers and experts, identifying it as the driving factor for the development of PA [47–51].

In view of the major challenges posed by global population growth, resource shortage, and climate change to traditional agricultural models, the purpose of this study is to explore the methods for promoting the development of PA by integrating RS technology and ML algorithms. In order to achieve this goal, based on the keywords such as "remote sensing (RS)", "machine learning (ML)" and "precision agriculture (PA)", we used databases such as the Web of Science, Scopus, Google Scholar, and PubMed to search the related literature from 2014 to 2024. We selected more than 12,000 related research articles and conducted a quantitative analysis of these articles (as shown in Figure 1). The results of the analysis show that the number of related publications showed an overall upward trend during the decade from 2014–2024 (as shown in Figure 1a). In order to ensure the comprehensiveness and depth of the study, on the basis of the preliminary search, we also combined the keywords such as "agricultural monitoring", "detection of diseases and insect pests", "land use and management", "yield prediction", and "agricultural sustainable development" for further screening. After a rigorous screening process, more than 330 peer-reviewed papers published between 2014 and 2024 related to agricultural science, environmental science, and related cross-disciplines were identified, from which it can be observed that the number of research papers is also increasing year by year (as shown in Figure 1b). In addition, from the perspective of international cooperation and regional distribution, researchers in China, the United States, Brazil, and other countries have made significant contributions to the application of remote sensing and machine learning in precision agriculture. However, at the same time, we also note that there is an obvious imbalance in the spatial distribution of these studies, and there are great differences in research contributions among different regions (as shown in Figure 2). Therefore, through the in-depth analysis and summary of the existing research results, we systematically sort out the application status of remote sensing technology and machine learning in precision agriculture and discuss the current challenges and possible future development directions in this field. Thus, this study exhibits important theoretical and practical significance.

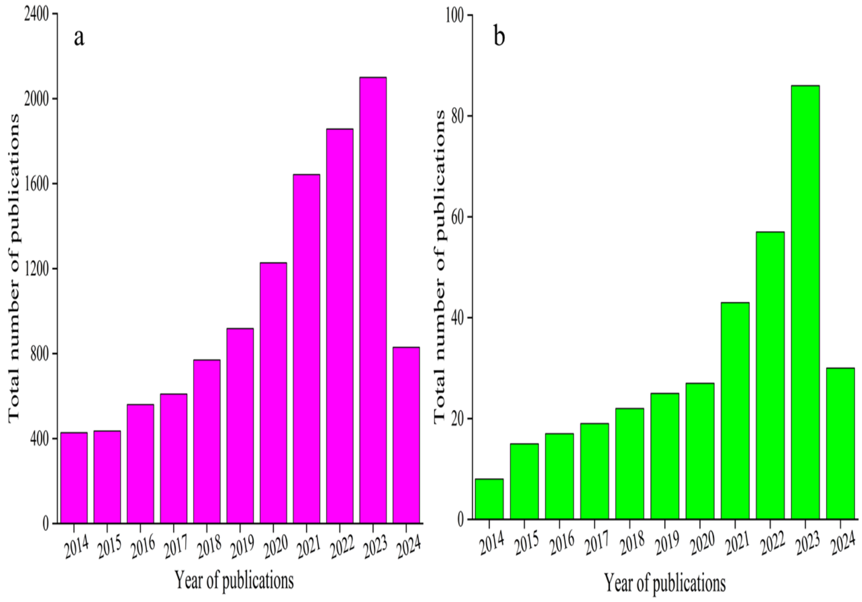

Figure 1. The changing trend of peer-reviewed papers published in the past 10 years, based on keyword retrieval over time. (**a**) Using the Web of Science, Scopus, Google Scholar, and PubMed databases, we searched 12,000 papers published over the past 10 years; (**b**) the changing trend of peer-reviewed papers published in agricultural science, environmental science, and related cross-fields over the past 10 years, based on keywords.

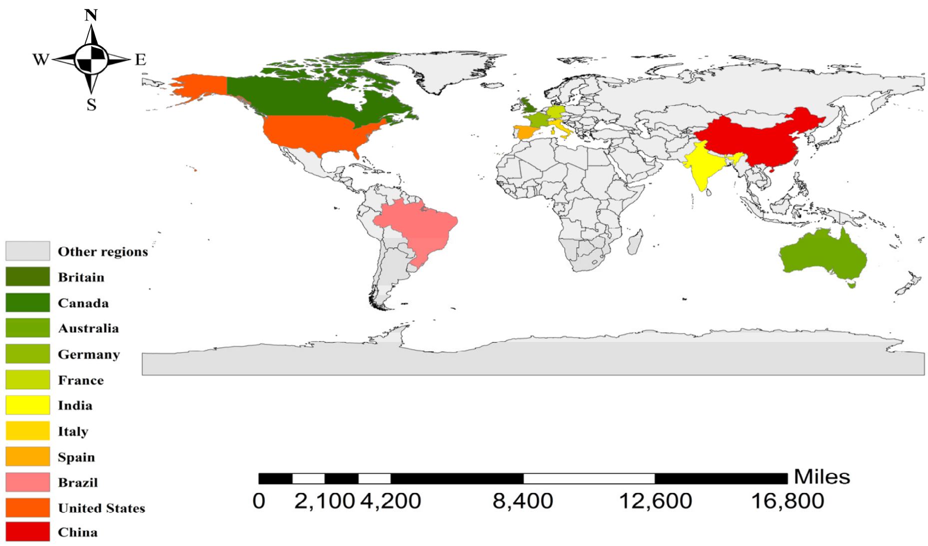

Figure 2. The geographical distribution of precision agriculture research based on the combination of remote sensing technology and ML; the change in color reflects the difference in research quantity.

2. Remote Sensing Technology and the Machine Learning Method

2.1. Remote Sensing Data in Precision Agriculture

There is no doubt that the application of RS technology in agriculture has greatly promoted agricultural reform. This technology enables us to collect global data on the earth's surface, remotely on a regular basis, providing unprecedented convenience for agricultural production and management [52–54]. Through a variety of sensors, we can directly or indirectly obtain information regarding almost all the key elements of agricultural practice, including crop growth data, soil moisture monitoring, pest presence and pest early warning notification, and yield prediction. At the same time, the wide geographical coverage and diversified resolution of RS technology also provide valuable data support for agricultural production and management [55]. As shown in Figure 3, remote sensing satellites with different resolutions play distinctive key roles in various PA practices and rely on different characteristics and advantages to comprehensively serve the specific needs of PA from many angles [56,57]. With the continuous updating and upgrading of remote sensing sensors, agricultural managers and practitioners will continue to benefit from the in-depth application of RS technology; for example, the use of RS data shows high practicability and effectiveness in evaluating and monitoring agricultural practice [58,59].

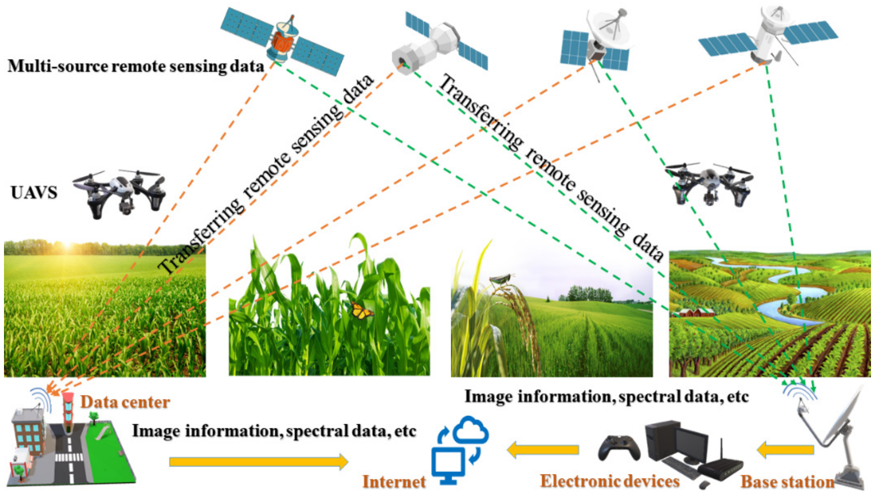

Figure 3. The comprehensive application framework of different remote sensing satellites in precision agriculture.

In general, when obtaining remote sensing data, the value of RS images with appropriate resolution, band, reliable quality, and cost-effectiveness can be maximized if they are selected according to specific agricultural problems [60,61]. For example, using daily 10 m NDVI data from Sentinel-2 images can allow for the quick, efficient, and accurate monitoring of the flowering date of apples, subsequently providing technical reference for the accurate classification and growth trend prediction of fruit trees [62]. In another study, the use of Landsat-8 images with a spatial resolution of 10 to 30 m provided a promising solution for disease detection in mixed forests in southern China [63]. In other studies regarding the detection of plant diseases and pests infecting vegetation, the detection accuracy does not seem to be satisfactory based on visible light (780 nm) data [64]. In a 2023 study by Zhu et al., although the use of UAV technology can confirm the importance of red-light bands and adjacent bands, it did not achieve the desired results in the investigation of plant diseases and pests invading vegetation [65]. However, it is gratifying that multi-spectral remote sensing data, with rich bands and a wide range of wavelengths, can capture subtle changes in infected plants affected by diseases and insect pests, thus showing excellent ability for early pest detection [66]. In their research in 2024, Ren et al. used the characteristics of UAVs to obtain crop growth status quickly and accurately in small and medium-sized areas [67]. By effectively assimilating remote sensing data with the WOFOST model using the Kalman filter algorithm, the accuracy of the yield simulation of different processing schemes is significantly improved, and more accurate and reliable yield prediction information is provided for agricultural producers.

In the practical application of PA, according to different requirements and application scenarios, commonly used RS data sources include hyperspectral, multispectral, and thermal infrared remote sensing; LiDAR remote sensing; SAR remote sensing; UAV technology;

etc. As shown in Figure 4, the application of various RS data sources in PA is shown in detail, including the time distribution and the proportion of RS data sources in PA. This information undoubtedly provides valuable references for agricultural managers and practitioners, not only to help them develop a more comprehensive and in-depth understanding of the characteristics and applicability of various RS technologies but also to provide strong support for them in making scientific and reasonable decisions in real-world situations.

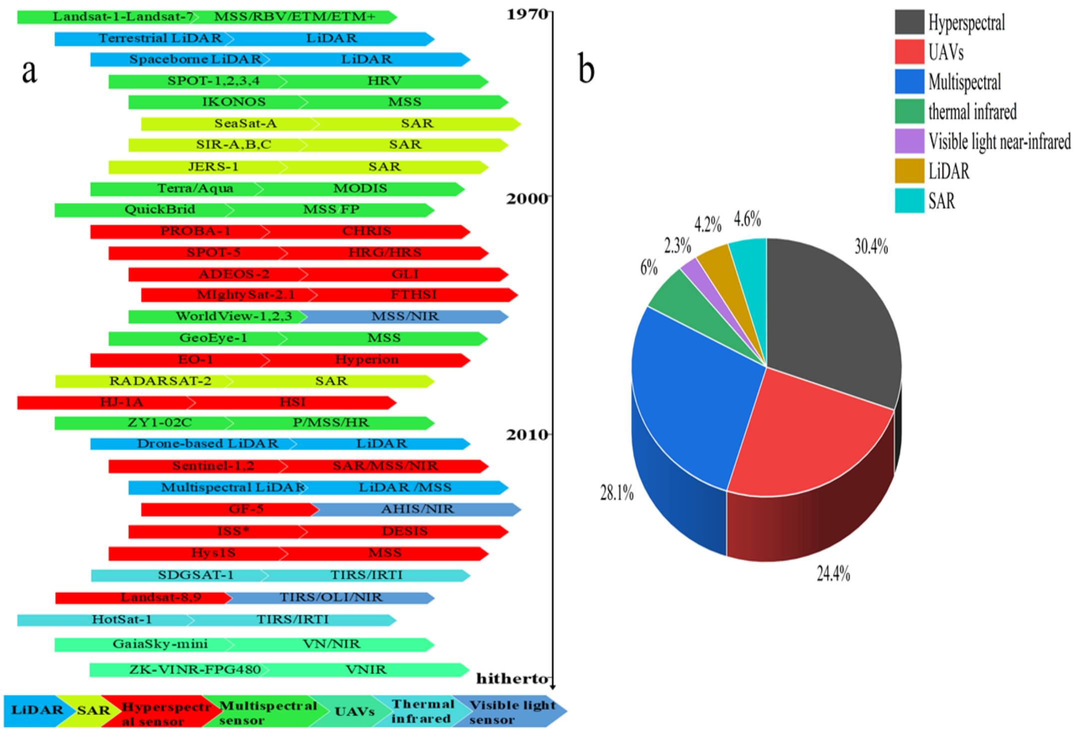

Figure 4. Remote sensing data commonly used in precision agriculture. (**a**) The distribution characteristics of different types of remote sensing data over time, marked in different colors; (**b**) the statistical analysis of the proportion of all types of remote sensing data sources, based on the literature retrieved in this paper.

2.2. Overview of the Use of ML Algorithms in Precision Agriculture

The concept of machine learning (ML) can usually be traced back to Alan Turing's classic research article published in 1950, i.e., the possibility that machines can exhibit behaviors similar to human intelligence [68,69]. This concept continued to develop in the following decades and gradually became a vital branch of computer science. The core principle of ML is to automatically learn and sum up the rules in the input data, realizing the accurate prediction or classification of unknown data by extracting key features and constructing mapping functions [70]. In addition, as the core component of artificial intelligence, ML gives computer systems the ability to perform a variety of tasks efficiently, and continues to promote the innovation and development of intelligent technology [71]. Generally speaking, ML mainly contains three elements, namely: a model, objective functions, and an optimization algorithm. The model explains the correlation between input and output and the meaning and range of the parameters, the objective function measures the difference between the model prediction and the actual results, and the optimization algorithm minimizes or maximizes the objective function by iteratively adjusting the parameters. As a result, the best model parameters are obtained [72,73]. According to different types of learning, ML can be divided into four main categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [74,75]. In Table 1, the applications of the four main categories of algorithms in PA and their scope of application are listed and described in detail.

Table 1. Common machine learning algorithms and references in the field of precision agriculture.

	Model Name	Application of Precision Agriculture	Reference
Supervised Learning	Naive Bayes	Classification of different crop diseases, soil types, etc.; prediction of the yield of wheat, corn, and other crops.	[76,77]
	Logistic Regression	Assessment of the risk level of pest occurrence; prediction of the yield of wheat, corn, and other crops.	[78,79]
	Linear Regression	Optimization of the amount of fertilizer application to improve the prediction accuracy of wheat, corn, and other crops yield.	[80,81]
	Lasso Regression	Detection of the extent to which crops are attacked by diseases and insect pests.	[82,83]
	AdaBoosT Algorithm	Classification and identification of different crop species and detection of crop diseases and insect pests.	[84,85]
	Linear Discriminant Analysis	Classification of soil types, identification of crop varieties, and determination of the effects of different soil fertilities on crop growth.	[86,87]
	Recurrent Neural Network	Analysis of crop growth time series data and prediction of time series changes in crop diseases and insect pests.	[88,89]
	Decision Tree	Selection of pest management strategies; identification of crop pest types.	[90,91]
	Nearest Neighbor Algorithm	Identification of different crop varieties; evaluation of soil fertility grades.	[92,93]
	XGBoost Algorithm	Prediction of yield of wheat, corn, and other crops based on climate, soil conditions, and other variables.	[84,85]
	Long Short-Term Memory Network	Forecasting the long-term trend of crop yield based on climate variables, such as precipitation and temperature, and prediction of the outbreak of crop diseases and insect pests by time series.	[94,95]
	Support Vector Regression	Crop growth monitoring and modeling, using remote sensing reflectance data to predict crop leaf area index, yield, etc.	[80,96]
	Artificial Neural Network	Identification of crop diseases and insect pests; crop growth monitoring and modeling; prediction of crop leaf area index, yield, etc.	[97,98]
	Convolutional Neural Algorithm	Identification of crop leaf diseases and detection of disease invasion degree of crop leaves; prediction of crop leaf area index, yield, etc.	[87,99]
	Random Forest	Identification of crop diseases and insect pests; crop growth monitoring and modeling; prediction of crop leaf area index, yield, etc.	[100,101]
	Support Vector Machine	Identification of crop diseases and insect pests; crop growth monitoring and modeling; prediction of crop leaf area index, yield, etc.	[102,103]
	CatBoosT Algorithm	Identification of crop leaf diseases and detection of disease invasion degree of crop leaves.	[96,104]
	Ridge Regression	Prediction of soil nutrients and key nutrient content based on soil sample data.	[105,106]
	Random Gradient Descent	Optimization of model parameters to improve the accuracy of agricultural prediction and decision-making models; application to complex agricultural system modeling and prediction.	[107,108]
Semi supervised learning	Generative Semi-Supervised Learning	Assessment of soil quality; prediction of soil fertility, acidity, alkalinity, etc.; prediction and control of diseases and insect pests.	[109,110]
	Autoencoders	Identification and classification of diseases and insect pests; assessment of the risk level of pest occurrence.	[111]
Unsupervised	Co-Training	Identification, classification, and risk assessment of diseases and insect pests; soil type classification.	[112]

Table 1. *Cont.*

	Model Name	Application of Precision Agriculture	Reference
Learning	Probabilistic Graphical Model	Identification of crop diseases and insect pests; crop growth monitoring and modeling; prediction of crop leaf area index, yield, etc.	[113]
	Independent Component Analysis	Identification, classification, and risk assessment of diseases and insect pests; soil type classification.	[114]
	Anomaly Detection Algorithm	Detection of crop wilt, soil moisture, and pH anomaly.	[115]
	Self-Organizing Maps	Classification of crops and rapid identification of soil types.	[116]
	K-Means Clustering	Accurate identification of crops.	[117]
	Principal Component Analysis	Accurate classification of crops based on their growth characteristics (such as color, texture, size, etc.).	[87]
Reinforcement	Deep Q-Network	Retrieval of key growth information, such as vegetation index, to effectively monitor crop growth and development.	[118]
	Policy Gradient Methods	Optimization of crop irrigation and fertilization strategies.	[89]
	Q-learning	Optimization of agricultural decision making and environmental interaction.	[119]

Recent studies have shown that with the improvement of computing performance and the enhancement of massive datasets, ML has shown strong application capabilities in many fields, especially in the field of PA [120,121]. In particular, a series of emerging algorithms and technologies, such as deep learning (DL), intelligent optimization, neural networks, computer vision, and data enhancement, continue to emerge. These improvements have not only injected a strong impetus into the field of ML but have also provided rich opportunities at all stages of agriculture. They enable agricultural practitioners to respond more effectively to challenges and to achieve specific goals [122]. As shown in Figure 5, the frequency distribution of the algorithm is obtained by searching the keywords "ML" and "PA". From the chart, we can see that ML is widely used in the field of PA, and the SVM algorithm displays the highest frequency, accounting for more than 20%, followed by the random forest (RF) algorithm, accounting for about 18%.

In addition, in the specific application of PA, different algorithms have revealed their own advantages, achieving a series of encouraging results. For example, Sladojevic et al. proposed a new plant leaf disease detection and classification model based on deep CNN. The model can accurately identify 13 different plant diseases and effectively distinguish plant leaves from the surrounding environment, which provides a powerful tool for plant health monitoring [123]. Li et al. have made remarkable progress in the field of vegetable disease detection. They propose a lightweight network improvement algorithm based on YOLOv5s. The algorithm effectively eliminates external interference and significantly enhances the ability for multi-scale feature extraction, thus improving the scope and performance of disease detection [124]. Ashwinkuma et al. developed a CNN based on the optimal mobile network, which is used to automatically detect and classify plant leaf diseases. The experimental results show that the CNN model performs well: the maximum accuracy is 0.985, the recall rate is 0.9892, the accuracy is 0.987, and the Kappa coefficient is 0.985 [125]. Yu et al. used DL target detection technology to extract image feature information through a complex network structure to achieve the non-destructive recognition of crop diseases. Compared with the traditional method, this technique delivers higher recognition accuracy, faster detection speed, and good stability in the visible light range [126]. Ang et al. creatively used Landsat-8 time series satellite images, combined with ML and the normalized difference vegetation index (NDVI), to successfully develop an effective new method of yield prediction [127]. Aydin et al. tested gradient lifting methods such as XGBoost, LightGBM, and CatBoost for soil sample classification and achieved high classification accuracy of up to 90%. Compared with the results of previous studies, the prediction accuracy was significantly improved [128].

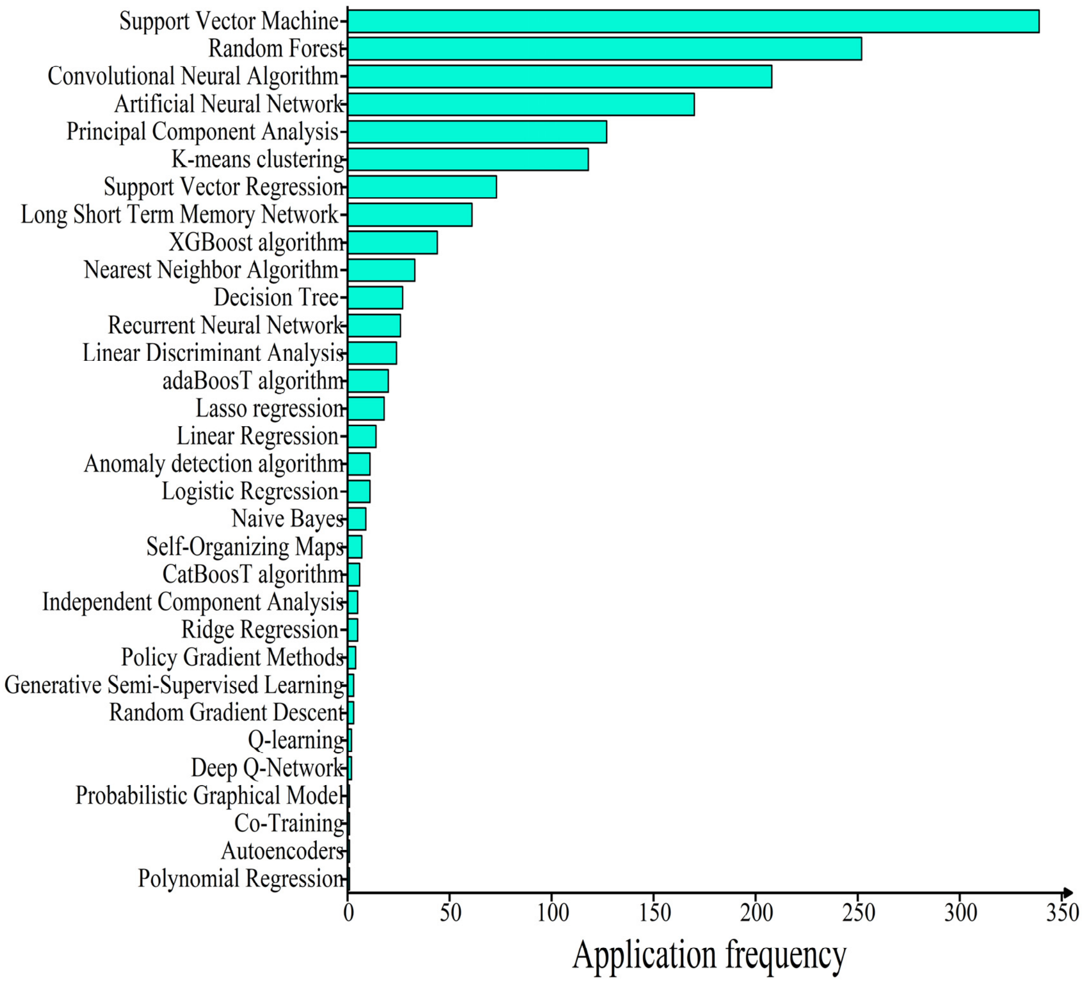

Figure 5. The distribution of the most commonly used machine learning algorithms is obtained based on the keywords "machine learning" and "precision agriculture".

3. Integrated Application of Remote Sensing Technology and the Machine Learning Method

3.1. Agricultural Monitoring and Identification

Recent scientific research shows that the integration of RS technology and ML methods resulted in remarkable progress from its application to agricultural monitoring and identification. RS technology can efficiently obtain crop planting area, growth status, and other important information, while ML technology can accurately detect targets and extract features from these rich RS data to achieve the precise identification and classification of crops. The continuous integration and development of these two technologies will usher in a new turning point in regards to solving related agricultural challenges such as horticulture line detection [129], crop recognition and classification [130,131], and vegetation distribution [132,133]. For example, Zhao et al. improved the standardized precipitation evapotranspiration index by integrating RS data, and the results show that the new SPEI can greatly enhance the capacity for agricultural drought monitoring [134]. Lyu et al. used EO-1 Hyperion images, combined with multi-terminal spectral mixing analysis and fully constrained least square pixel mixing techniques, to successfully identify typical vegetation species and improve the accuracy of grassland degradation monitoring [135]. Xiao et al. fused Sentinel-2 and MODIS RS images using the enhanced spatiotemporal adaptive reflection fusion model and then accurately obtained the spatial distribution of irrigated rice fields using the RF algorithm. Based on the Penman–Monteith model and making full use of the daily observation data of the meteorological station, the dynamic monitoring of water resources in the critical irrigation period has been realized, and remarkable results have been achieved [136]. This application increases the feasibility for the spatiotemporal fusion of multi-source RS data and makes it possible to continuously monitor the irrigation dynamics of paddy fields on a large scale.

In addition, it is very important to evaluated the planting and distribution of crops on a large scale in a timely and efficient manner. Although scholars have conductive extensive research on the basis of low and medium resolution RS, due to the widespread existence of mixed pixels and the lack of red edge bands, it is difficult to effectively identify small plots of farmland using these techniques, resulting in unsatisfactory recognition accuracy [137,138]. However, the research of Guo et al. in this field has brought new breakthroughs. Using GF-6 WFV images, they constructed several DT models, which not only efficiently obtained the crop planting area and its spatial distribution information, but also significantly improved the accuracy of image recognition [139]. In their latest research, Zhang et al. used GF-1 RS images, combined with advanced multi-scale segmentation algorithms, to improve the accuracy of forest type identification in the Engebei ecological demonstration areas and used nearest neighbor classification and RF classification, respectively, comparing the recognition results. The results showed that the effect of RF classification was superior, and the Kappa coefficients obtained over two consecutive years were 0.92 and 0.90, respectively [99]. Through extensive research, scientists have reached a consensus: ML algorithms, including RF, SVM, DT, etc., offer great potential in the field of agricultural monitoring and recognition and can significantly improve the efficiency and accuracy of monitoring and recognition [140–147].

3.2. Stress Detection of Diseases and Insect Pests

Crop diseases and insect pests are not only one of the core factors affecting plant yield and quality, but they also one of the main causes of crop damage. As emphasized by the United Nations Food and Agriculture Organization, the damage caused by diseases and insect pests to agroecosystems should not be underestimated. Unfortunately, in early agricultural production, the problem of diseases and insect pests is often marginalized and not given enough attention, resulting in huge economic losses [148]. Therefore, the implementation of efficient and accurate detection of plant diseases and insect pests not only plays a vital role in ensuring the health of the agroecosystem, improving crop yield and quality, and reducing economic losses, but also plays a key role in the development of PA. in recent years, it has attracted the attention of many scholars [149]. The premise for achieve this goal is to accurately detect and classify diseases and insect pests, distinguishing different types and estimating quantities, in order to implement accurate pest prevention and control strategies. Traditional pest monitoring mainly depends on the manual identification of pests by insect experts or technicians; this method is not only subjective and labor-intensive, but also impractical in large-scale applications [150]. However, with the popularity of sensors and devices embedded with Internet connections, the combination of RS and ML has opened up a new method for the detection of diseases and insect pests in modern agriculture [151]. Mahanta et al. obtained rich spectral features of vegetation based on a variety of sensor devices and used ML models to identify spectral patterns related to specific diseases. Finally, the evaluation of the health of insects invading the forest was realized, and the detection efficiency was greatly improved [152].

Most diseases and insect pests exhibit characteristics of concealment, latency, infectivity, and uncertainty, which undoubtedly increase the difficulty and cost of control and create great challenges to agricultural production [153,154]. However, it is worth noting that RS data from satellite sensors show that plants affected by the disease can be distinguished in a relatively short period of time by identifying their spectral characteristics which differ from those of healthy plants [155]. Figure 6 shows the pest monitoring process based on different remote sensing data such as IDS maps, MODIS and Landsat-8 data, and drone images. More importantly, through further use of ML for analysis, we can not only determine the degree of damage but also accurately identify the type of disease [156,157]. In the early detection of diseases and insect pests, many researchers tend to use traditional methods, i.e., to establish empirical statistical models between diseases and insect pests and their related factors (such as environment, climate, soil, and vegetation index) [158,159], in order to achieve the effective monitoring of diseases and insect pests. These methods include multiple linear regression, partial least squares regression, support vector regression, and RF regression. For example, Ebrahimi et al. use support vector regression to detect parasites in crop canopy images, which greatly improves the detection accuracy [160].

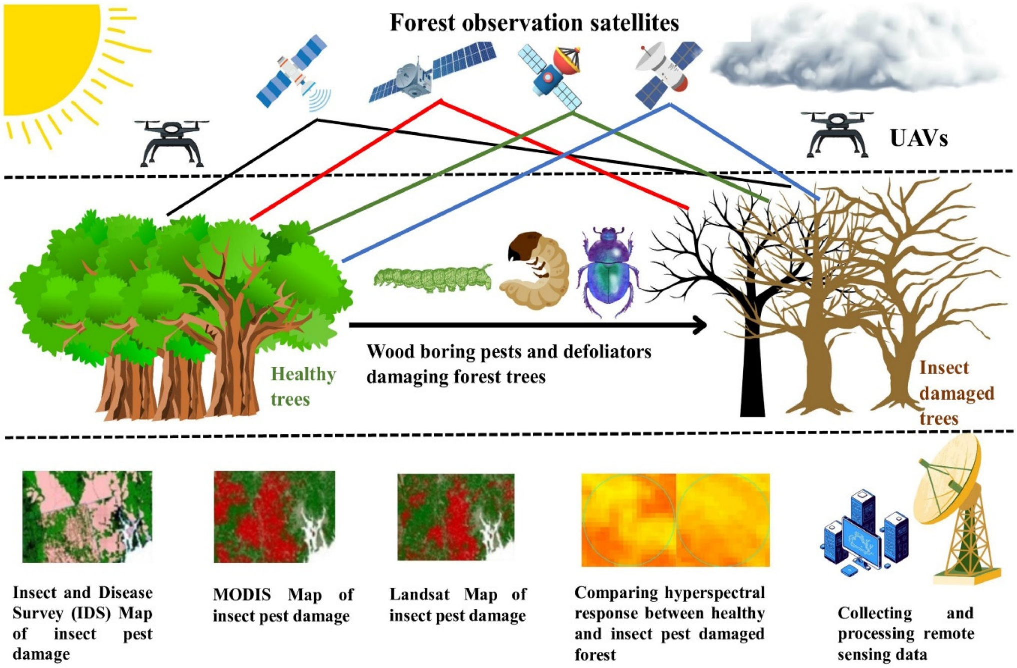

Figure 6. The process of detecting insect infestation and evaluating forest health was realized based on IDS, MODIS, and Landsat-8 mapping, along with hyperspectral response technology.

In addition, through the comprehensive use of advanced image processing techniques such as image segmentation [161], feature extraction [162], target detection [163–166] and classification, researchers can solve complex problems in plant disease detection more accurately and efficiently [167]. Image segmentation technology is used to distinguish normal and abnormal leaves in RS images, while feature extraction is used to extract meaningful information, such as color, texture, shape, etc., from the segmented regions [168,169], providing a more detailed and accurate method of analysis for disease detection [170,171]. For example, studies by Zhang et al. have shown that the TinySegformer model can provide a robust and practical solution for large-scale agricultural pest detection because of its high efficiency and accuracy, along with its light weight [172]. The interactive segmentation method based on GrabCut proposed by Lu et al., which is applied to field RS, can quickly extract locust images from various segments [173]. Barbedo et al. proposed an automatic detection algorithm for wheat scab based on hyperspectral technology. The algorithm displays a greater than 91% classification accuracy and shows excellent robustness under the impact of variety of complex factors such as shape, direction, and shadow [174]. Mumtaz et al. combined optical RS, image processing, and depth learning methods to accurately detect and grade wheat rust [175]. Bao et al. proposed an RS UAV method based on DDMA-YOLO, which can not only reduce the workload and time consumption of pest detection, but also effectively improve the detection efficiency [176].

Many studies have shown that the image fusion method can greatly enhance the accuracy of vegetation disease detection by fusing image information from different sensors or multi-stage processing [177–181]. For example, some scholars apply DL technology to the fusion of RGB images and segmented images, developing a multi-head DenseNet architecture. After the strict verification of the public dataset and the application of 50% discount cross-validation technology, the method shows excellent performance, and all the evaluation indicators have reached a very high level, e.g., the average accuracy, recall, accuracy, and F1 score reached 98.17%, 98.17%, 98.16%, and 98.12%, respectively [182]. Based on the multi-source fusion UAV images and visible light, Ma et al. successfully constructed a variety of ML models, which significantly improved the accuracy of cotton Verticillium wilt detection [183].

It is worth mentioning that some researchers have adopted the improved DL algorithm framework for plant disease detection, achieving remarkable results [184–187]. Dong et al. creatively proposed an effective scale-aware network architecture (ESA-Net) based on low-cost RS images [188]. After strict verification, ESA-Net showed excellent performance in plant disease detection and achieved strong competitive results. Amarathunga et al. proposed a new architecture based on a visual converter, which integrates the attention mechanism driven by domain knowledge and effectively improves the accuracy of micro-pest detection and recognition at the species level [189]. Ye et al. designed an end-to-end automatic disease detection framework based on a multi-scale MA-UNet model and a single-phase image based on UAV aerial photography data and Landsat-8 satellite RS markers, which greatly improved the efficiency and accuracy of disease monitoring [190].

3.3. Management and Analysis of Soil and Land

As the cornerstone of human survival and development, land not only carries the key mission of agricultural production, providing us with food to maintain our livelihood, but is also an indispensable key prerequisite for ensuring human well-being [60,191]. Therefore, the management and analysis of soil and land resources is particularly urgent and important. In the field of soil monitoring and management, traditionally, we rely on field survey methods to obtain the spatial distribution data for soil groups [191]. However, these methods have many shortcomings, such as a long monitoring period, high cost, complex operation procedures, many subjective judgment factors, and relatively limited accuracy [192]. Therefore, using traditional methods for soil monitoring is not only time-consuming and labor-intensive, but also may be inadequate for meeting the needs of modern soil management regarding accuracy and efficiency [16]. With its more accurate, richer, and more professional characteristics, RS has brought revolutionary changes to soil monitoring and management activities. It provides multi-temporal images, enabling us to fully capture dynamic changes in land and soil characteristics [193–195]. In addition, RS offers a wide range of data sources with large amounts of information and high accuracy, providing unprecedented possibilities for the accurate assessment of soil conditions [196]. The use of advanced ML technology can achieve efficient and accurate processing and analysis of RS data, realizing the automation of data processing and feature extraction. It is very important to improve the efficiency and accuracy of soil and land management [197–199].

A survey found that the application of various types of RS data provides convenience and opportunities for soil management [200]. At the same time, among the different RS soil applications, multi-spectral RS is the most widely used [201]. Duan et al. used the mean value of reflectivity and entropy texture parameters extracted from Landsat-8 images, combined with MLC, SVM, ANN, and RF ML, to identify soil groups in depth, achieving good results. In 2024, Zhou et al. proposed a general ML method based on spatiotemporal constraints using Sentinel-1 and Sentinel-2 data [202]. Through verification, its accuracy and practicability have been fully affirmed [203]. In 2023, Musasa et al. conducted a detailed review of soil problems in arid environments, clearly pointing out that the Landsat-8 satellite mission plays an indispensable role in promoting soil assessment and monitoring [204]. In addition, in view of the significant challenges such as insufficient information acquisition and limited measurement accuracy in early soil moisture monitoring technology [205], the introduction of ML technology is a revolutionary change, which significantly compensates for these deficiencies [206,207]. In addition, high-resolution data show significant applicability in soil applications, especially in soil resource estimation and mapping [208–211]. Moreover, UAVs show great potential for use in soil analysis and evaluation, and many studies have fully proved its effectiveness in practical applications. For example, Bertalan et al., through the mapping of soil moisture based on UAV images, revealed the spatial heterogeneity of soil moisture and provided strong support for PA [212]. Menzies Pluer et al. used UAV to create the spatial distribution model of farmland soil characteristics and nutrient concentration, which provided a novel and low-cost method for soil management [213]. In addition, scholars also pointed out that the combination of UAV data fusion and ML is very important for the accurate field estimation of soil texture [214–216]. At the same time, in many studies on the integrated application of RS and ML in soil management, we found that the discussion of soil organic carbon and salinity is also an eye-catching research direction [217–221].

As one of the key factors in global ecological change, land use or land cover (LULC) has a far-reaching impact on the balance of the ecosystem and the sustainable development of human society [222]. It represents the different ways in which human beings maximize the use of land resources and manage related resources, and it is very important for land management and analysis [223]. Therefore, in the research field of land management and analysis, we pay special attention to the temporal and spatial distribution of LULC and its applications. It goes without saying that the application of ML to RS data is of great significance for efficient and accurate land management and analysis [224]. On the one hand, traditional land management and analysis methods are often time-consuming and costly, and it is difficult to provide up-to-date information on various land use/land cover changes [225]. On the other hand, with its strong data acquisition and processing ability, RS can extract high-resolution multispectral information covering large areas that are difficult to access in real time, making land management and classification more cost-effective and time-saving [226,227]. Figure 7 shows the whole process of determining farming patterns using Landsat-8 and MODIS RS data, greatly improving the efficiency of agricultural practices [228]. In recent years, with the continuous development of ML technology, it is becoming more and more popular for use in the mapping, analysis, and spatiotemporal land analysis of LULC changes using RS data [229,230]. Examples of land management and analysis based on different ML methods include: RF [100,101,231], SVM [102,103,232], DT [90,91,233], maximum likelihood classification [234,235], ANN [97,99,236], CNN [237,238], and hybrid multiple model [239,240].

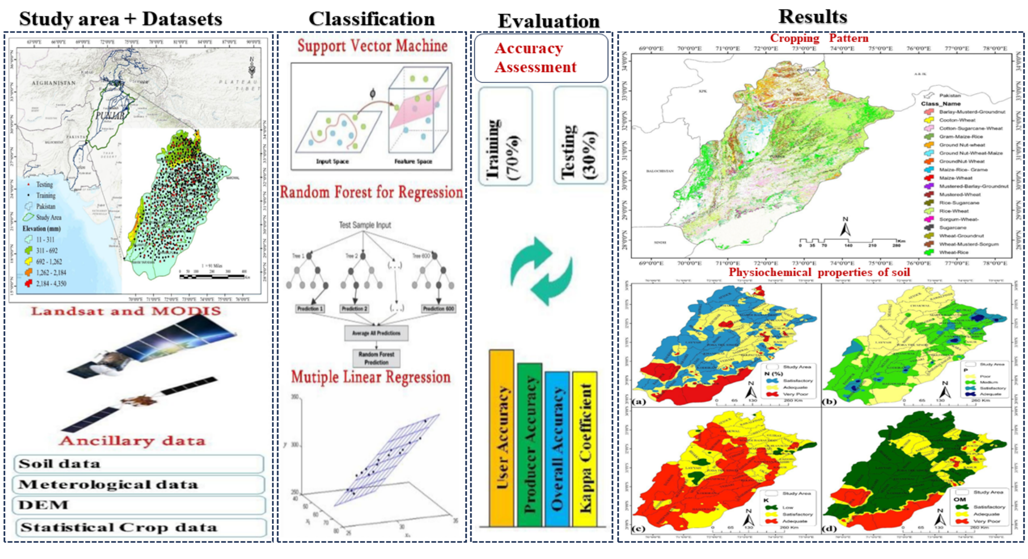

Figure 7. A general process for determining tillage patterns and cultivated/non-cultivated land areas based on multi-source remote sensing data.

3.4. Prediction and Decision Making Regarding Crop Yield

Determining crop yield plays an indispensable role in crop field management, and crop yield prediction is one of the important cornerstones to ensure food security [241,242]. Traditional crop yield prediction methods usually involve destructive sampling, which not only wastes a lot of human and material resources in practical application, but also is inefficient and cannot meet the needs of the development of modern PA [243]. In order to overcome this bottleneck, we conducted an in-depth and systematic review of the literature, which covered many aspects, such as RS data sources, biological and abiotic factors, physical and chemical parameters, modeling methods, etc. The aim is to provide a more accurate and efficient crop yield prediction scheme, as well as to provide strong support for the sustainable development of yield prediction and decision making.

We have learned that there are differences in the applicability and accuracy of the operational assessment of crop status and yield based on different ML algorithms and RS data from different sources. Multi-spectral and medium-resolution RS represented by MODIS data are widely used in early crop yield prediction, revealing potential uses [244,245]. Hyperspectral data, especially data from Landsat-8 satellites and hyperspectral imagers, offer unique advantages in regards to prediction. Related studies have shown that they exhibit great potential in regards to yield prediction for crops such as citrus, wheat, corn, sugarcane, etc. [246–250]. In addition, airborne LiDAR and high spatial and temporal resolution images are more suitable for crop yield prediction in fine abundance models [251–254]. A number of studies have shown that UAV data provide accurate and efficient support for PA prediction, especially in crop yield estimation accuracy and phenotypic analysis [255–261]. As shown in Figure 8, Liu et al. predicted corn LAI based on UAV multispectral images combined with ML technology, which provided support for improving the accuracy of yield prediction and further revealed the great potential of UAV in yield prediction [262].

In addition, as an integral part of PA practice, yield forecasting usually does not exist in isolation, but it is the result of the interweaving and interaction of climate, soil, water, diseases and insect pests, management, and other factors. For example, in an in-depth study, Anwar et al. revealed that Australian wheat yields are extremely sensitive to climatic factors [263]. Bai et al. made it clear that assessing the impact of extreme weather on crop production is a key prerequisite for exploring agronomic measures to address climate change, and that fluctuations in climate variables closely related to crop production can have a profound impact on regional and global food production [264]. The importance of soil as a key factor affecting crop yield cannot be ignored. By combining RS data with ML, we can evaluate soil properties more accurately and, taking into account cost-effectiveness and time benefits, we can achieve the accurate prediction of crop yield [265,266]. Fry et al. discussed the spatial variability between field soil properties and soybean yield and found that there was a significant correlation between different soil properties and changes in soybean yield, mainly affected by soil texture and organic carbon content in the topsoil (the first 20 cm) rather than by surface topography [267]. In exploring the actual effect of water on yield, Zain et al. failed to consider the adaptability of the model, which led to adverse results [268]. In another study, Wang et al. developed an accurate polynomial function model, which can effectively adapt to the characteristics of irrigation and application in different areas, provides a scientific guidance strategy for water and fertilizer management, and realizes the accurate prediction of crop yield combined with advanced ML [269]. In addition, the impact of diseases and insect pests and management on yield estimates is also of concern [270–272].

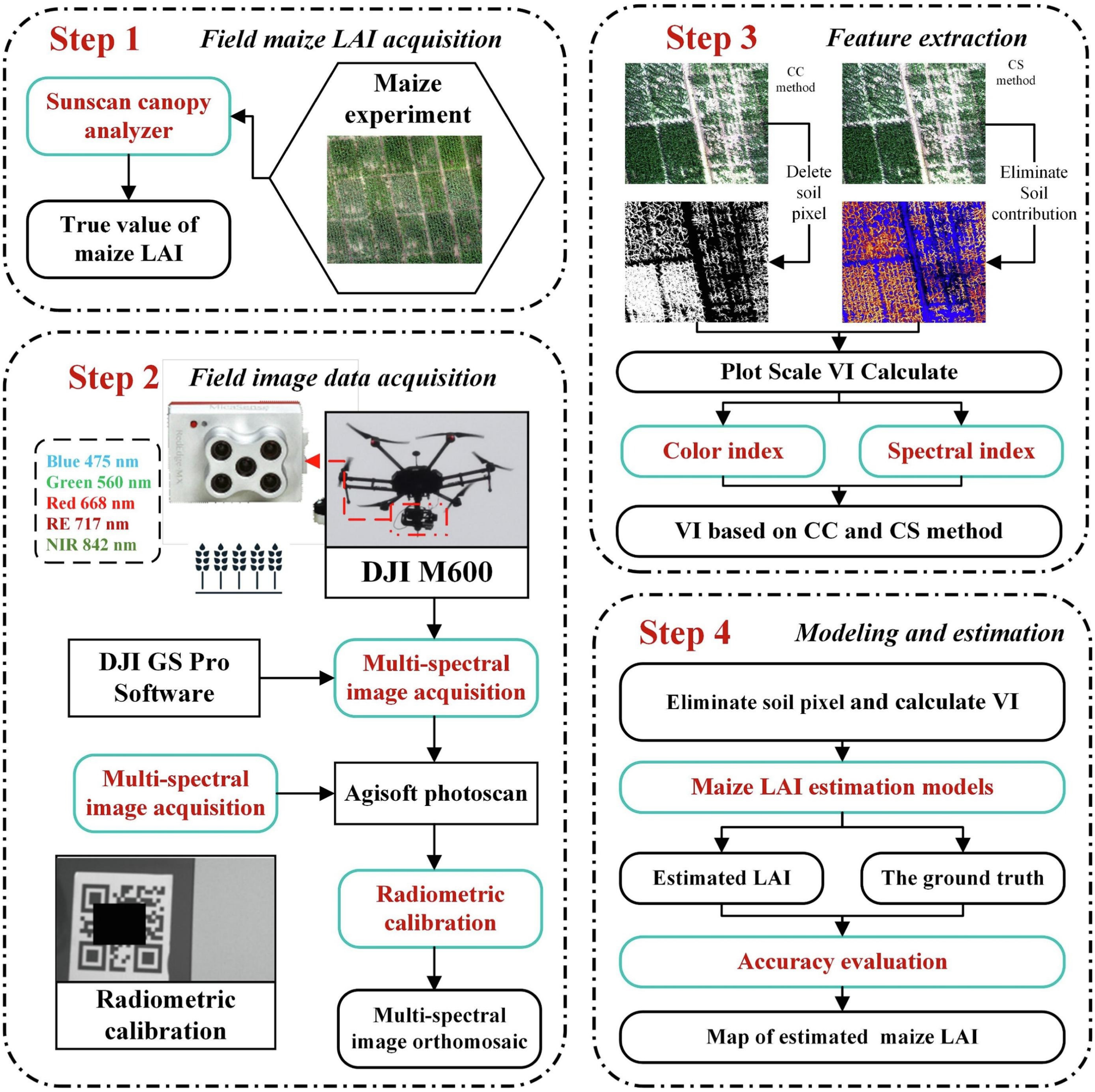

Figure 8. Prediction framework of maize LAI based on UAV images and machine learning.

In recent years, the combination of RS technology and ML for crop yield estimation and decision making has become a research direction with great potential and prospect. The integration of this method into the agricultural field not only improves the accuracy and efficiency of crop yield estimation but also provides strong technical support for the precise management of agricultural production [259]. In this process, the selection of crop physical and chemical parameters is particularly important, as it is directly related to the accuracy and reliability of the yield prediction model. Commonly used physiochemical parameters include vegetation coverage (FVC) [273], photosynthetically active radiation absorption (FPAR) [274–276], evapotranspiration (ET) [277–279], leaf area index (LAI) [245,280,281], chlorophyll content [282–284], and various vegetation indices (VIs), such as the normalized difference vegetation index (NDVI) [285–287] and the enhanced vegetation index (EVI) [288]. These physical and chemical parameters and indexes are not only widely used in actual agricultural production, but are also closely related to yield estimation.

In addition, the crop yield prediction model is also constantly adapting to a variety of new situational changes. For example, although the early traditional ground survey methods and sampling statistics methods based on empirical knowledge have been significantly researched and practiced, they cannot meet the needs for improved production prediction accuracy and reduced costs [289]. With the application of crop growth and data assimilation models, the yield prediction accuracy will be significantly improved [290]. For example, Zhang et al. and Kheir et al. have made yield predictions based on the APSIM crop model, achieving remarkable results [291,292]. In addition, the WOFOST model also performs well in regards to crop yield prediction, and a number of studies have revealed its potential use in forecasting [293,294]. The SAFY model provides a new perspective and method for the estimation of crop yield in a large area [295]. However, crop models are not perfect. They may be limited in large-scale applications, they easily accumulate errors, and problems such as over-fitting are possible [296]. Similarly, ML models may encounter fitting problems in the training process, especially in the case of small datasets or improper feature selection. Fortunately, ML and data assimilation methods provide new solutions to the problems inherent in crop models and ML [297]. By combining RS data and crop models, and with the help of ML optimization, we can not only make up for the shortcomings of the model in some aspects but also significantly improve the prediction accuracy and enhance the applicability. This innovative method is gradually becoming widely considered and favored by researchers [298–300].

4. Discussion

4.1. Current Challenges

4.1.1. Acquisition and Processing of Multi-Source RS Data

Although there are free and open source media and low resolution data resources, such as MODIS, which provide the basis for scientific research and application, the scarcity of high-quality and high-resolution RS data is still a significant problem. This scarcity mainly stems from the multiple complexities in the process of data acquisition, including the unpredictability of meteorological conditions, the limitations of equipment performance, and the impact of complex terrain on the signal. These factors work together to impact data quality and increase the difficulty and cost of data acquisition. The accessibility, real-time, integrity, and privacy protection of RS data are also important factors restricting the sustainable development of agricultural RS [301,302]. In addition, for the processing of RS data, their highly specialized and technology-intensive characteristics cannot be ignored. In data preprocessing, multi-source data fusion, and subsequent data interpretation and application, each link requires fine technical operations and profound professional knowledge. Improper handling will not only reduce the accuracy and reliability of data but also lead to unnecessary waste of resources and loss of efficiency [303,304]. For example, Zhao et al. proposed a framework for the robust classification of multi-view RS images under the condition of missing data, effectively reducing the practical costs. This research not only improves the classification accuracy but also reduces the uncertainty and deviation in the process of data processing, helping to achieve more efficient agricultural management decision making [305].

It is worth noting that the construction of an RS database system, as one of the effective strategies to alleviate the above problems, has become increasingly important. For example, studies have shown that the development of a strong and publicly accessible RS water quality database system can effectively improve the efficiency of water resource management and monitoring [306]. In addition, it can not only provide rich and standardized data resources to meet the needs of ML models for large amounts of data, but it can also promote rapid data retrieval and scientific research sharing, injecting new vitality into agricultural RS research and application. At the same time, with the continuous improvement of the database system, the long-standing problems in the field of agricultural RS, such as insufficient data standardization, the limited scale of datasets, different data quality, etc., are expected to be solved gradually [307]. The research shows that the application of multi-source RS fusion technology and high-resolution sensors may bring revolutionary changes to the field of agricultural RS. The progress of these technologies will greatly enrich the data dimensions, improve the monitoring accuracy, and provide strong data support for the practice of PA based on ML [308]. For example, by combining multi-source RS technology, Joshi et al. have achieved rapid and large-scale early warnings and accurate control of wheat diseases and insect pests [309]. Based on hyperspectral reflectance and satellite multispectral images, Wu et al. significantly improved the accuracy of wheat grain water content estimation and successfully reduced the risk of grain loss and additional drying costs [310].

4.1.2. Interpretability and Generalization of the Model

Generally speaking, the ML model is easier to explain than is the DL model, due to the complexity of the model structure. Although some newer models may improve accuracy, understanding and accepting these models will also be challenging for agricultural practitioners. For example, although the DL model performs well for many tasks, because of its black box nature, it may be difficult for agricultural workers to understand the decision logic behind it [311]. Therefore, in the application of PA, a DT or rule-based model is often easier for agricultural practitioners to understand and accept because of its relatively simple structure. For example, Marin et al. used multiple decision tree models to quickly understand the types of vegetation diseases using spatially continuous monitoring, thus improving the efficiency of decision making [312]. In addition, the interpretable model can not only promote the transparency of agricultural decision-making but also accelerate the knowledge transfer from technical experts to front-line producers, which is very important for improving the science and efficiency of agricultural practice. For example, in a study of precision irrigation, the use of a rule-based ML model greatly promoted water resource management and agricultural policy decision making. Typically, providing information about the features, variables, and algorithms that affect the results of the model is an effective way to enhance the interpretability of the model [313]. For example, Hao et al. realized the high-precision prediction of wheat yield by analyzing the key variables of the APSIM-Wheat model through Sobol sensitivity analysis [314]. Under the influence of many factors, such as crop growth environment, varieties, soil state, and climatic conditions, the model shows insufficient ability to extract fine features in the face of new data. It is often necessary to optimize the generalization ability of the model through data enhancement, model integration, and the introduction of regularization technology in order to effectively prevent overfitting and maintain stable performance in the face of new data. For example, Fawakherji et al. used a data enhancement strategy for improved segmentation to significantly improve the accuracy of the model for crop and weed segmentation [315]. In addition, regularization technology can help reduce the complexity of the model, thus improving the generalization ability of the model. For example, by applying L2 regularization in the process of model training, the dependence of the model on training data can be effectively reduced, and its performance in the face of new data can become more stable [316].

4.2. Prospects for the Future

4.2.1. Trend of Intelligence and Automation

With the application of intelligent and automation technology in PA, many problems existing in traditional agricultural models, such as insufficient datasets, inaccurate analysis, and untimely decision making, have been solved. This is due to the use of high-precision multi-source RS data, further enhancement of data preprocessing to improve data quality, expansion of data sample diversity, and integration of expert knowledge, all of which improve the accuracy of intelligent decision making. For example, based on expert dialogue and multi-standard decision-making technology, Goodridge et al. proposed an expert system that can intelligently diagnose plant diseases, significantly improving the accuracy of plant disease detection [317]. In addition, the development of intelligent agricultural equipment and the promotion of farmers' training have lowered the technical threshold and promoted the wide application of new technologies. One study points out that by developing easy-to-operate smart agricultural equipment, farmers can more easily master new technologies, save water, and reduce labor demand by promoting the cultivation of different crop types, improving the profitability of each farm [318].

The intelligent fusion of multi-source RS data effectively solves many problems inherent in agricultural data, such as ensuring the consistency of data formatting, optimizing processing speed, improving the stability of the algorithm, and enhancing the generalization ability and interpretability of the model. As a result, the uncertainty in the whole process of agricultural production is reduced. For example, Zhou et al. enhanced the generalization ability through the deep migration learning classification model constructed by integrating ground sensor data and UAV data, realizing the intelligent RS recognition of corn straw type [319]. In the future, RS technology and ML are expected to achieve cross-border integration with advanced technologies such as the Internet of things (IoT), human–computer interaction visualization, data assimilation, and blockchains. This will further promote comprehensive monitoring, yield forecasting, and disease surveillance in PA and provide more accurate, efficient, and sustainable solutions for agricultural production. For example, intelligent systems that use the Internet of things to track and schedule accurate irrigation have been studied to help farmers effectively plan irrigation and make informed decisions [320].

4.2.2. Data Sharing and Multidisciplinary Interaction

In the context of global connectivity, international cooperation and data sharing mechanisms are constantly strengthening, and the application of PA should go beyond geographical restrictions. Different countries and regions should work together to share more accurate RS data and smarter ML algorithms to address global agricultural issues such as climate change, food safety, and other challenges [321]. In addition, ML algorithms are closely combined with RS technology, and automatic machinery and intelligent robots are used to realize the intelligence and refinement of field management. At the same time, experts in many fields such as agricultural economy, ecology, and physics are integrated to form a comprehensive agricultural management system. For example, a cloud-based intelligent irrigation system was introduced in one study to optimize irrigation water use through comprehensive big data collection, storage, and analysis, significantly promoting informed decisions regarding water resource management [322]. In addition, strengthening the cooperative research of RS and ML can not only effectively reduce the use of chemical fertilizers and pesticides, accelerate the transformation of agricultural scientific and technological achievements, protect the ecological environment, and promote the green transformation of agriculture, but it also is very important to promote the research results of PA to significantly benefit farmers and realize the transformation from theoretical knowledge to scientific and technological practice. For example, different countries and regions should use their market channels and technical support capabilities to popularize new technologies by establishing partnerships with agricultural research institutions and by working with agribusinesses to encourage farmers to adopt new technologies through policy guidance and support and to participate in the application of new technologies through peasant groups [323]. In addition, combining this science and technology with the United Nations Sustainable Development goals (SDGs) can not only broaden the scope of science but also promote the development of practice from a broader perspective, i.e., by improving agricultural production efficiency and implementing the sustainable development agenda to contribute to the "zero hunger" goal [324]. Although it still faces technical, economic, and social challenges, with the continuous updating of the application of RS technology and ML in agriculture, its potential to promote the modernization and sustainable development of the agricultural industry will be further tapped.

5. Conclusions

The comprehensive application of RS and ML algorithms can not only promote the development and progress of PA but also provide a possible solution to the challenges of global population growth, resource shortage, and climate change. In some fusion applications of PA, there are significant differences in different types of RS data, among which hyperspectral RS data is the most widely used type, accounting for more than 30%, while the application of UAV technology has the most potential, accounting for about 24%, of the data used. It is expected to play a more important role in PA in the future. In addition, the most widely used ML algorithm is SVM, accounting for more than 20%, followed by the RF algorithm, accounting for about 18%, of the algorithms used. It is worth noting that in the future, the rapid development of the DL integrated platform, the multimodal fusion algorithm, cloud computing, and edge computing is expected to further promote the progress of PA. The monitoring and identification of crop growth status, pest detection, land or soil management, and crop yield prediction are still the main aspects of the comprehensive application of RS technology and ML. However, in regards to obtaining and processing high-quality RS data and improving the interpretability and generalizability of the model, considering the uncertainty of integration development, we need to continue to explore new algorithms and technologies to promote interdisciplinary cooperation and the integration of multi-domain knowledge, further promoting the intelligence and automation of PA and the development of more intelligent agricultural robots, automation equipment, and expert systems to promote the sustainable development of PA.

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