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Review article

Effectiveness of Machine Learning and Deep Learning Algorithms in Remote Sensing for Food Crop Mapping: A Systematic Literature Review

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Abstract

The global conversation on sustainable development highlights the problems of food (in)security, considering rapid population growth, climate change, land degradation, and escalating competition for natural resources. Ecologically sound agricultural management and well-informed policymaking depend on accurate and trustworthy food crop maps. Remote sensing has become essential for mapping food crops, and machine learning (ML) and deep learning algorithms are becoming increasingly important. This systematic literature review examines the effectiveness of ML algorithms and deep learning architectures in remote sensing-based food crop mapping. This review follows the PRISMA guidelines and covers peer-reviewed studies published between 2017 and March 2026. A comprehensive search across five electronic databases (Google Scholar, SpringerLink, ScienceDirect, Scopus, and Wiley) identified 1,589 records, of which 80 met the inclusion criteria after screening, eligibility assessment, and quality appraisal. The extracted variables included algorithm type, crop species, sensor modality, spatial platform (satellite or Unmanned Aerial Vehicle), accuracy metrics, and validation strategy. According to the analysis, U-Net, the value-guided explanation model, and the one-dimensional convolutional neural network have the highest average overall accuracy for mapping food crops. However, crop performance varied depending on crop type, sensor characteristics, and agroecological conditions. These findings provide an organized framework for future research on food crop management and monitoring. The study found that food security and sustainable farming methods depend on accurate and reliable food crop maps, which can be improved by applying state-of-the-art deep learning methods. Stakeholders and policymakers can develop data-driven strategies to optimize land use, minimize environmental risks, and enhance global food sustainability using these algorithms.

Keywords: Effectiveness; Machine Learning; Deep Learning; Food Crop Mapping; Remote Sensing.

1. Introduction

Global food security is central to the sustainability of human life and should thus be outlined or detailed for practical concerted efforts in its implementation (Battersby, 2017). Up to 828 million people went hungry in 2021, and the 2022 Sustainable Development Goals Report shows that 2.4 billion people did not always have access to enough food (UNDESA, 2019). Current food production is estimated to be insufficient to feed over 10 billion people in 2060 unless efforts are made to double the total yield (Machichi *et al.,* 2023; Calicioglu *et al.,* 2019; Foley, 2011). Agricultural acreage has been considerably expanded to ensure food security for the growing global population (Karthikeyan, 2020; Siebert *et al.,* 2015). Food production still uses unsustainable methods that lead to land degradation and excessive use of energy, water, fertilizers, and pesticides (Benton *et al.,* 2021), which is detrimental to the environment (Smith *et al.,* 2019). Sustainable agricultural management is a strategic approach to address this issue (Aliyu *et al.,* 2021; Joshi *et al.,* 2023). This calls for accurate and current data on food crop types and their geographic distribution (Ridwana *et al.,* 2022; Rußwurm *et al.,* 2023). This requires accurate mapping of diverse agricultural landscapes (Meier and Mauser, 2023). Precision agriculture, monitoring farming activity, building a food crop database, and researching environmental effects on food crops can all benefit from food crop maps (Defourny *et al.,* 2019; Gallo *et al.,* 2023). They also serve as basic data for regional-scale crop yield prediction models (van Klompenburg *et al.,* 2020). Depending on their level of accuracy, both the data and the model can indicate food insecurity to support decision-making about necessary early warning and exports and imports of food crops (Morales *et al.,* 2023; Praful and Tzenios, 2023). Food crop maps can serve as the foundation for site-specific insecticides, fertilizer interventions, and land productivity enhancement strategies in low-productivity areas (Habtu and Katihally, 2023). The agricultural sector also benefits from these data when planning farming stocks and determining crop prices (Zhang *et al.,* 2022). Maintaining and achieving food security depends on a thorough awareness of production and spatial distribution provided by food crop mapping. These systemic pressures increase the demand for spatially explicit and temporally consistent agricultural monitoring, transforming crop mapping into a data-intensive and analytically complex task.

Field survey mapping has many benefits and drawbacks that should be considered. The high level of accuracy and detail is one of the key advantages, with data often obtained down to centimeter-level precision (Song *et al.,* 2017). Field surveys enable thorough data collection on physical characteristics and other environmental factors. However, field surveys have some disadvantages, particularly when covering large areas, the process is frequently laborious and slow (Arrasyid *et al.,* 2019; De Groote and Traoré, 2005; Kamal *et al.,* 2016). The high expenses of travel, specialized equipment, and labor may strain project budgets. Accessibility is another problem that restricts the areas that can be efficiently surveyed, especially in dangerous or difficult terrain. Field surveys may become more challenging due to unfavorable weather conditions, which may result in delays or lower data accuracy. Possible human errors, such as subjective observations or mistakes made during manual data entry, may also affect the reliability of the final dataset. In addition, mapping plots of food crops requires a lot of time and permits from farmers and landowners. For this reason, field surveys are frequently regarded as ineffective and inefficient (O'Connor *et al.,* 2019).

Remote sensing has been employed as a substitute method for mapping food crops since the late 1960s (Fu *et al.,* 1969). Mapping food crops using remote sensing has several advantages and disadvantages (Khanal *et al.,* 2020). One of the main benefits is the capacity to swiftly and effectively cover vast regions, offering a variety of spatial data that would be impossible to obtain through ground surveys. Remote sensing makes it feasible to collect data frequently and repeatedly, allowing for the tracking of crop health and growth over time. This is crucial for controlling farming methods and identifying shifts. Additionally, it provides helpful hyperspectral and multispectral data that can draw attention to specifics about pest infestations, crop conditions, and soil health—information that is typically obscured from view (Kasampalis *et al.,* 2018). However, remote sensing has disadvantages as well. Haze and clouds can obscure aerial or satellite imagery, thereby decreasing the accuracy of the data. Furthermore, the detailed analysis of small-scale or heterogeneous fields and resolution of remote sensing data might make this impossible. Despite these limitations, remote sensing remains a potent instrument for agricultural mapping, offering a comprehensive and efficient approach to food crop management and monitoring. However, as satellite constellations generate increasingly dense multi-temporal datasets, conventional classification approaches often struggle to capture nonlinear and spatiotemporal crop patterns, motivating the adoption of machine learning (ML) and deep learning (DL) frameworks.

A growing body of research published in scientific journals indicates that remote sensing is a cost-effective technique that reduces time, labor, and resource consumption (Sishodia *et al.,* 2020; Weiss *et al.,* 2020; Shanmugapriya *et al.,* 2019; Khanal *et al.,* 2020). Object-based image analysis (OBIA), supervised classification, and unsupervised classification are popular image classification techniques for food crop mapping. Supervised classification involves training an algorithm using labeled data to classify different crop types. Its main advantage is its high accuracy when sufficient and representative training data are available. However, it is time-consuming and requires expert knowledge to correctly label training samples.

Unsupervised classification uses the spectral characteristics of pixels to cluster them without knowing the crop types. It is faster and less labor-intensive because it does not require labeled training data. However, it often results in lower accuracy and may require post-classification refinement to make sense of the clusters. OBIA separates images into meaningful objects using spatial and spectral information. This approach can handle complex landscapes and yield more accurate results than pixel-based approaches in areas with heterogeneity. However, OBIA is computationally demanding, and its successful implementation necessitates advanced software and knowledge (Ma *et al.,* 2017). Despite their widespread use, these conventional approaches often depend on manually engineered features and may struggle to capture nonlinear and high-dimensional patterns in multi-temporal datasets. This limitation has motivated the increasing adoption of ML and DL frameworks in remote sensing-based crop mapping.

The ML and DL algorithms in remote sensing are superior and efficient for mapping plants at high accuracy, even when applied to a wide area (Royimani *et al.,* 2019). ML refers to a class of data-driven algorithms that learn statistical relationships from input features, whereas DL represents a subfield of ML characterized by multi-layered neural network architectures capable of automatic hierarchical feature extraction. Large volumes of data can be accurately and swiftly analyzed by ML algorithms, which can also spot patterns and relationships that conventional approaches might overlook. Depending on data availability, both algorithms can meet a mapping project's specific needs. ML is suitable when interpretability and a clear understanding of the domain are required, whereas DL performs better for assignments requiring a thorough comprehension of intricate data (Liu *et al.,* 2022a; Luo *et al.,* 2023; Wang *et al.,* 2022a; Yang *et al.,* 2023; Zhong *et al.,* 2019). The two algorithms can be very useful instruments for extracting important information by making big data more accessible (Rogan *et al.,* 2008). They provide relevant foundations for future technological innovation and artificial intelligence and have an impact on decisions and policies of the agricultural sector, especially those related to the management of food crops.

Numerous studies have been conducted on the remote sensing mapping of food crops, and the number of publications is steadily increasing. A systematic literature review (SLR) is required to monitor the status of related research, the difficulties encountered, and the course of future investigations. Many SLR-based studies have focused on remote sensing for plant diseases, yield prediction, and general crop mapping (Machichi *et al.,* 2023; Derisma *et al.,* 2022; Leukel *et al.,* 2023; van Klompenburg *et al.,* 2020). However, none of the existing studies provide a comprehensive SLR evaluating the effectiveness of ML and DL algorithms in remote sensing for mapping different types of food crops. This study addresses this gap by conducting a structured and systematic synthesis of ML- and DL-based approaches for food crop mapping.

The expected outcome of this SLR is a thorough and profound comprehension of the effectiveness of ML and DL algorithms in remote sensing for mapping different types of food crops. This review examines the literature to determine the current status of research in the field, point out its shortcomings and challenges, and suggest potential solutions or areas for development. The review also seeks to identify patterns and trends in the application of these algorithms, offering insights into the most promising methods and tactics. By identifying gaps in the literature and proposing new lines of inquiry, this SLR ultimately aims to guide future research. This will improve food crop mapping accuracy, efficacy, and progress.

2. Methods

2.1. Protocol for Literature Review

In the SLR, a protocol was first created using Kitchenham and Charters's (2007) popular review guidelines to ensure transparency, rigor, and reproducibility. The review protocol, including research questions, inclusion and exclusion criteria, search strategy, data extraction scheme, and quality assessment procedures, was defined before the search process. The protocol outlines the research questions to be addressed to limit the scope of the study before searching for relevant studies through selected databases. The databases used were ScienceDirect, Scopus, SpringerLink, Wiley, and Google Scholar because of their excellent scientific journals and trustworthy reference materials. A set of exclusion and quality criteria was used to screen and evaluate the pertinent studies. Subsequently, data from these studies were extracted and combined to answer the research questions.

The three steps and procedures used in the current study are planning, carrying out, and reporting the review (Figure 1). Planning the review, or the first step, involved deciding on research questions, creating a protocol, and testing the protocol to see if the chosen strategy was workable (Carver *et al.,* 2013). A predefined review protocol was established to ensure methodological rigor, specifying the research questions, inclusion and exclusion criteria, search strategy, and data extraction procedures. This step started by determining the research questions that will direct the review's scope and direction to guarantee that the study tackles pertinent and particular problems in the field. Another crucial task is creating a protocol that specifies the methodology and criteria of the review and guarantees an organized and methodical approach (Smith *et al.,* 2011).

The protocol includes details such as the publication locations to be considered, the initial search string to find relevant studies, and the selection criteria for publications to help identify the most relevant and high-quality research. To determine whether the chosen strategy is workable and realistic, the protocol must be validated at this point. This entails examining the protocol to ensure that it is feasible within the parameters of the review and that it successfully gathers the required data. The planning stage lays a strong foundation for the later phases of the SLR by ensuring that the protocol is appropriate and comprehensive. Finally, updating the protocol considering preliminary results and input guarantees that it remains applicable and suitable for its intended use. This iterative process aids in improving the strategy by addressing any problems or gaps found during the initial planning. The planning phase is essential for defining precise goals, a strong methodology, and a verified protocol, all of which together guarantee the methodical and exhaustive character of the literature review (Snyder, 2019).

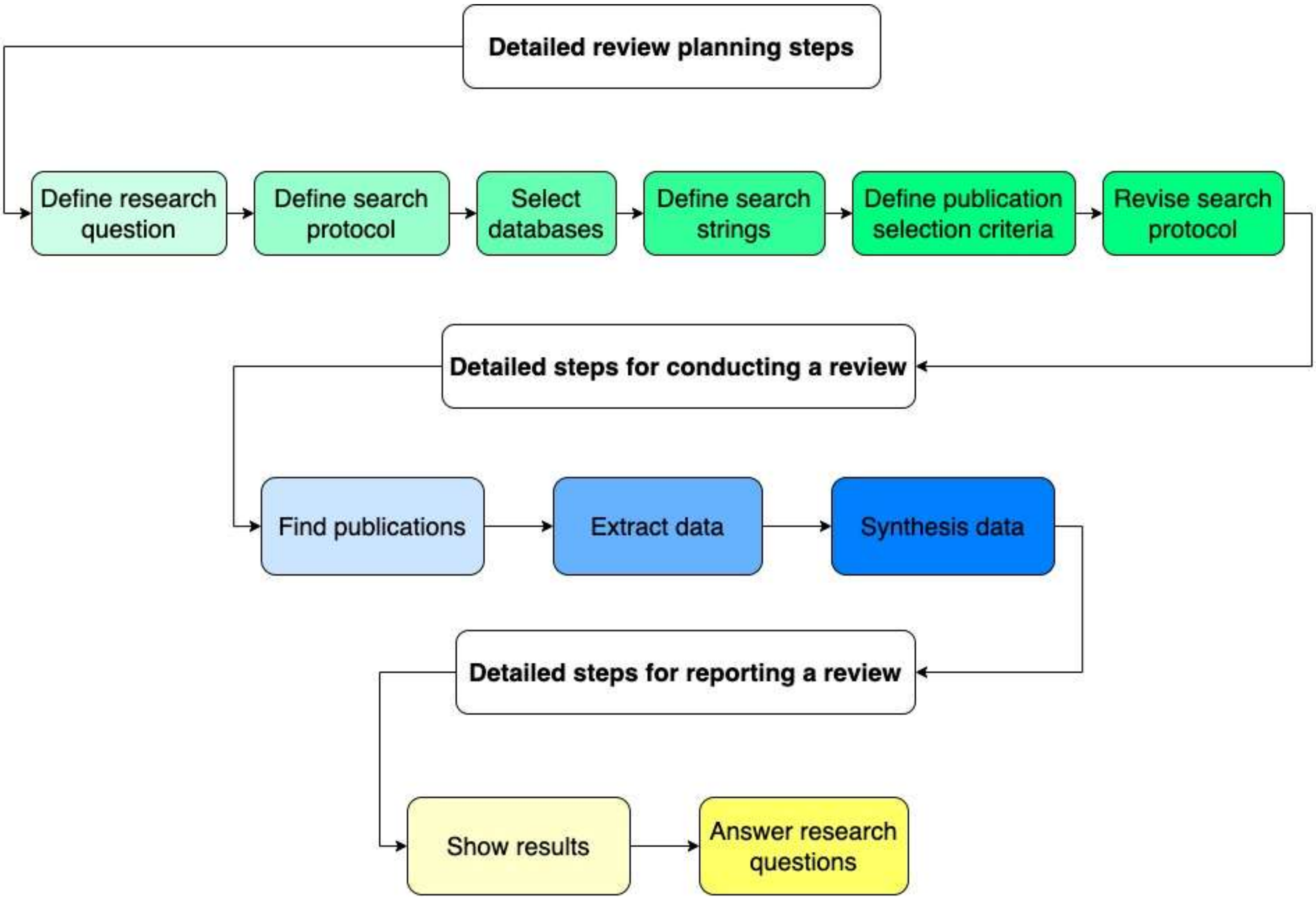

Figure 1. Flowchart of the Processes Involved in Planning, Conducting, and Reporting the Review.

The primary objective of the second stage of the SLR is to select and examine relevant publications (Van Dinter, 2021). The first step in this process is a comprehensive search of all selected databases to identify studies that meet the predefined criteria. The objective of this study is to compile as many publications as possible that pertain to the research inquiries. The characteristics of the pertinent publications are extracted after they have been located. These characteristics include important information such as the authors, year of publication, publication type (journal article, conference paper, etc.), and other particulars relevant to the research questions. This step is essential because it facilitates the methodical organization and classification of the data. Following the extraction of these characteristics, the information is combined to find trends, patterns, and gaps in the current literature. Analyzing the gathered data to derive significant insights and draw conclusions is the process of this synthesis. The goal of this study is to provide a thorough summary of the current state of research on mapping food crops using remote sensing and ML and DL algorithms. By synthesizing the data, the review can highlight the most important studies, common methodologies, important findings, and areas that require more research. In the end, this phase produces an extensive synopsis of the state of the field's knowledge, providing insightful analysis and direction for future research projects.

The research questions of the SLR last phase are documented by the findings and by offering thorough responses to the primary objectives (Shaffril *et al.,* 2021). This phase is essential for converting the collected data and synthesized information into a meaningful and cohesive narrative that meets the main goals of the review. First, the results are meticulously recorded, frequently containing thorough explanations of the conclusions, pertinent information, and any observed trends or patterns. The information in this documentation is logically and clearly arranged to make it easy for readers to access and comprehend. Data can be successfully presented using visual aids, such as tables, charts, and graphs. The primary goal of this phase is to answer the research questions. By methodically examining the results, the review offers concise, fact-based responses to the initial research questions. This process entails connecting the synthesized data to each research question to ensure that every aspect is fully covered. The results of this phase greatly advance our knowledge of how well ML and DL algorithms work with remote sensing to map food crops. These insights can promote the development of knowledge by highlighting effective methodologies, filling in the gaps in the current research, and providing suggestions for new lines of inquiry.

Researchers, policymakers, and practitioners can greatly benefit from the documented results and responses. The review can help these stakeholders make well-informed decisions by offering evidence-supported conclusions. For example, researchers may find new areas for study, and policymakers may use the insights to create guidelines or allot funds for agricultural monitoring. All things considered, the last phase of the SLR ensures that the research findings are fully recorded, the research questions are fully addressed, and the acquired knowledge is successfully conveyed to aid decision-making and promote the advancement of knowledge in the field.

2.2. Research Questions

This SLR aimed to fully comprehend the effectiveness of the latest ML and DL algorithms for mapping food crops using remote sensing. Therefore, relevant studies were selected and analyzed from several dimensions to answer the following specific research questions:

1. Research Question 1: Which ML and DL algorithms are the most widely used in remote sensing for food crop mapping?
2. Research Question 2: Which ML algorithms and DL architectures are most effective for mapping food crops using remote sensing?
3. Research Question 3: What challenges are faced in using remote sensing to map food crops?

2.3. Search Strategy

All databases were searched on March 5, 2026, covering publications from January 2017 to March 2026. ML and DL have limitless areas of application, meaning that many published studies may not be within the scope of this review article. Consequently, the search began by narrowing the basic concepts to only relevant ones. In the first step, the words “machine learning” OR “deep learning” AND “crop mapping” were entered, and the search was conducted automatically on the five databases. Keywords were used to obtain a broad overview of the topic of interest. Then, the abstracts of the returned articles were examined to identify synonyms for the three keywords. After processing the initial search results and applying the exclusion criteria, a more complex search query was created to ascertain if any relevant studies were missed. The final search string was as follows: ["machine learning" OR "deep learning"] AND ["crop mapping" OR "crop classification" OR "crop identification" OR "crop monitoring" OR “crop type”] AND “remote sensing”: anywhere. Consequently, 1,589 published works were obtained by executing this search string.

2.4. Selection/Exclusion Criteria

Two reviewers conducted the screening process independently to minimize selection bias. The procedure consisted of three stages: title screening, abstract screening, and assessment of full-text eligibility. Disagreements between reviewers were resolved through discussion and consensus. The chosen research was evaluated using the criteria for exclusion to define the parameters of the systematic review to eliminate published works that were deemed unnecessary. The criteria for exclusion (EC) were as follows:

EC 1: This publication is not related to food crop mapping, ML, or DL.

EC 2: English is not used in the manuscript.

EC 3: Duplicates publications that have been retrieved from other databases.

EC 4: The full text of the publication is not accessible.

EC 5: The article is a survey/review.

Figure 2 illustrates how to choose and exclude articles from the database for a PRISMA review. The number of publications obtained from the five databases is displayed in Table 1 using the string search and selection criteria. Of the 1,589 published works captured using the string search, only 1,580 studies remained after screening using the first three exclusion criteria. With the five exclusion criteria, only 80 studies were retained for further analysis. Data were extracted from these selected studies and then combined and synthesized to determine whether the studies should be omitted or kept based on the exclusion criteria to answer the three research questions.

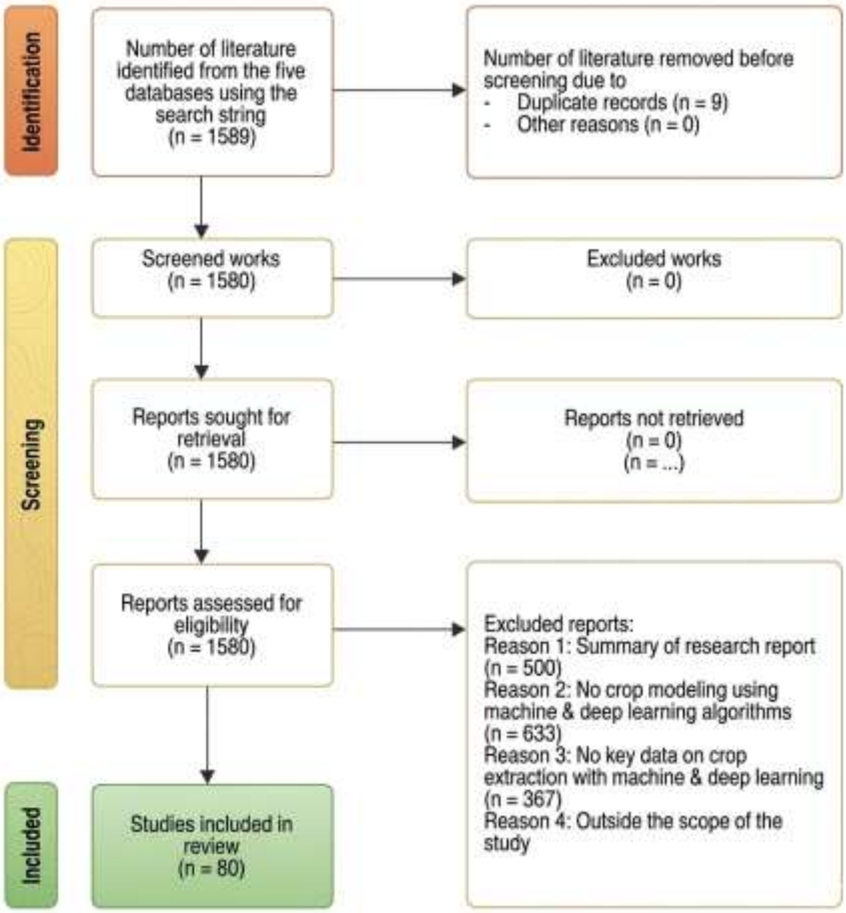

Figure 2. Flowchart of relevant study selection based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework.

Table 1. Distribution of Selected Publications Based on Their Home Database.

Database	Number of initially retrieved papers	Number of papers after exclusion criteria	Percentage of articles (%)
Google Scholar	581	31	39
Springer Link	176	5	6
Science Direct	514	15	19
Scopus	299	29	36
Wiley	19	0	0
Total	1,589	80	100

For many reasons, the Google Scholar, Springer Link, Science Direct, Scopus, and Wiley databases were carefully and strategically chosen. These databases provide thorough coverage and easy access to excellent peer-reviewed literature when combined. Google Scholar is a great resource for a variety of literature because it offers a vast array of scholarly publications, including books, theses, articles, and conference papers, from a range of disciplines. The extensive collection of scientific and technical content provided by Springer Link is particularly strong in technology, agriculture, and environmental science. Science Direct's vast database of top-notch, peer-reviewed journals and articles in the domains of science, technology, and medicine ensures reliable and credible research studies. Scopus is one of the largest abstract and citation databases of peer-reviewed literature and is well-known for its exacting indexing standards and thorough coverage of research outputs, including papers, conference proceedings, and patents. Accessing comprehensive studies and reviews in agricultural science and remote sensing technologies is made possible by Wiley's extensive collection of scientific, technical, medical, and scholarly research journals. These databases also cover a wide range of disciplines related to food crop mapping, such as agriculture, remote sensing, environmental science, computer science, and ML, to ensure a multidisciplinary approach. They also provide access to a large archive of scholarly publications, citation tracking, and sophisticated search features to facilitate effective and efficient literature searches. These databases allow researchers to conduct a thorough, multidisciplinary, and high-quality review of the literature on remote sensing and ML for mapping food crops, capturing the most impactful, up-to-date, and pertinent studies.

2.5. Data Extraction

A structured data extraction form was developed. The following variables were recorded from each eligible study: publication year, study location, crop type(s), remote sensing platform (satellite/UAV), sensor type (optical, SAR, multispectral, hyperspectral), algorithm(s) used (ML or DL), and accuracy metrics (e.g., overall accuracy, F1-score, Kappa, IoU). This structured extraction ensured consistency and comparability across studies. The attributes of each of the 80 retrieved publications were analyzed to answer the research questions, as explained below:

Research Question 1: The analysis considered the type of platform (satellite, unmanned, or manned aerial vehicle) as well as the sensing technology (radioactive detection radar, Lidar, multispectral, and hyperspectral). When it came to satellite imagery, the name and attributes of the satellite were recorded to determine whether it was a suitable sensor for a given crop species.

Research Question 2: The analysis documented the model, basic algorithm, and crop species discussed or investigated in the literature. In publications where multiple models were used, an overall accuracy evaluation metric was created.

Research Question 3: This analysis explains the challenges faced by the authors and the potential solutions proposed or reported in each study.

A risk-of-bias assessment was conducted to enhance methodological rigor. Each study was evaluated based on the following criteria: Clarity of dataset description, Transparency of algorithm configuration, Reporting of validation strategy, Reporting of class imbalance handling, and Completeness of performance metrics. Each criterion was scored on a scale of 0–2 (0 = not reported, 1 = partially reported, 2 = clearly reported). Studies with insufficient methodological transparency were excluded from the quantitative analysis. This quality assessment ensured that only studies meeting minimum methodological standards were included in the final analysis.

3. Results and Discussion

3.1. Results

The different findings gathered to address the research questions for the study are presented and discussed in this section. Distribution of selected publications by year (Figure 3). Most articles were retrieved from Scopus, Google Scholar, and SpringerLink. Additionally, the number of scientific publications on the mapping of food crops using ML and DL algorithms has been steadily rising annually. In 2022 and 2023, the number of publications increased significantly from 6 to 12 and 14, respectively, indicating that this topic received more attention. There are several reasons for the notable rise in publications in recent years about mapping food crops using DL and ML algorithms. First, the worldwide demand for sustainable and efficient agricultural practices has increased interest in innovative technologies that can improve crop monitoring and yield prediction. ML and DL algorithms provide comprehensive information about crop health, growth trends, and possible problems, such as pests or diseases. Large amounts of data from remote sensing and other sources can be analyzed using these methods (Wang *et al.,* 2022).

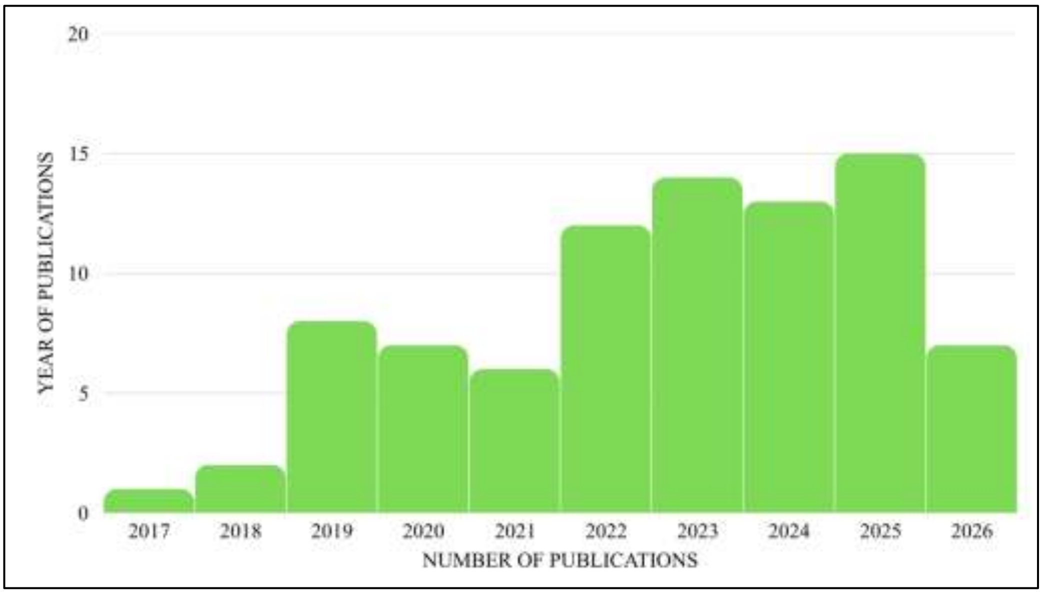

Figure 3. Distribution of Selected Publications by Year, 2017–2026.

Second, advances in processing capacity and the accessibility of sizable datasets have made it easier to apply these complex algorithms to real-world agricultural problems (Alibabaei *et al.,* 2022). Easy access to high-resolution satellite imagery and other remote sensing data has also contributed to the expanding use of these technologies in agriculture. Furthermore, people are more conscious of the significance of food security, especially in light of climate change and population growth (Fonta *et al.,* 2011). Researchers and policymakers are focusing more on creative solutions to guarantee consistent food supplies, and ML and DL are viewed as important facilitators in this endeavor. Furthermore, more funding opportunities and cooperative projects in this field have resulted from the recognition of the potential of these technologies to transform conventional farming methods (Altieri *et al.,* 2017). Studies examining the relationship between artificial intelligence and agriculture have also gained more attention from conferences, workshops, and journals, which has increased the number of publications.

Figure 4 shows the spatial distribution of publications on ML and DL mapping of food crops. With 35 publications, China had the most pertinent works, followed by India (n = 13) and the United States (n = 5). Fewer than three studies have been conducted on this subject in other nations. China, India, and the United States are known to make significant investments in research and development, particularly in the fields of science and technology, because of their many research centers, top-notch universities, and government policies. Furthermore, as part of the "Made in China 2025" plan, China has boosted its investment in technology, including artificial intelligence, recently (Wübbeke *et al.,* 2016).

Figure 4. Spatial Distribution and Frequency of Publications on Food Crop Mapping Using ML and DL Algorithms from 2017 to 2026.

Table 2 shows the profile of each selected publication, including the authors, algorithms used, crop type, sensors, and maximum overall accuracy (%). This information serves as an initial reference in selecting and determining the most effective algorithm for mapping different food crops when using certain sensors to produce the desired level of accuracy. The reviewed studies were reclassified into two analytical categories to avoid misleading comparisons across heterogeneous platforms: (1) satellite-based crop mapping and (2) UAV-based crop mapping.

Satellite imagery typically provides medium- to high-resolution data (e.g., 10–30 m for Sentinel-2 and Landsat) with broad spatial coverage, making it suitable for regional- and national-scale monitoring. However, in heterogeneous agricultural landscapes, medium-resolution imagery is more prone to mixed-pixel effects and spectral confusion. In contrast, UAV imagery offers centimeter-level spatial resolution, enabling highly detailed crop discrimination at the field scale. Nevertheless, UAV-based studies are often limited in terms of spatial extent and operational scalability. Because of these substantial differences in spatial resolution, scene complexity, and mapping objectives, the accuracy values reported for UAVs and satellite platforms are not directly comparable. Therefore, performance trends are interpreted within rather than across platforms.

Table 2. Attributes of the Selected Publications (Algorithms with the Greatest and Weakest Performance are Written in Bold and Italicized, Respectively).

No.	Published works	Algorithms used	Crop/Object depicted	Image sensors	Max. Overall accuracy (%)	Number of cited articles
1	(Ashourloo et al., 2020)	SVM, ML	Potato	Sentinel-2 (A and B)	92	41
2	(Fang et al., 2020)	SVM, RF, and CART	Winter wheat, vegetation, urban areas, water bodies, and others	Sentinel-2	92	51
3	(Gao et al., 2018)	SVM	Rice, watermelon, lotus, water body, bare land, forest, and grassland	Gaofen-3 (PolSAR), Sentintel-2A	85.27	29
4	(Ge et al., 2023)	RF, Deeplabv3+, and SGEM	Rice	Gaofen-3 (PolSAR)	95.73	5
5	(He et al., 2022)	RF, SVM, KNN, NB, ANN, and XGBoost	Wheat, corn, sugar beet, and sunflower seeds	MODIS13Q1	79	10
6	(Kumari et al., 2022)	OB-XGBoost, OB-RF, and OB-SVM	Soybean, soybean + red gram, jowar, sugarcane, cotton, and	Sentinel-1 and Sentinel-2	92.5	10
7	(Latif et al., 2023)	RF, SVM, NB, and CART	Cropland and non-cropland	Sentinel-2 MSI	82	2
8	(Liu et al., 2022b)	LASSO, RF, XGBoost, At-LSTM, and Informer	Rice	MODIS	81	20
9	(Ma et al., 2020)	PCIB, RF, K-means, and ISODATA	Corn, spring wheat, grape, pear, forest, and others	Gaofen-1	84	34
10	(Machichi et al., 2022)	SVM, RF, LSTM, CNN, and CerealNet	Barley, soft wheat, durum wheat, and oats	Sentinel-2	94	5
11	(Maiti et al., 2022)	IPPPM, RF	Rice and non-rice fields	Sentintel-2	88	14
12	(Oldoni et al., 2022)	STARFM, ESTARFM, and FSDAF	Soybean and corn products	Landsat 8/OLI and MODIS	93.11	4
13	(Rußwurm and Körner, 2020)	RF, LSTM-RNN, Transformer, DuPLO, MS-ResNet, and TempCNN	Fallow, fallow + flowers, alfalfa, grassland, protein plants, corn, winter wheat, summer wheat, beetroot, potato, grassland + machining, grassland + cattle, winter rye, winter spelt, winter barley, summer oat, peas, winter triticale, beans, rape seed, summer oats, and winter triticale	Sentinel-2	92	235
14	(Sonobe et al., 2017)	SVM, RF, multilayer FNN, and KELM	Beans, beetroot, grassland, corn, potato, and wheat	Sentinel-1A and 2A	96.8	159
15	(Sonobe 2019)	SVM, RF, FNN, and KELM	Beans, beetroot, corn, potato, and winter wheat	ASNARO-2 XSAR HH and Sentinel-1 C-SAR VH/VV	85.4	21
16	(Sun et al., 2019)	LSTM	Corn, wolfberry, vegetable, orchard, garden, and other crops	Sentinel-1, Landsat-8	88.3	25
17	(Torbick et al., 2018)	RF	Corn, cotton, rice, soybeans, winter wheat, alfalfa, tomatoes, grapes, almonds, and pistachios	Sentinel-1, 2, Landsat-8, and Harmonized Landsat and Sentinel	93.2	62
18	(Wang et al., 2022a)	SVM, RF, KNN, stacking, Conv1D, and LSTM	Wheat, corn, early rice, and early rice-late rice	MOD13A2	77.12	35
19	(Xu et al., 2020)	DCM, transformer, RF, and MLP	Corn, soybean, and other crops	Landsat analysis ready data, Landsat 7 and 8	82	153
20	(Yan et al., 2023)	U-Net, DeeplabV3+, PSPnet, TransUnet, ETUnet,	Ricefields	Unmanned Airborne Vehicle (UAV)	95.05	8
21	(Ahmed et al., 2023)	RF	Cover crop and non-cover crop	Landsat-8	97.7	-
22	(Zhao et al., 2019)	1D CNNs, LSTM RNNs, GRU RNNs, and RF	Rice, sugar cane, banana, pineapple, and Eucalyptus	Sentinel-1A	95.9	123
23	(Zhen et al., 2023)	RF, SVM, CART, and NB	Corn, rice, and soybeans	MODIS	75	6
24	(Zhong et al., 2019)	MLP, LSTM, Conv1D, XGBoost, RF, and SVM	Rice, safflower, corn, alfalfa, cucurbits, tomatoes, almond pistachios, orchard, field crops, truck, pasture, subtropical, and vineyards	Landsat-7 and 8	85.54	784

Table 2. Continued.

No.	Published works	Algorithms used	Crop/Object depicted	Image sensors	Max. Overall accuracy (%)	Number of cited articles
25	(Zhou *et al.*, 2019)	DCNs, LSTM	Rice, double rice, rice-rape, rape-cotton, rape-rice, rape-rice-rape, and other crops	ZY-3, Sentinel-1A	88.26	34
26	(Zhou *et al.*, 2019)	SVM, RF, and LSTM	Rice, double rice, rice-rape, rape-cotton, rape-rice, rape-rice-rape, and other crops	ZY-3, Sentinel-1A	83.67	89
27	(Abubakar *et al.*, 2021)	RF, SVM	Corn, trees, water bodies, and built-up land	Sentinel-2A	87.4	6
28	(Guo *et al.*, 2023)	GNB, QDA, MLP, DT, RF, and SVM	Ricefield	RADARSAT-2	97.37	3
29	(Liu *et al.*, 2019)	DT	Ricefield	MODIS	93.9	19
30	(Rawat *et al.*, 2022)	1D-CNN, MPCM	Rice, corn, sugar cane, and other water bodies	Sentinel-2A/2B	96	7
31	(Verma *et al.*, 2019)	RF	Rice, corn, finger millet, and non-agricultural land	Sentinel-1 and Sentinel-2	83.87	38
32	(Ashourloo *et al.*, 2022)	SVM, RF,	Wheat and barley	Sentinel-2	84	22
33	(Bhavana *et al.*, 2023)	SVM, CNN, RF, and ANN Bayes Classifier	Rice, chili, corn, lily, Colocasia, curry, mint, okra, banana, betel leaves, sugar cane, water, rivers, and other ingredients are used	PlanetScope	94.3	3
34	(Gao *et al.*, 2023)	RF, SVM	Corn, cotton, rice, and other non-crop crops	Landsat 8	86	6
35	(Ge *et al.*, 2021)	U-Net, RF	Rice and corn	CDL Landsat	96	33
36	(Htitiou *et al.*, 2022)	RF	Sugar beet, pomegranate, urban, alfalfa, fallow, cereals, olives, and citrus	Sentintel-2A	88	36
37	(Guo *et al.*, 2022)	SVM, RF, KNN, ANN, 1D-CNN, and C-AENN	Peanut, rice, corn, and other crops	Sentinel-1	97.94	19
38	(Hachimi *et al.*, 2021)	SVM, RF	Sugar beet, cereal, alfalfa, citrus, olive, and forest	Sentinel-2A	91.49	6
39	(Luo *et al.*, 2023)	RF, SVM, and ANN	Built-up, corn, peanut, cotton, water, tree, millet, shrub, and fruit tree	Sentinel-2	93	24
40	(Lee *et al.*, 2020)	RF	Rice, red dates, taro, persimmons, betel nuts, nursery/seedling plots, woodland, grassland, bare land, and others	Aerial photography	91	5
41	(Li *et al.*, 2022a)	RF, XGBoost, U-Net, and Deeplabv3+	Wheat, corn, sunflower seeds, and squash	Sentinel-2	99.45	20
42	(Li *et al.*, 2022b)	CNN, LSTM, LSTM-ATT, C-LSTM, CNN-ATT, ViT, H-ViT, and MSViT	Soybeans, rice, woody wetlands, corn, cotton, and other crops	Sentinel-1 and Sentinel-2	96.8	29
43	(Lin *et al.*, 2022)	Topology, ABNet, ANN, S-Only, and S-R	Rice, corn, and soybeans	Sentinel-2, Landsat-8	96.4	57
44	(Mohammadi *et al.*, 2021)	FCN + IOU, transformer, RF, and MULP	Soybean and corn products	CDL, Landsat	91.8	6
45	(Mohammadi *et al.*, 2023)	3DFCN, DCM, transformer, RF, and MLP	Soybean and corn products	Landsat ADR and CDR	90.1	16
46	(Seydi *et al.*, 2022)	RF, XGBOOST, R-CNN, 2D-CNN, 3D-CNN, and others. CBAM, proposed method	Alfalfa, broad bean, wheat, barley, and canola	Sentinel-2	98.54	43
47	(Wang *et al.*, 2022b)	U-Net, DeepLab V3+, PSPNet, RF, U-Net++	Corn, peanuts, soybeans, and rice	Sentinel-2A	91	20
48	(Xu *et al.*, 2020)	DCM, transformer, RF, and MLP	Soybean and corn products	Landsat ARD and CDL	87.8	153
49	(Yi *et al.*, 2022)	Conv1DN, LSTM, RF, and SVM	Wheat, corn, melon, fennel, sunflower, and alfalfa	Sentinel-2	87	14
50	(Zhang *et al.*, 2021)	BP-NN, K-NN, NB, CART, MLR, and SVM	Rice, cotton, lotus, peanuts, bare paddy fields, bare upland fields, and abandoned cropland	WorldView-2	83.9	8

Table 2. Continued.

No.	Published works	Algorithms used	Crop/Object depicted	Image sensors	Max. Overall accuracy (%)	Number of cited articles
51	(Aashi *et al.,* 2025)	RF	Maize, rice, chilies, fallow cotton, and other crops	Sentinel-1 and Sentinel-2	95	1
52	(Dharmaratne *et al.,* 2024)	3D–ResNet–BiLSTM–MT	Winter wheat, soybeans, and corn	Sentinel-1 and Sentinel-2	93	2
53	(Fikriyah *et al.,* 2025)	DT, SVM, and	Ratoon rice	Sentinel-1 and Sentinel-2	92	4
54	(Hedge *et al.,* 2025)	DTM, RF, Bi-GRU, DB BiLSTM,BiLSTM, Auto-RMVPF, and SPRI	Rice	Sentinel-1	95	3
55	(Karim *et al.,* 2025)	ViT-ChangeFormer	Crop land, buildup, water bodies, and other	Landsat 8 and Sentinel 2 satellites	96	0
56	(Wijaya *et al.,* 2026)	DSSNet,	Paddy and non-paddy fields	Sentinel-1 and Sentinel-2	89	0
57	(Yewle *et al.,* 2025)	RicEns-Net	Rice	Sentinels 1, 2, and 3	61	0
58	(Asadi *et al.,* 2024)	SVM, RF, and CNN	Alfalfa, barley, bean, corn, broad bean, flax, potato, sugar beet, and wheat	Sentinel-1 and Sentinel-2	88.03	37
59	(Cheng *et al.,* 2025)	FKAN, KAN, RF, ChinaWheat10	Winter wheat, soybeans, and corn	Sentinel-1 and Sentinel-2	90	3
60	(Islam *et al.,* 2025)	U-Net, FAPNET, and PLANET	Rice	Sentinel-1 and Sentinel-2	97	0
61	(Khan *et al.,* 2024)	Bi-LSTM	Maize, reed, rice, sugarcane, trees, water, tobaco, urban, and other vegetation	Sentinel 2 and the Planet Scope	96	9
62	(Li *et al.,* 2024)	TDMSANet, CNN, Transformer, and LSTM	Walnut, almond, fallow, alfalfa, wheat, corn, sunflower, tomato, and cucumber	UAVSAR, RapdiEye	90.28	25
63	(Mahrus *et al.,* 2024)	RF	Built-up Area, Sand, Vegetation, Paddy, and Sugarcane	Sentinel-2	85.82	0
64	(Maleki *et al.,* 2024)	RF, XGBoost, and MLP	Sunflower, soybean, and maize crops	Sentinel-1 and Sentinel-2	93.50	12
65	(Mallya et al., 2025)	Gradient-boosted tree, ML, MLP, RF, and SVM	Paddy, Bi-seasonal, Irrigated, Dry, Perennial	Sentinel-2	84.08	0
66	(Mirzaei et al., 2024)	KNN, MNB, RF, SVM, and 1D- and 3D-CNN	Wheat Herbage Barley Pea Triticale Fava bean Cardoon Maize Rice Tomato Soybean Sunflower Sorghum Apple Olive Almond Pear Cardoon Alfalfa	Sentinel-2	92	13
67	(Nagendram and Satyanarayana, 2024)	RF, XGBoost, CR, and NB	Chilly, paddy, and maize	Sentinel-2	97	4
68	(Simeon et al., 2025)	RF, XGBoost, K-Nearest, LRR)	Rice	Sentinel-2	94	0
69	(Venkatanaresh & Kullayamma, 2025)	CapsNet, DenseNet, ResNet, D-AE, and AE	Onion, chili, banana, papaya, mango, maize, potato, rabi paddy, etc.	Sentinel-2	91.20	1
70	(Zheng *et al.,* 2024)	RF, SVM, XGBoost, ResNet18, DMLOHM, and AD-MOHM	Rice, corn, ZBM, citrus, and plum	Landsat 8, Sentinel 1, and Sentinel 2	93.99	0

Table 2. Continued.

No.	Published works	Algorithms used	Crop/Object depicted	Image sensors	Max. Overall accuracy (%)	Number of cited articles
71	(Antony *et al.*, 2024)	DTOADL-FCC, SBODL-FCC, DNN, AlexNet, VGG16, ResNet, and SVM	Maize, banana, forest, and other crops	MODIS and Sentinel-2	97.98	7
72	(Chen et al., 2026)	RD, GGC, and RF	Corn, Soybean	Sentinel-2	88.90	4
73	(Di *et al.*, 2026)	RF, SVM, CART, and GBM	Paddy, rice, maize, and soybean	Landsat and the MODIS	91	1
74	(Gao *et al.*, 2024)	RF, SVM, CART, and GTB	Rice	Sentinel-2	97.06	7
75	(Hou *et al.*, 2025)	RF	Maize, oats, potatoes, and sesame seeds	Sentinel-2	97.35	4
76	(Hu *et al.*, 2025)	DTEMA + SLIC, HRNET-W48, U2-Net, EfficientNet-B5, and TransUNet	Cotton, maize, peanut, rape, rice, wheat, soybean, sorghum, sunflower, tobacco, vegetable, and bareland	iCrop dataset of agricultural images	94.79	3
77	(Indarto *et al.*, 2026)	RF	Cloud, built-up areas, sand, vegetation, paddy fields, cloud shadow, sugarcane, maize, sweet potato, shrubland	Sentinel-2	80	0
78	(Li *et al.*, 2025)	FastDTW-HC	Barley, wheat, and rapeseed	Sentinel-1 and Sentinel-2	96	7
79	(Mucsi *et al.*, 2026)	2D-CNN (DSS-2D) and multi-temporal 3D-SE-ResNet.	Alfalfa, winter wheat, winter barley, triticale, rapeseed, maize, sunflower, and soybean	EnMAP Hyperspectral	97	0
80	(Pham *et al.*, 2024)	1D-CNN and a Transformer Network models	Grassland, wheat, barley, oat, maize, sugar beet, rapeseed, sunflower, legumes, fodder crops, and fallow	Landsat 8 and Sentinel 2 satellites	89	16

3.2. Discussion

Table 3 shows the frequency distribution of algorithms used to address the first research question (RQ1). The three most popular algorithms in food crop mapping studies were Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). In comparison, few studies used alternative modeling, architectures, and algorithms. In ML, an ensemble learning method called RF builds a combination of the outputs of several decision trees to increase precision and resilience (Appiahene *et al.,* 2020). Its main advantage is its capacity to manage high-dimensional data and deliver strong performance even with a high feature count. Furthermore, RF is less prone to overfit than individual decision trees. However, its main drawbacks are that it is computationally taxing, particularly when working with large datasets, and its complexity may make it more difficult to comprehend.

The SVM component of ML is a powerful classification technique that selects the most effective hyperplane to split the feature space into different classes (Pisner *et al.,* 2020). SVMs offer reliable performance with both linear and nonlinear data through kernel trick extensions, making them extremely effective in high-dimensional spaces. The main advantages of SVMs are their high accuracy and capacity to manage intricate class boundaries. However, choosing the right kernel and hyperparameters can be difficult and require extensive tuning, and SVMs can be memory-intensive and slow to train, particularly with large datasets.

In DL, time-series data and sequences are modeled using a recurrent neural network (RNN) type known as long short-term memory (LSTM), which circumvents the vanishing gradient issue and captures long-term dependencies (Kim *et al.,* 2018). LSTMs perform exceptionally well in tasks involving sequential data, including time-series prediction, language modeling, and speech recognition, because they can retain and apply long-term context. The main advantage of LSTMs is that they outperform traditional RNNs on temporal tasks. However, LSTMs require a significant amount of training time and resources and are computationally costly. Because of their intricate architecture, they can be difficult to fine-tune and require a large amount of training data to perform well.

RF, SVM, and LSTM performed well in various mapping and image analysis studies (Filho *et al.* 2020). For this reason, scholars commonly rely on algorithms with proven performance to investigate topics with similar contexts of application. Besides, there have been many examples of scientifically sound implementations and tools for RF, SVM, and LSTM. Several popular ML libraries and frameworks, such as scikit-learn for RF and SVM and TensorFlow or PyTorch for

LSTM, are easy to use and enable straightforward implementations (Chaudhary and Kumar, 2022). Last but not least, RF and SVM tend to be easier to interpret, which might be one of the primary reasons behind their broad applications, particularly in food crop mapping that may involve stakeholders with varying degrees of technical expertise (Belgiu, 2016; Dang *et al.,* 2021; Noi, 2018).

Table 3. Algorithms Used in the Selected Publications and Their Frequency of Use.

Machine learning algorithm	**Number of times used**	**Deep learning architecture**	**Number of times used**
Random Forest (RF)	54	Long Short-Term Memory (LSTM)	9
Support Vector Machine (SVM)	30	Extreme Gradient Boost (XGBoost)	7
Multilayer Perceptron (MLP)	5	Transformer	6
Classification and Regression Trees (CART), Naïve Bayes (NB)	4	Artificial neural networks (ANNs)	4
K-nearest neighbor (KNN)	4	Deeplabv3+, Convolutional Neural Networks (CNN), One-dimensional Convolutional Neural Network (Conv1D), and Deep Crop Mapping (DCM)	7
Decision tree (DT)	4		
Kernel-based extreme learning machine (KELM)	2		
Maximum Likelihood, Least absolute shrinkage and selection operator, Principal components isometric binning (PCIB), K-means, ISODATA, Stacking, Improved phenological pixel-based paddy-rice mapping (IPPPM)	1	Feedforward neural networks (FNN), U-net, Pyramid Scene Parsing Network (PSPNet)	2
		Value-guided explanation model (SGEM), Attention-based long short-term, Informer, CerealNet, Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM), Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM), Flexible Spatiotemporal Data Fusion (FSDAF), LSTM- Recurrent Neural Network (RNN), DUal view Point deep Learning architecture for time-series classification (DuPLO), Multiscale Residual Networks (MS-ResNets), Temporal Convolutional Neural Network (TempCNN), Enhanced-TransUnet (ETUnet), Gated recurrent unit RNNs (GRU RNNs), Deep convolutional networks (DCNs), Gaussian naive Bayes (GNB), Quadratic discriminant analysis (QDA), Modified possibilistic c-mean (MPCM), Convolutional-autoencoder neural network (C-AENN), Deep neural networks (DNN), Multi-branch self-learning Vision Transformer (MSViT), Artificial antibody network (ABNet), 3D Fully Convolutional Neural Network (FCN) + Intersection Over Union (IOU), Convolutional block attention module (CBAM), Backpropagation neural networks (BP-NN), Multinomial logistic regression (MLR), 3D–Res-Net–BiLSTM–MT, deep learning model Bi-GRU, DB BiLSTM,BiLSTM, Auto-RMVPF and SPRI, ViT-ChangeFormer, DSSNet, RicEns-Net, TDMSANet, DTOADL-FCC, SBODL-FCC, DNN, AlexNet, VGG16, DTEMA + SLIC, HRNET-W48, U2-Net, EfficientNet-B5, TransUNet	1

The algorithms in the order of performance in food crop mapping to answer RQ2 are presented in Fig. 5. Here, high performance or effectiveness is based on the level of accuracy of a model or an algorithm when applied several times by researchers in different locations using various sensors to distinguish between types of food crops. As shown in the table, U-Net was the most effective algorithm, with an average overall accuracy of 97.72%, followed by the value-guided perception model algorithm and one-dimensional convolutional neural network (Conv1D), with average overall accuracies of 95.73% and 92.96%, respectively.

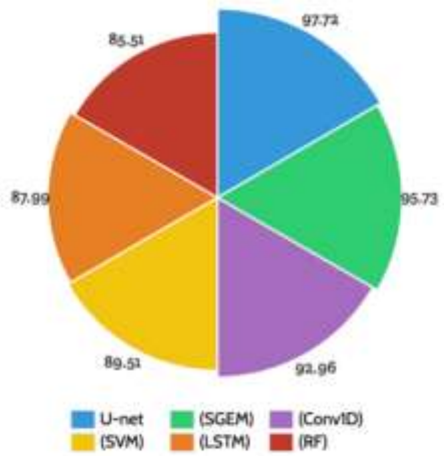

Figure 5. The Most Effective Algorithms for Food Crop Mapping with Overall Accuracy (%, Avg.).

Despite the promising performance reported in many studies, remote sensing-based crop mapping still faces several technical and operational challenges that influence classification accuracy and model generalizability. One of the most frequently reported limitations relates to sensor-related constraints, particularly the mixed-pixel problem in medium-resolution satellite imagery. A single pixel may represent multiple crop types or land-cover classes in heterogeneous agricultural landscapes, which complicates classification and reduces thematic accuracy. Moreover, spectral similarity among crop species during certain phenological stages often leads to confusion between crops with comparable spectral signatures, particularly when using optical multispectral imagery.

Another important issue concerns inconsistencies in validation strategies across studies. While some studies employ hold-out validation, others rely on k-fold cross-validation or independent test datasets. These methodological differences can significantly influence the reported accuracy metrics and limit the results' comparability across studies. Furthermore, the growing use of UAV imagery introduces additional methodological trade-offs. UAV platforms provide very high spatial resolution, enabling detailed crop discrimination at the field scale. However, UAV-based approaches typically cover smaller spatial extents and require intensive data processing workflows, whereas satellite imagery provides broader coverage but often suffers from mixed pixels and lower spatial resolution.

To address the third research question (RQ3), every chosen publication was examined to identify the difficulties encountered by researchers in mapping food crops using ML and DL algorithms. In addition, improvements made or proposed to the algorithms or models were documented. Accurately classifying and differentiating crops can be made more difficult by the variability in spectral signatures caused by various crop types, growth stages, and environmental factors (Potgieter *et al.,* 2021). Atmospheric factors, such as haze and cloud cover, can degrade the quality of remote sensing data, producing incomplete or erroneous imagery (Xia and Jia, 2022).

Another important factor to consider is temporal resolution; the revisit time of satellites may limit the frequency of imaging required to effectively track the growth and health of crops (Li *et al.,* 2014). Integrating multiple data sources, such as combining optical and radar imagery, requires sophisticated processing techniques and expertise to extract meaningful information (Joshi *et al.,* 2016). Spatial resolution is also a key consideration. While high-resolution images provide detailed information, their coverage is often limited and can be costly to acquire, whereas lower-resolution images might not capture the finer details required for accurate mapping (Zhao *et al.,* 2020). Last but not least is the difficulty of ground-truth validation, which necessitates the labor-intensive and time-consuming process of gathering ground data to validate and calibrate remote sensing models. According to Mura *et al.* (2015), overcoming these obstacles calls for the development of remote sensing technology, better data processing algorithms, and reliable techniques for combining various types of data.

The challenge also relates to improving algorithms and models used by incorporating variations in input parameters (such as NDVI and EVI) and applying them to a wider range of study areas with various types of food crops (Dharma *et al.,* 2022; Wang *et al.,* 2022a). The more algorithms used to address differences in meteorological, topographical, phenological factors, and crop practices, the better the resulting model will perform. However, this potential should be accompanied by efforts to increase the overall accuracy of the model (Aashi *et al.,* 2025). Another challenge is the generally low average accuracy; more studies are needed to investigate the less explored features of SAR data, including time-series features, gray features, textures, and correlation coefficients, that can be used to monitor plant growth, specifically for modeling in cloudy or tropical areas (Tian *et al.,* 2019). The use of DL models is challenging because it requires more combinations of optical and SAR image data to train appropriate architectures, including extracting and organizing thousands of spatiotemporal spectral features to improve plant classification (Ajadi *et al.,* 2021; Chen *et al.,* 2020; Kordi and Yousefi, 2022).

Many promising solutions can be generated using DL methods in mapping food crops with remote sensing. Advanced data fusion methods enable the integration of optical, radar, and multispectral images, contributing to a more complete description of the crop status and reducing atmospheric attenuation problems (Himeur *et al.,* 2022). Deep image processing, such as CNNs, improves classification accuracy by learning complex patterns independently of variable conditions (Rawat and Wang, 2017). Temporal resolution challenges are effectively addressed by analyzing crop growth from multiple timestamps with LSTM networks (Rußwurm and Körner, 2017). The augmentation of existing datasets to enhance the model's performance using synthetic data produced with GANs is also beneficial. Automatic feature extraction also minimizes the dependence on manual work and thus speeds up data processing. Cloud computing provides the necessary computing capacity for a scalable analysis approach for large datasets. Transfer learning (using pre-trained models) increases accuracy when labeled data are scarce. Strong ground-truth validation, supported by semi-supervised and active learning, accelerates training with fewer labeled examples. Finally, attention mechanisms and other techniques designed to maintain model explainability and interpretability should be utilized to make results interpretable and actionable for stakeholders (Shah and Konda, 2021). These methods improve the accuracy, reliability, and scalability of agricultural monitoring systems with ML and DL.

Based on the synthesis of the reviewed literature, several research directions can be identified to further advance the application of machine learning and deep learning in remote sensing-based crop mapping. First, developing foundation models for remote sensing represents a promising direction. These large-scale pre-trained models can learn generalized representations from massive datasets and may enable cross-regional transferability of crop classification models.

Second, explainable artificial intelligence (XAI) is gaining increasing attention in agricultural monitoring. While deep learning models often achieve high accuracy, their decision-making processes are frequently difficult to interpret. XAI methods can improve model transparency and support decision-making processes for agricultural management and policy development. Third, the integration of UAV and satellite data in real-time monitoring systems represents another important research direction. UAV imagery provides high spatial resolution for detailed field-level analysis, whereas satellite imagery provides consistent temporal coverage over large areas. The combination of these platforms could enable more comprehensive and timely crop monitoring systems.

Finally, future research should focus on the development of standardized benchmark datasets and validation protocols to improve comparability across studies. Harmonized evaluation frameworks would allow a more reliable assessment of algorithm performance and support the development of robust operational crop mapping systems. These research directions highlight the need for continued methodological innovation to improve the accuracy, scalability, and operational applicability of remote sensing-based crop mapping.

4. Conclusion

In recent years, the scientific community has carefully considered mapping food crops using ML and DL methods based on remote sensing data. Rapid technological advancements and the high performance of ML- and DL-based models in the field of agriculture have also enabled successful food crop mapping, which has encouraged shifts toward precision and sustainable agriculture in many nations. The scientific methodological framework that was previously used only in basic research has now been widely applied worldwide. This SLR examines the most recent scientific advancements in food crop mapping, including different kinds of food crop commodities, data from multiple remote sensing sources, and the efficiency of ML and DL algorithms in food crop classification. Despite significant scientific advancements in this area, it is still unclear which ML and DL algorithms are best suited for mapping specific food crops due to a number of factors, including topography, phenology, and local climate conditions. However, this review identified a few algorithms—random forest (RF), support vector machine (SVM), and long short-term memory (LSTM)—that are frequently utilized for mapping food crops in distinct countries with the highest accuracy. Meanwhile, U-Net, the value-guided explanation model (SGEM), and the one-dimensional convolutional neural network (Conv1D) have the highest level of accuracy. Considering the current challenges in their applications, future research studies should be conducted to determine which algorithms are most effective in distinguishing food crops in different study areas.

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Author Contributions

Conceptualization: Ridwana, R., Kamal, M.; **methodology**: Ridwana, R., Arjasakusuma, S.; **investigation**: Ridwana, R.; **writing—original draft preparation**: Ridwana, R.: **writing—review and editing**: Ridwana, R., Kamal, M.; **visualization**: Ridwana, R. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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