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The Advances, Challenges, and Perspectives in the field of vegetation Classification with emphasis on Horticultural Species Using machine learning Methods

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ABSTRACT

As urbanization expands and food security becomes critical, remote sensing and machine learning (ML) have emerged as essential tools for large-scale vegetation mapping. This paper reviews the advances, challenges, and perspectives in vegetation classification, focusing on horticultural and agricultural crops. It explores how ML techniques handle complex datasets to create accurate predictive models for sustainable land management.

Research indicates that classification accuracy depends on image type, study area, and the algorithm used. Approximately 30% of reviewed studies prioritize features such as spectral indices, textures, and elevation data. Methodologically, supervised learning dominates at 94%—comprising hierarchical (46%), mathematical (24%), and layer-based (24%) models—while unsupervised methods account for only 6%. Regarding focus, 31% of studies target horticultural products, 27% agricultural crops, and 42% other vegetation types.

These findings underscore the necessity of integrating diverse satellite data, features, and ML methods for scalable and precise classification. The study emphasizes that the future of precision agriculture lies in interdisciplinary collaboration between agricultural sciences, data mining, and remote sensing. By providing a comprehensive review with temporal and graphical analyses, this article establishes a new classification framework for the field. It serves as a vital resource for researchers and policymakers aiming to optimize resource utilization and address global food security and climate crises.

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1. Introduction

Horticultural crops are one of the most essential types of agricultural production in the world (Kozhoridze, Orlovsky et al. 2018). The horticultural industry is also a crucial component of the agricultural industry's structure, which creates higher competitive advantages. There are various types of horticultural plants, which are divided into different groups based on their characteristics and uses, including citrus fruits, seeds, pits, small seeds, dried fruits, and medicinal plants (Chen, Sarkar et al. 2021). The accurate identification and classification of horticultural species and crops are scientifically and operationally crucial, with numerous positive impacts as a fundamental process in agriculture and horticultural management (Yang, Huang et al. 2017) .The traditional method of obtaining agricultural land information primarily relies on numerous manual field surveys, which require a significant amount of human resources, thereby reducing economic efficiency, and the data update speed is slow. In this case, the development of remote sensing technology provides advanced and suitable technical tools to solve this problem, and it is widely used in orchard classification (Johansen, Phinn et al. 2009; Xu, Qi et al. 2018).

In general, remote sensing data obtained from multi-source sensors have different spatial, temporal, spectral, polarization, and wavelength resolutions. Therefore, selecting appropriate data is a critical step in performing successful orchard classification (Chen, Huang et al. 2017). The first category is spatial information; high-resolution imagery, such as QuickBird and WorldView imagery, certainly provides more accurate spatial information of the surface (Duarte, Silva et al.). The second category is spectral information, where the differences between spectral profiles are utilized to aid in classifying remotely sensed images into land cover classes. Higher discrimination ability results from the use of more spectral bands (Chen, Huang et al. 2017; Duarte, Silva et al. 2018). The third category is temporal information; accurate and timely information about the nature and extent of the land surface and its change over time is essential for the preparation of more accurate classification maps (Duarte, Teodoro et al. 2018). It is not easy to distinguish gardens from other vegetation types in garden mapping, although different spectral bands can help in vegetation classification (Peña, Liao et al. 2017). Orchard land cultivation has unique characteristics, and there are differences in texture characteristics between different types of orchards and other crops (Sarron, Malézieux et al. 2018). Most orchards have trees that are several years old, and their chronological information provides valuable taxonomic insights (Brinkhoff, Vardanega et al. 2019). Therefore, remote sensing images rich in spatial and temporal information are the first choice in the garden classification process.

In the past and to date, researchers have been interested in vegetation classification, employing various methods for this purpose. In the distant past, more studies were conducted in the field of comprehensive vegetation classification, and traditional methods and censuses were used for small areas. Daniel Lloyd studied vegetation indicators in this field and their use in 1990 (Lloyd, 1990). With the advancement of science and the use of satellite images, previously faced problems were quickly solved, allowing researchers to expand their study areas. C. Brown de Colstoun et al. (2003) employed a decision tree algorithm and a Landsat-7 image (de Colstoun, Story et al.). In general, vegetation classifications involve a variety of factors, including the use of specific indices, spectral data, texture types, different elevation data, various satellite images, and multiple classification methods. Andreas Hemp (2006) reviewed the Braun-Blanquet method and elevation data (Hemp, 2006) .Rahul J. Shrivastava et al. (2007) used the Landsat spectral index and imagery (ETM+) (Shrivastava & Gebelein, 2007). Renaud Mathieu et al. (2007) addressed object-based classification with IKONOS imagery (Mathieu, Aryal et al. 2007). Temporal changes have led to more detailed research in plant classification, and some researchers have been attracted to the classification of agricultural lands, including croplands and orchards. Manuel A. Aguilar et al. (2015) used decision trees in the field of orchard crops (Aguilar, Vallario et al. 2015). In 2017, Qian Song et al. investigated the application of the random forest (RF) algorithm and Geofen multi-temporal images in crop fields (Song et al., 2017). Arbab Mansoor Ahmad et al. (2020) utilized K-means, support vector machines (SVM), and artificial neural networks (ANN) algorithms in their work (Ahmad, Minallah et al.). To increase accuracy and reduce errors, ground data has also been used to control the work or to merge multiple satellite images, thereby completing the information and improving the resolution. Nhemaphuki et al. (2021) demonstrated that combining optical and radar data with the RF algorithm increased classification accuracy by approximately 97%, whereas using optical data alone yielded an accuracy of approximately 96% and radar data alone 69% (Nhemaphuki, Chetri et al.). Additionally, a 2020 study by Phiri et al. in tropical regions with high cloud cover demonstrated that combining multitemporal Sentinel-1 and Sentinel-2 data yields improved separation of cropland and horticulture (Phiri et al., Simwanda et al.). Zhiying Yao and colleagues also used the RF method in 2023, using Worldview-2, Landsat-8, and Sentinel-2 images and integrating their spatial and temporal features (Yao, Zhao et al. 2023).

Classification of horticultural species using artificial intelligence (AI) methods and satellite imagery offers a transformative approach to addressing the challenges of modern agriculture. Traditional methods, such as manual classification and simple spectral indices, are inefficient due to their high labor requirements and limited scalability. In contrast, the integration of remote sensing and AI techniques, including decision trees, random forests, and deep learning, has provided unprecedented opportunities for more accurate, scalable, and efficient classification of horticultural species. High-resolution spatial data, combined with multispectral and temporal data from sensors such as

Sentinel-2 and Landsat-8, have enabled more advanced monitoring and increased classification accuracy. However, challenges remain, including distinguishing horticultural species from other vegetation types, managing diversity in horticultural species, and the limited interpretability of AI models. Additionally, machine learning-based methods require fine-tuning of parameters and are highly sensitive to the training data. Deep learning methods, such as convolutional neural networks (CNN) and multi-objective hybrid models, are capable of recognizing complex patterns but require extensive training data and high processing power. Additionally, the lack of a coherent classification for garden species and the complexity of distinguishing similar vegetation types are other existing challenges. This study presents a comprehensive review of existing methods, enabling researchers and users to select the most suitable method based on various applications, input data characteristics, computational constraints, and required accuracy. Given the fragmentation of previous studies and the lack of a comprehensive survey in the field of monitoring and classification of garden species, this study aims to provide an overview of the current status of this field by collecting and analyzing multi-source data, applying machine learning methods, and examining existing challenges and requirements. The aim is that this survey can serve as a valuable platform for guiding future research and help researchers in choosing appropriate frameworks and directions for future studies.

The main features of this study are as follows:

- Provide a new and integrated classification of methods, data, and features used in the classification of vegetation types.
- Comparative analysis of past studies to create a comprehensive and timely view of the state of research.
- Provide practical guidance for researchers, decision makers, and agricultural planners in resource management and increasing classification accuracy.
- Provide a framework that can help improve food security and sustainable agricultural development.

2. Methods

In order to compile this review article, a collection of reputable scientific sources, including articles published in international journals and reputable conferences, was first collected. A total of 106 relevant articles were identified and reviewed. These articles were classified into three general categories based on the type of vegetation cover, including horticultural species, crops, and other vegetation. In addition, each article was analyzed and compared from three main perspectives: the type of data used (optical images, radar, and field data), the type of features (indices, spectra, textures, and elevation data), and the classification methods (supervised and unsupervised). The general framework of this review is presented in the form of a flowchart (Figure 1) that shows the process of collecting sources, thematic classification, and analytical axes. The basis of the discussion and analysis of this study is also based on tables, figures, and graphs extracted from these articles.

In order to classify vegetation cover and the extent of agricultural lands, including crops and gardens, one must first obtain the required data. In this context, one of the most important data sources required is satellite images, which include optical images and radar data. The next required data can be field data, which can be used as training and control data. After selecting and obtaining data, the data preprocessing stage is introduced. The use of remote sensing data requires preliminary corrections. By performing these corrections, it is guaranteed that the changes in various reflections caused by changes in ground conditions are correctly detected and the effect of external factors on them is eliminated (Kennedy, Townsend et al. 2009). In addition to common errors in images, some errors are specifically related to remote sensing images. Before entering the classification process, it is essential to eliminate these errors as much as possible. The physical principles of remote sensing often lead to these types of errors, which can be mitigated primarily through image preprocessing. They are often divided into four categories: radiometric, atmospheric, geometric, and elevation corrections (Cihlar 2000). The next step is the selection of classification methods, which includes selecting the training data and generating the model. Finally, the issue of accuracy assessment has been discussed, in which the results and outputs are examined, and the accuracy of the work is evaluated using different methods. Figure 2 shows a general schematic of the work process, which includes data collection, preprocessing, classifier selection, and results analysis.

The development of vegetation and agricultural area studies is of great importance because of their direct connection to food security. These studies have been continuously considered in the past due to the vital role of agriculture in food supply and economic development. Figure 3 illustrates some of the studies conducted in this field, which are categorized into three main areas: horticultural crops, crops, and other vegetation.

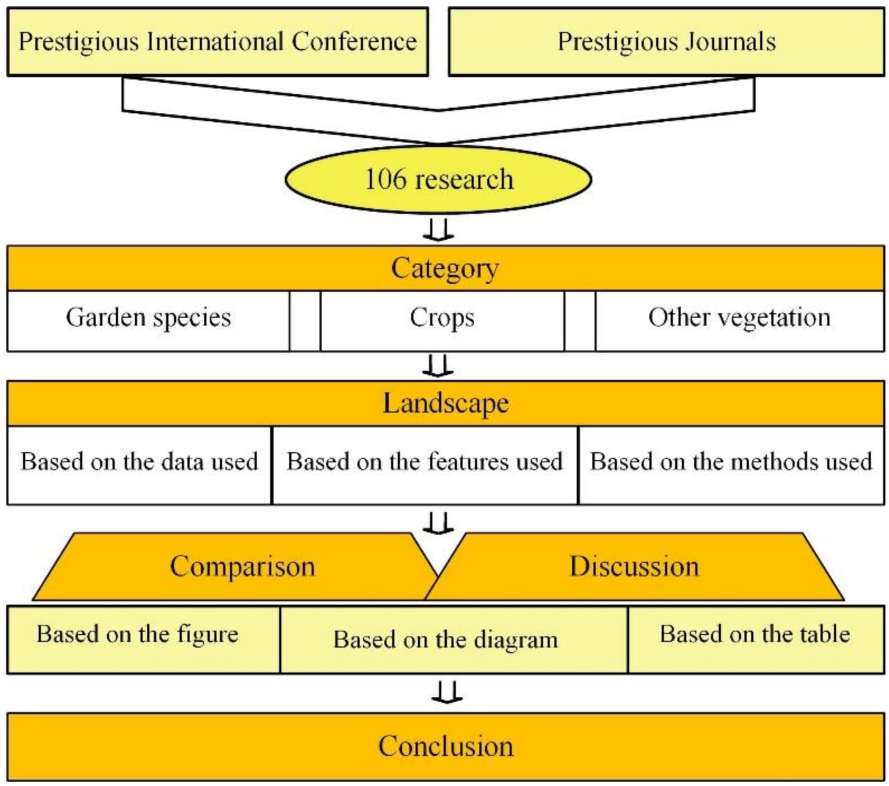


Figure 1: The process of conducting this review study.

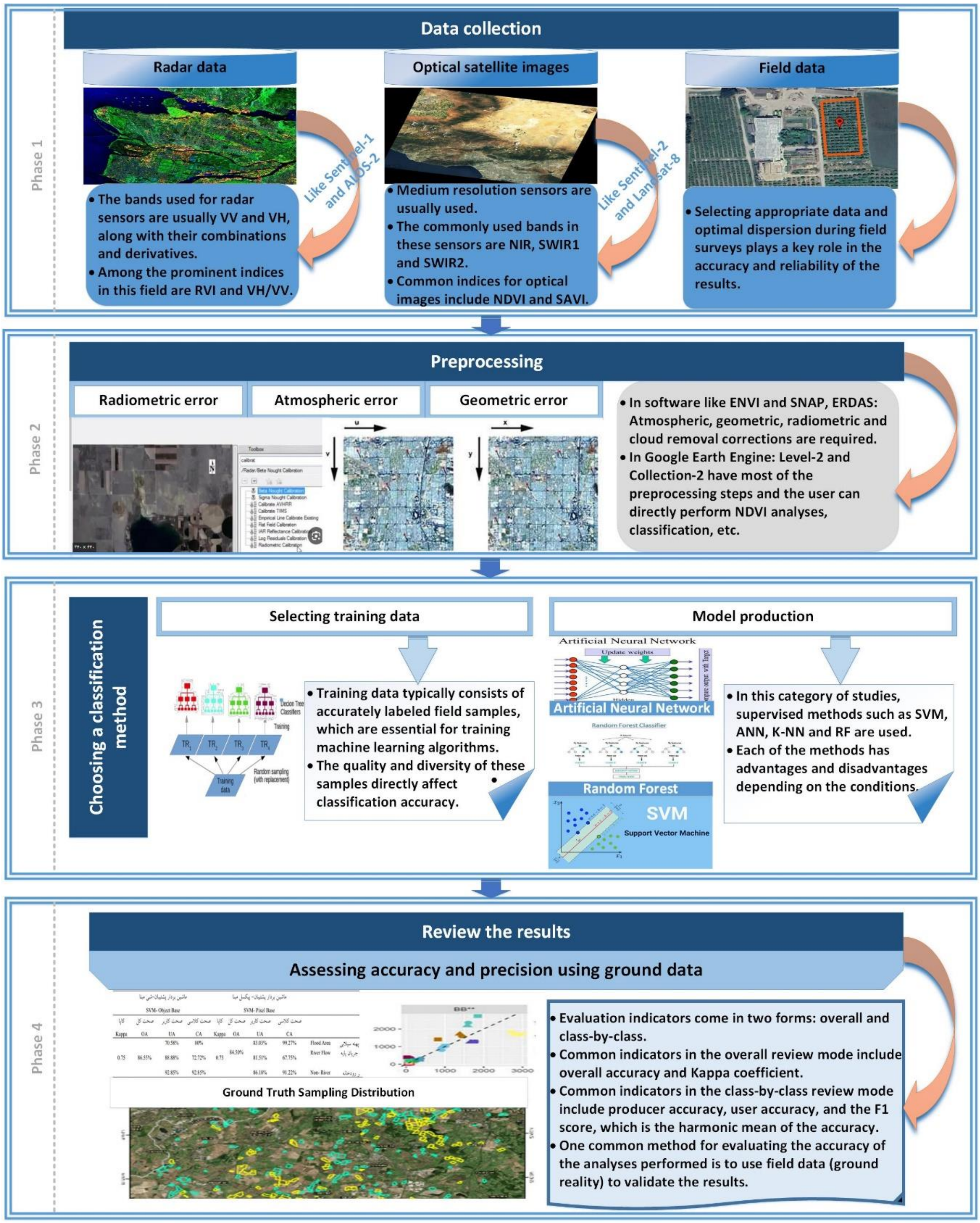


Figure 2: General flow of the classification process in the field of vegetation.

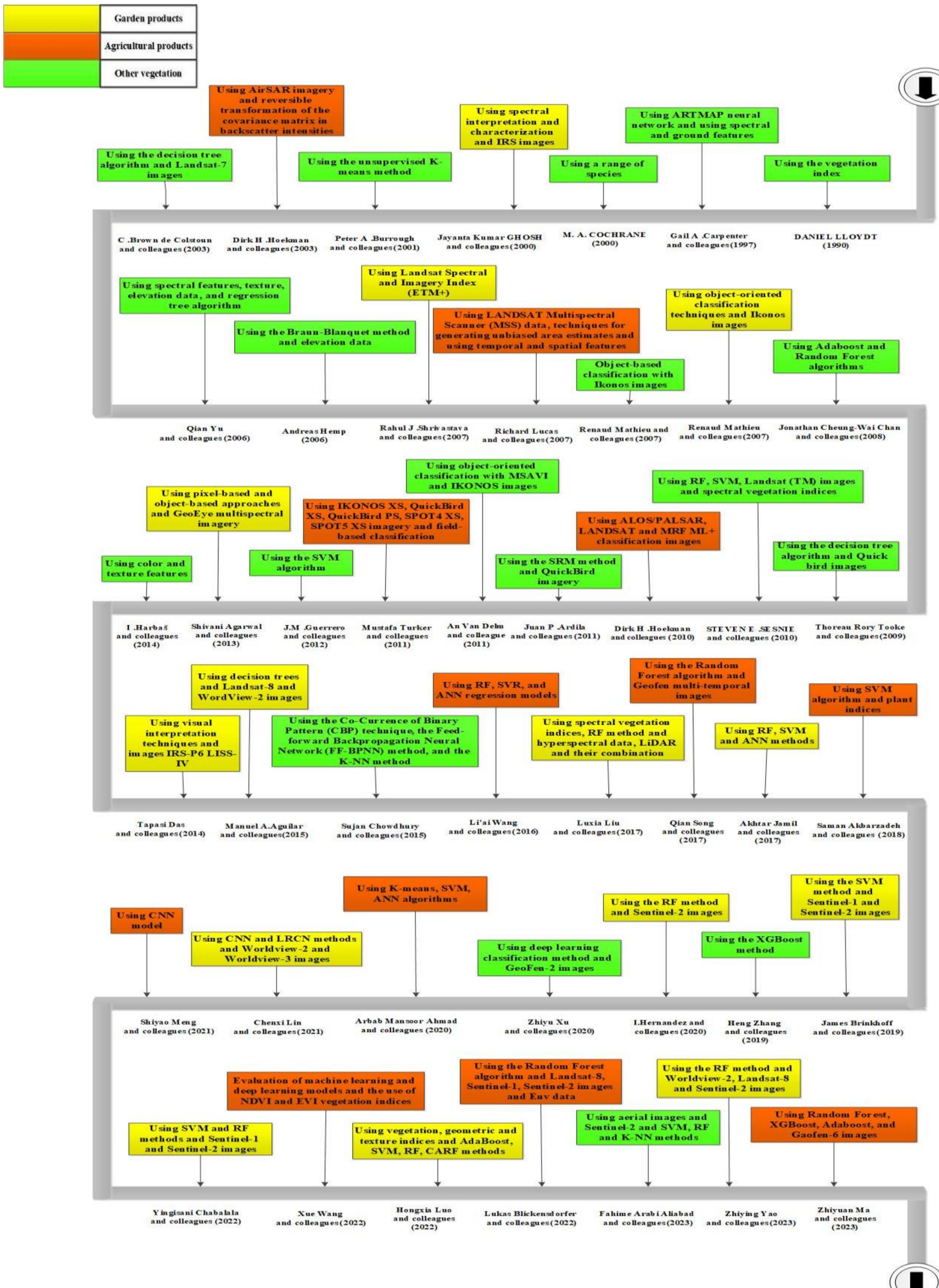


Figure 3: A review of previous studies, their data, and the methods employed. This review illustrates the progression of research and the focal points of prior studies related to the present topic. It also categorizes the studies into three main domains—orchard species, agricultural crops, and other vegetation cover—providing a comprehensive perspective on the existing approaches.

In the early studies of vegetation cover, due to a lack of facilities, researchers tried to classify vegetation cover using traditional methods and studies in limited areas. Then, with the use of satellite images and remote sensing techniques, a significant development occurred in this field. Features such as indices, spectra, color, texture, and various elevation data were used for classification. Figure 4 shows a graphical diagram to categorize previous research based on the type of features used in the vegetation classification process. This diagram organizes the studies conducted in three main areas, including the classification of garden species, crops, and other vegetation, based on the type of features extracted (index, spectrum, texture, and elevation data). This diagram facilitates a quick and structured understanding of the trend in the use of feature types across different classification areas. It also provides examples of studies related to each feature type, helping the reader to analyze trends and select appropriate features for future research.

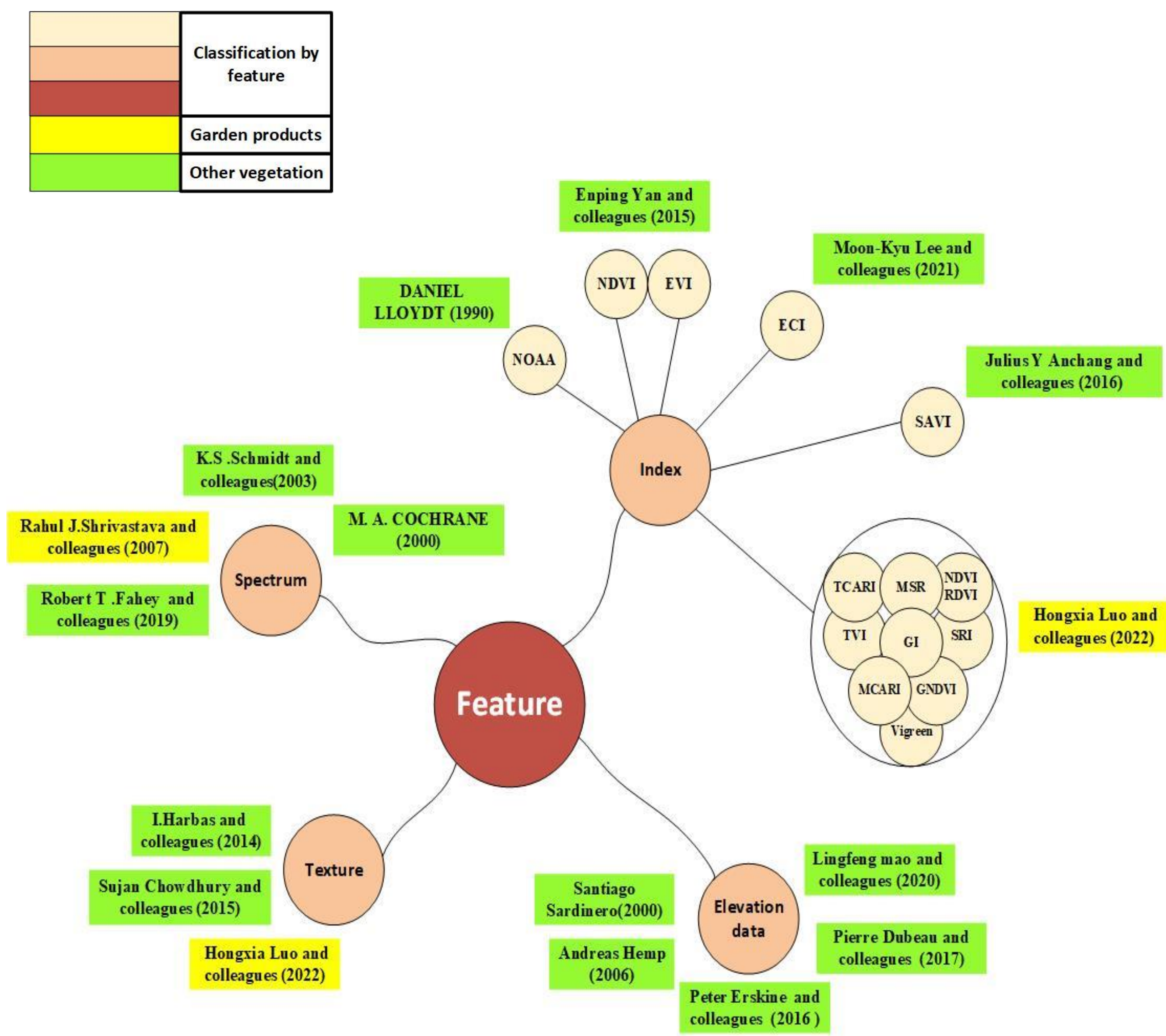


Figure 4: Chart showing the classification of selected studies based on the features used for classifying vegetation cover and orchard species. This chart illustrates the types of features that previous research has focused on and how the share of each feature group is distributed within those studies.

The simultaneous use of satellite images with different resolutions and characteristics can improve the analysis of phenology and evolution in studies related to vegetation monitoring. These changes enhance the accuracy of various analyses, enabling more precise classification and identification of hidden patterns in satellite data. By combining images, researchers and experts can gain a better understanding of different terrestrial environments and benefit from this information. In recent years, the integration of optical and radar satellite data has been considered a practical approach to improve the accuracy of vegetation classification, especially in agricultural areas. Optical images, such as those from Sentinel-2, are considered an important tool for vegetation analysis because they provide accurate spectral information on the physiological state of plants in the visible and infrared ranges. However, the high sensitivity of these images to atmospheric conditions, especially cloud cover, is one of their fundamental limitations (Zhang & Xie, 2012). In contrast, radar data, such as Sentinel-1, which operates in the microwave range, can image independently of light and atmospheric conditions, offering an advantage in areas with cloudy or high precipitation. These data are sensitive to the structural and moisture properties of the land surface and can provide complementary information to optical data (Amani, Kakooei et al. 2020). However, interpreting radar data requires more specialized knowledge due to the presence of speckle noise and the complex behavior of reflections. Figure 5 illustrates some of the implementations utilizing various satellite data.

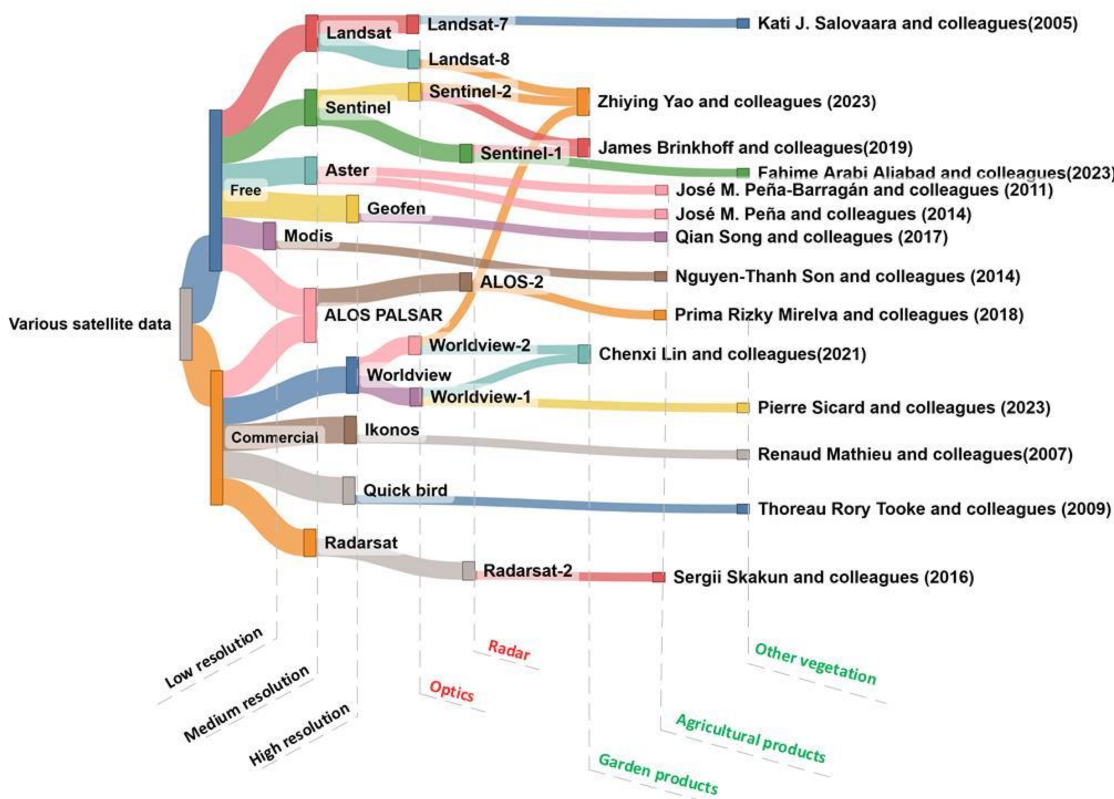


Figure 5: A chart categorizing studies conducted in the field of monitoring horticultural species, crops, and other vegetation based on the type of satellite data used. The data are divided into two groups: free and commercial, and separated by resolution (low, medium, high) and sensor type (optical, radar, or hybrid). This chart aims to provide an overview of trends and data preferences in past research.

In summary, it can be said that the most widespread type of classification in this field has been based on various classification methods. These methods are divided into two categories: supervised and unsupervised. Unsupervised methods, such as Isodata and K-means, have been employed. In supervised methods, they are categorized into three subsets: hierarchical models, mathematical models, and layered models. In hierarchical models, algorithms such as decision trees, like XGBoost, and crowd learning algorithms, such as AdaBoost and Random Forest (RF), have been employed. In mathematical models, SVM and k-nearest neighbors (K-NN) are among the methods used. In this field, layered models are categorized into two main types: deep learning and shallow learning. Deep learning methods include CNN and deep neural networks (DNN). Shallow learning methods such as ANN have also been used (Figure 6). These advances demonstrate the advancement of science in this field.

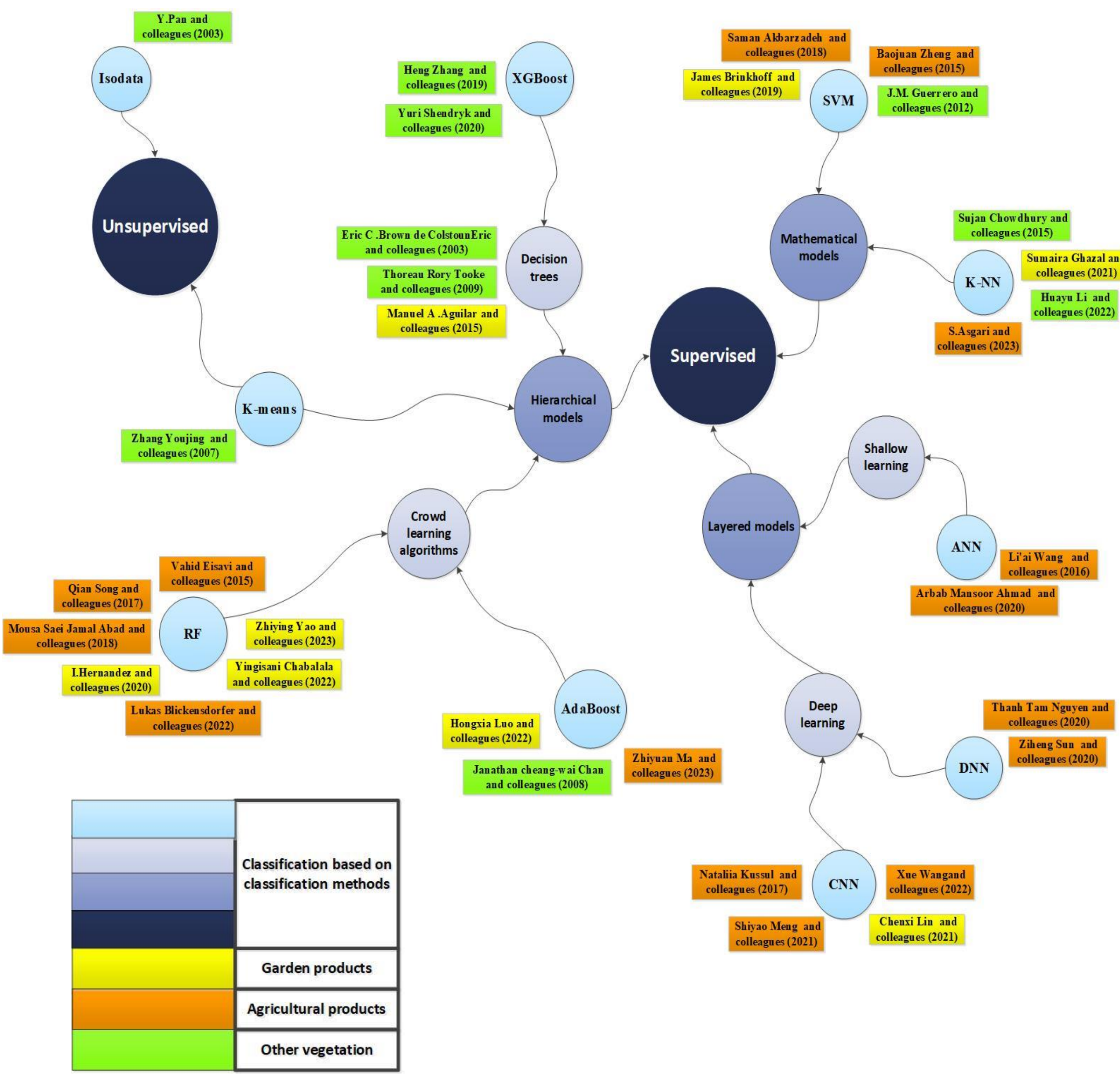


Figure 6: A chart categorizing research based on widely used classification methods in the field of monitoring horticultural species, crops, and other vegetation. This chart aims to analyze the trend of algorithm usage and provide a roadmap for future studies.

2.1. Assessment methods

The assessment and validation of the accuracy and precision of the classified maps are fundamental and crucial steps in the research process. This step enables us to evaluate the effectiveness of the proposed method. Without this assessment, it is not guaranteed that the classification has been carried out completely and accurately. The concept of accuracy means the degree of correspondence between the labels assigned to the image pixels in the classification process and the actual ground labels. There are various methods for assessing accuracy and precision, which are explained below.

It is essential to evaluate the results obtained from classification, as failing to do so means that the classification is incomplete. The word "accuracy" refers to the degree of correspondence between the labels assigned to image pixels in the classification process and the labels of the ground reality data. One of the most common measures suitable for evaluating accuracy is the ambiguity matrix (Mather & Tso, 2016). The ambiguity matrix is a square matrix of dimensions n × n, where n represents the number of image classes. This matrix illustrates the relationship between the two data sets (ground reality data and labels assigned during processing) (Tamimi, Ebadi et al, 2017) Several metrics can be extracted from the ambiguity matrix to assess accuracy, including user accuracy, producer accuracy, overall classification accuracy, kappa coefficient, quality measure, and F1 score (Figure 7) (Abas Kiani, 2013).

2.2. Comparison and analysis of different classification methods

In evaluating the performance of machine learning methods for classifying remote sensing images, various methods, including random forests, support vector machines, ANN, and maximum similarity classifiers, have been compared with each other. The results show that random forests outperform other methods and also require less time. In the comparison between SVM and ANN, SVM has better accuracy compared to ANN, particularly when using small training sample sizes, due to its reduced sensitivity to the training sample size. Additionally, the comparison between the KNN method with maximum similarity and the decision tree reveals that the KNN method exhibits similar or better performance than the maximum similarity and the decision tree, primarily due to its simplicity and efficiency. As a result, the KNN method is a suitable option for situations where there is a computational complexity constraint.

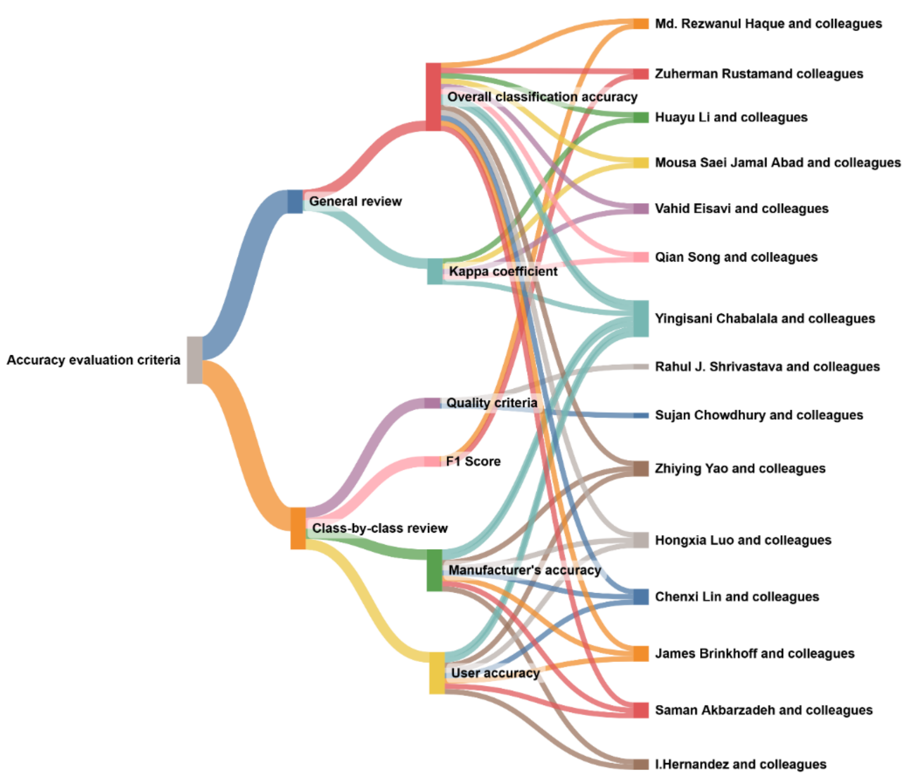


Figure 7: Graph of accuracy assessment criteria based on the ambiguity matrix at two levels of review: overall and class-by-class. This graph helps to understand the trend of using accuracy assessment criteria in vegetation classification studies (horticultural species, crops, and other vegetation).

From another perspective, ensemble learning methods can be compared to individual or non-ensemble learning methods. Ensemble learning techniques such as bagging, boosting, and random forests have higher overall accuracy compared to individual classification trees. In some studies, these methods have achieved similar accuracy to more sophisticated machine learning algorithms such as support vector machines. On the other hand, ensemble learning techniques, such as random forests and bagging, outperform non-ensemble learning techniques, such as SVM and neural networks, in terms of computational load, depending on the characteristics of the training data and the predictor variables used in classification.

Ensemble learning techniques can be useful in complex mapping scenarios because their iterative nature produces multiple classifiers that ensure a convergent approach to pixel labeling and significantly improve classification accuracy because the error of a single classifier is greater than the error of a collection of multiple classifiers. Classification trees suffer from overfitting to the data, which occurs instead of generalizing patterns in the data. In contrast, ensemble learning algorithms can generate a large number of trees for classification so that the learning algorithm can ensure generalization of patterns in the data. In general, ensemble learning techniques can outperform non-ensemble classifiers, especially in complex measurement spaces.

If we look at the subject from another perspective, we can compare ensemble learning algorithms with each other. For example, bagging algorithms and random forests are similar in terms of the number of trees used in the algorithm. In both algorithms, the bootstrap sampling technique is used to generate a set of trees. In these algorithms, the land cover class for each pixel of the image is determined by the set of trees based on the majority voting rule. However, there is a difference in the selection of variables used in bagging and random forests. For example, the random forests algorithm randomly selects potential split variables at each node, while the bagging algorithm uses all potential split variables. Therefore, an RF algorithm in which all split variables are used can be considered a bagging algorithm. Also, the random sampling of calibration data and feature variables in bagging and random forests algorithms is different from the conceptually different technique used in boosting. Boosting algorithm iteratively works on the classification of data by giving more weight to pixels that were misclassified in the previous iteration. The concept that boosting algorithm uses is different from bagging and random forests. Therefore, boosting algorithm works slightly differently, but it is on par with bagging and random forests in terms of the number of trees required to achieve a fixed accuracy value. Also, boosting algorithm is more robust than bagging and random forests to noisy and outlier data and also performs better on the size of calibration data. This suggests that in projects such as large-area mapping, where the cost and time to collect a large number of calibration samples of limited quality are limited, the boosting algorithm will be better than bagging and random forests. The AdaBoost method is also sensitive to noisy and outlier data, but it performs better against the overfitting problem. In this algorithm, it is not necessary to know the error bounds based on weak classifiers, and it also does not need to know the number of classifiers. In short, due to the conceptual and technical differences between crowd learning algorithms, each algorithm may be the best option for different cases. Therefore, to choose the right algorithm, one should choose the appropriate algorithm according to the problem at hand, the specific needs of the project, and the constraints available.

In a comparison between the two classification algorithms, random forests and AdaBoost, both algorithms have similar classification results, however, random forests have improvements in performance and are also trained more stably and faster. In another comparison between the bagging tree, random forests, AdaBoost tree and AdaBoost random tree methods, it can be concluded that the AdaBoost random tree and RF methods achieve similar accuracy to the results of the AdaBoost tree and bagging tree methods, however, they are associated with a greater reduction in computational load. Also, the AdaBoost tree and AdaBoost random tree methods have better classification results than the bagging tree and RF methods. Regarding the comparison of the performance of machine learning methods, it is observed that in some cases, when two identical methods are compared in two different studies, they reach contradictory results. However, according to the comparisons made, it can be concluded that methods based on the combination of classifiers, or in other words, ensemble learning methods, are introduced as effective and suitable methods to improve classification performance. Also, among the non-ensemble methods, the support vector machine method is a suitable and common method in remote sensing.

Given the wide range of applications of machine learning methods for extracting optimal features from data, it is observed that combining classifiers is significantly effective in improving the efficiency and quality of feature extraction. These methods, by cooperating and coordinating between different classification models, bring the ability to improve performance and extract better features. In addition, research results show that using simultaneous feature extraction methods and combining classifiers can significantly increase the accuracy and performance of classification compared to using either of these methods alone. In fact, combining these two approaches in a common process can increase the interaction and synergy of information in the data and, as a result, significantly improve the recognition of important patterns and features. Therefore, these types of classifiers can be introduced as efficient and effective methods in extracting optimal features from data and thus improving classification performance and accuracy. Considering the advantages of combining these two approaches, these methods are introduced as very valuable and efficient basic tools in various fields.

Given that machine learning and deep learning methods have attracted the attention of researchers in the discussion of product classification,this section examines and compares the advantages and disadvantages of a number of algorithms used in the classification of agricultural products (Table 1).

Table 1: Advantages and disadvantages of classification methods.

Machine learning algorithms	Benefits	Disadvantages
Decision trees	• Feature selection (Wang & Li 2008) • Simple and convenient interpretation (Wang and Li 2008) • Easy implementation (Chutia, Bhattacharyya et al. 2016)	o Possibility of overfitting (Alexander, Tansey et al. 2011) o Pruning trees due to noise and outliers in training samples (Alexander, Tansey et al. 2011) o Instability (Alexander, Tansey et al. 2011)
Random Forests (RF)	• Low sensitivity to noisy data (Chutia, Bhattacharyya et al. 2016) • Insensitive to training data variability (Chutia, Bhattacharyya et al. 2016) • Insensitive to overfitting (Chutia, Bhattacharyya et al. 2016) • Fast training (Chutia, Bhattacharyya et al. 2016) • Very simple implementation (Chutia, Bhattacharyya et al. 2016) • Suitable for big data classification (Ghimire, Rogan et al. 2012) • Having repeatability leads to better results (Ghimire, Rogan et al. 2012)	o Sensitivity to sampling design (Chutia, Bhattacharyya et al. 2016) o Classification performance is affected by the correlation between two trees (Chutia, Bhattacharyya et al. 2016)
Boosting	• Insensitive to training data variability (McIver and Friedl 2002, Lawrence, Bunn et al. 2004) • Good performance on limited training data size (Gislason, Benediktsson et al. 2006) • More robust to data noise (DeFries and Chan 2000) • Ability to reduce classification errors, due to its repetitive nature (McIver and Friedl 2002, Lawrence, Bunn et al. 2004)	o Has a long computational process due to its iterative nature (McIver and Friedl 2002, Lawrence, Bunn et al. 2004)
adabust	• Fast, simple and flexible (Galar, Fernandez et al. 2011) • Insensitive to overfitting (Galar, Fernandez et al. 2011) • Weak requirement to know the error bounds based on classifiers (Galar, Fernandez et al. 2011) • Availability of the number of boosting rounds in the training process (Galar, Fernandez et al. 2011)	o Fails to handle weak learners (Galar, Fernandez et al. 2011) o Too complex on noisy and outlier data (Galar, Fernandez et al. 2011) o Poor at error prediction (Galar, Fernandez et al. 2011)
K Nearest Neighbor (KNN)	• Simple, efficient, easy to implement and non-parametric (Agrawal and Nagwanshi 2016) • Low error rate in the training process (Agrawal and Nagwanshi 2016)	o Longer time required for classification (Suthaharan 2016) o Difficulty in obtaining the optimal value (Suthaharan 2016)
Support Vector Machine (SVM)	• High classification accuracy (Mountrakis, Im et al. 2011) • Suitable for big data use cases (Mountrakis, Im et al. 2011) • Good generalization capability even with few training samples (Mountrakis, Im et al. 2011) • No need to know the statistical distribution of the data (non-parametric) (Mountrakis, Im et al. 2011) • Easy to control the complexity of the decision rule and error frequency (Mountrakis, Im et al. 2011) • No overfitting (Mountrakis, Im et al. 2011)	o Difficult interpretation for solving parametric model (Mountrakis, Im et al. 2011) o Sensitive to noise (Mountrakis, Im et al. 2011) o Complex method for classification (Suthaharan 2016) o Sensitive to parameter tuning (Mountrakis, Im et al. 2011) o Increased computation time by converting to higher dimensional space (Suthaharan 2016)
Artificial Neural Network (ANN)	• Fast testing process (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) • Provides good results in complex cases (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) • Can be trained with limited samples (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) • No need to know the statistical distribution of the data (non-parametric (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015)	o Need for user-defined initial parameters (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) o High sensitivity to parameter design (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) o Need for noise-free training data (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015) o Slow training process (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015)

Supervised learning algorithms pose challenges when dealing with large and complex data. The data volume is unmanageable, the number of classes is large, and high processing speed is required (Suthaharan 2016). However, ensemble learning algorithms can play a significant role in complex scenarios. These algorithms iteratively generate multiple classifiers, which helps improve classification accuracy, since the error of a single classifier is greater than the error of a collection of multiple classifiers (Ghimire, Rogan et al. 2012). The boosting method is more stable and robust than decision trees to calibration data noise and provides higher accuracy (DeFries and Chan 2000, Gislason, Benediktsson et al. 2006). In contrast, the AdaBoost method is more sensitive to noisy and outlier data, but it performs better than many learning algorithms against the overfitting problem. Unlike boosting, this method does not require knowledge of error bounds based on weak classifiers for better performance (Galar, Fernandez et al. 2011). Random forests are very easy to implement and only require adjusting the number of random subsets of trees or a separate test set for the input features. The method does not have the overfitting limitation. However, the correlation between trees and the strength of an individual tree in the forest can have a large impact on the classification performance of the entire RF (Chutia, Bhattacharyya et al. 2016). One limitation of the decision tree method is that it may overfit the data (Alexander, Tansey et al. 2011). Unlike neural networks, decision trees have interpretable rules and fast computations, and also have feature selection capabilities (Wang and Li 2008). SVM have higher power for experimental data than other classical methods and can effectively deal with problems such as overfitting and local optimum problems that are commonly observed in neural network learning. One of the weaknesses of SVM is that their parameter tuning is not a specific rule and is done experimentally and by trial and error in many cases. Also, the performance and accuracy of the classifier of SVM are affected by their parameters and the subset of input features. These machines do not assume a specific statistical distribution for the data, and since remote sensing data do not have a specific statistical distribution, this is considered an important feature. SVM rely on only a small number of points to define the separating hyperplane, so they are not as sensitive as training samples and can achieve better accuracy than ANN using a small number of training samples (Mountrakis, Im et al. 2011). Neural networks have been widely used by many researchers in the field of classification. One of the disadvantages of these networks is that the amount of training data required depends significantly on the complexity of the problem and the training process with iterations is very time-consuming and expensive (Amin Ghasemi Esfahlan 2011, Maryam Salehi Farahani 2013, Roozbeh Khanblouki 2015).

In general, according to the studies conducted, results in accordance with Figure 8 have been obtained from comparing the output accuracy of some methods.

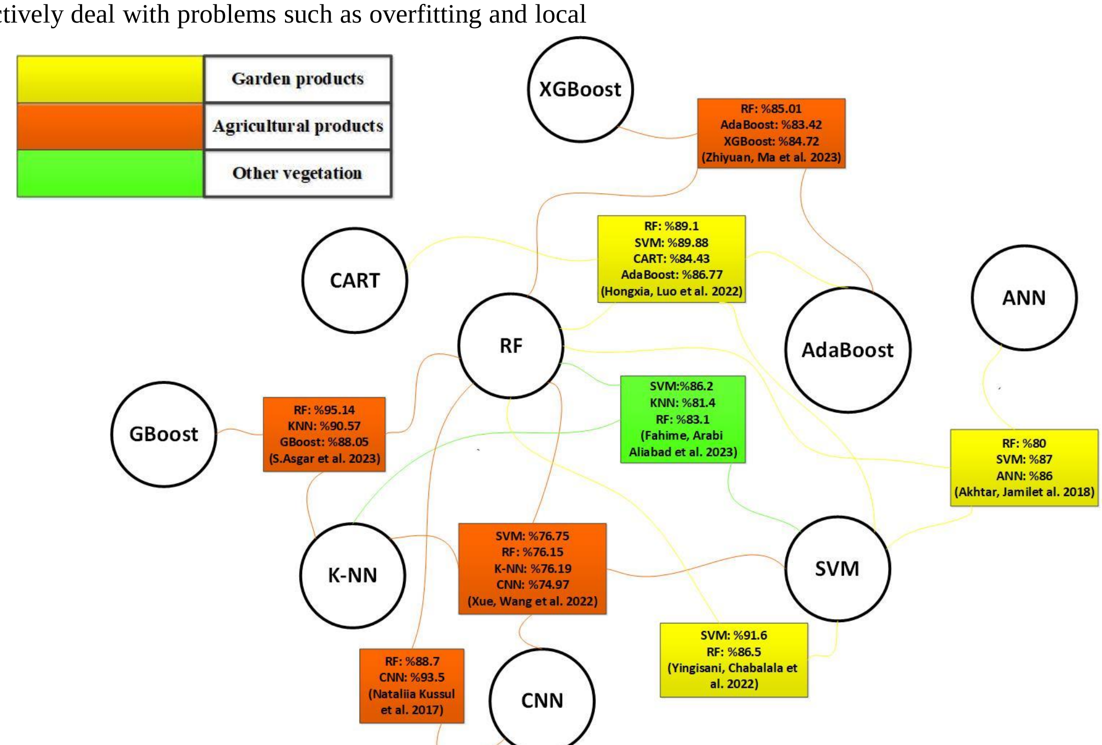


Figure 8: Comparison of the output accuracy of some classification methods for future researchers to exploit and select more appropriate methods. This chart allows for the analysis of the relative efficiency of the methods and helps to identify optimal methods in the field of vegetation classification (horticultural species, crops and other vegetation).

3. Discussion

The rapid developments in agriculture highlight the growing importance of precision agriculture for global food security. Precision agriculture, as a new approach, involves the use of advanced technologies and accurate data to optimize agricultural processes. This approach has a significant impact on increasing production, improving product quality, and reducing waste in the field of agriculture. In particular, given the increasing global population and the growing need for food, precision agriculture can play a key role in strengthening food security. Therefore, as the population grows in the coming years, food production must multiply to provide food globally. This goal requires the use of new methods and higher accuracy in managing agricultural resources. Therefore, new methods with higher accuracy in the field of vegetation classification, including cropland, have been considered. The use of satellite imagery is one such method that allows farmers and researchers to more accurately monitor the state of vegetation and horticultural crops. In addition, precision agriculture not only helps increase productivity but can also reduce negative impacts on the environment. Using accurate data, farmers can optimize water and fertilizer use and prevent pollution caused by the excessive use of these resources. As a result, the development and implementation of new technologies in agriculture, such as the use of satellite imagery for vegetation classification and horticultural management, will not only help increase production but also preserve natural resources and promote global food security. These approaches must be accompanied by international cooperation and investment in research and development to effectively respond to future challenges in the field of food supply.

3.1. Advances in classification techniques

- Early studies were conducted with field methods and on a limited scale, but with technological advances, spectral, texture, index and elevation data analyses have replaced them.
- The use of radar and optical satellite images (such as Sentinel-1 and 2) in combination has significantly increased the accuracy of perennial crop classification (Brinkhoff, Vardanega et al. 2019).
- The integration of machine learning algorithms with remote sensing data has improved vegetation analyses and more accurate species identification.
- The development of software such as QPhenoMetrics and QGIS plugins has facilitated the process of processing and accurate vegetation mapping (Duarte, Silva et al. 2018).
- In addition to improving agricultural productivity, these advances have provided an infrastructure for sustainable management of natural resources and responding to food security challenges.

3.2. Challenges in data quality and algorithm complexity

- ➢ Data quality
  - Negative impact of atmospheric conditions (clouds, rain, dust) on the resolution of satellite images
  - Reduced classification accuracy due to clouds and environmental noise
  - Vegetation instability due to seasonal changes and environmental conditions
  - Errors resulting from data collection and processing processes (e.g., field errors and coordinate system transformation)
- ➢ Algorithm complexity
  - Requirement of high computational resources and technical expertise to use deep and ensemble learning algorithms (Chan and Paelinckx 2008).
  - Requirement of large volumes of training data to train models
  - Difficulty in interpreting and validating complex models
  - Presence of mixed pixels in agricultural landscapes, which reduces classification accuracy (Hoekman and Vissers 2003).
- ➢ Solutions
  - Use advanced algorithms for cloud removal (such as maximum pixel value combination)
  - Develop more robust algorithms for separating mixed pixels
  - Use artificial intelligence and machine learning to improve classification accuracy and extract more accurate information

3.3. Research prospects and future applications

- ➢ Future research directions

Looking to the future, the integration of multimodal data sources, including UAV imagery and ground sensors, holds promise to improve classification accuracy and provide a more comprehensive understanding of horticultural species (Sarron, Malézieux et al. 2018). This hybrid approach can help researchers and farmers obtain more accurate information about crop and vegetation status using diverse data. One promising area of future research is the use of transfer learning. In this method, pre-trained models are adapted for specific tasks, which can accelerate the development of accurate classification models (Wang and Li 2008). This technique can be very effective, especially in situations where training data is limited, allowing researchers to use existing knowledge to solve new problems. Real-time monitoring of agricultural areas using artificial intelligence and remote sensing technologies can revolutionize land management practices. This approach allows farmers and natural resource managers to make timely decisions and improve crop management and resource use (Peña, Liao et al. 2017). Multimodal models also play an important role in this field. By combining different types of data, such as images, text, and sensor information, these models can provide a deeper understanding of the state of vegetation and agricultural products. For example, merging image data with textual information about weather conditions or soil type can help to better identify plant needs.

- Future-oriented applications and tools

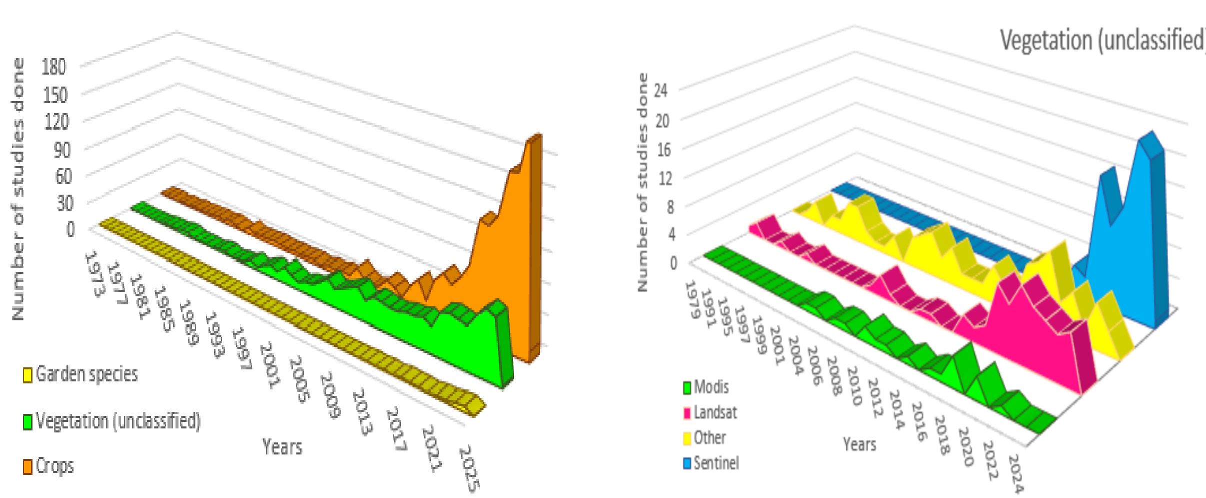
The development of advanced software tools that are capable of processing multimodal data can help facilitate analyses. Tools such as QGIS and ArcGIS, with their advanced data integration capabilities, allow for more detailed analysis. These tools can collect information from different sources and present them in a unified environment for analysis. Finally, the prospects for future research in the field of vegetation classification and horticultural products indicate the high potential of new technologies. By integrating multimodal data sources and using advanced machine learning algorithms, researchers will be able to increase classification accuracy and provide valuable information about the state of agriculture. These developments will not only help increase productivity but also enable sustainable management of natural resources.

3.4. Implications for sustainable agriculture and food security

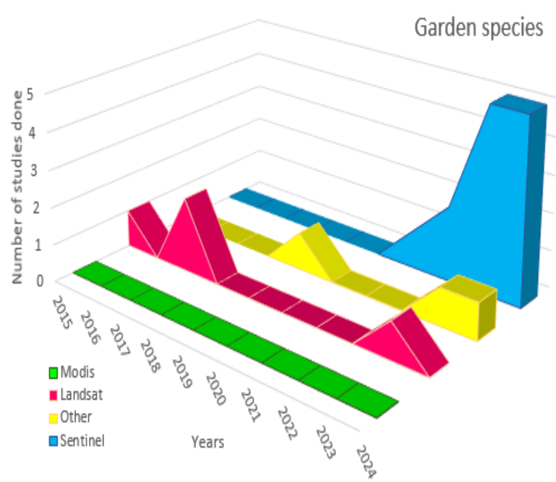
- Rapid and accurate classification of large-scale satellite images is an effective tool for monitoring changes in vegetation cover, biodiversity, and optimal allocation of water resources.
- The use of machine learning algorithms and remote sensing data allows farmers to plan planting, harvesting, and resource management more accurately.
- Smart agricultural technologies help reduce water, fertilizer, and chemical pesticide use and reduce the environmental impacts of agricultural activities (Hossein Farahani 2017).
- Combining diverse data and advanced algorithms increases the accuracy of analyses and paves the way for more efficient use of natural resources.
- In the face of global population growth, the findings of this study show that the development of agricultural technology-based agriculture plays a key role in sustainable food supply (Adineh 2023).
- The use of new approaches not only improves agricultural performance, but also helps increase social welfare and economic sustainability.

3.5. Analysis of Research Trends and Methodologies

In this study, Scopus website was used for further analysis and statistics regarding the research conducted in the field of study in question, the results of which can be seen in Figure 9. In part a, it shows the trend of studies in three types of classification with garden species, crops and vegetation without classification, which indicates that the first study was conducted in 1973 and continues to now. As can be seen in the figure, the number of studies in the field of crops has been more than the other two categories, and in recent years, its number and difference with other studies have been significant. The number of this type of studies reached its highest level in 2024, namely 214 cases. Classification in the field of garden species has the lowest number of studies, as a total of 19 cases have been mentioned in the past years. It should be noted that this field has been of interest to researchers since 2013. In sections b, c, and d, the three previous classification modes are examined and compared in the field of using different satellite data, including Sentinel, Landsat, MODIS, and other satellite images. The results of the studies show that most studies have been conducted with Sentinel images. MODIS images have also been seen in the classification of vegetation cover without classification more than the other two modes, so it can be said that there were no cases in the case of garden species. In section e, the percentage of studies conducted in different scientific fields is compared with each other. Section f also displays the keywords used for graphical diagrams on the Scopus site.



a b



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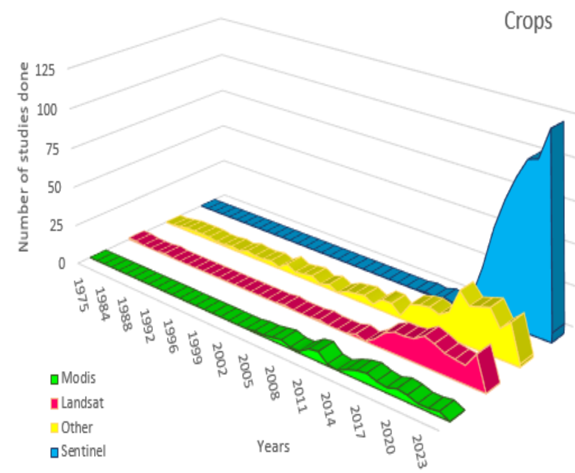

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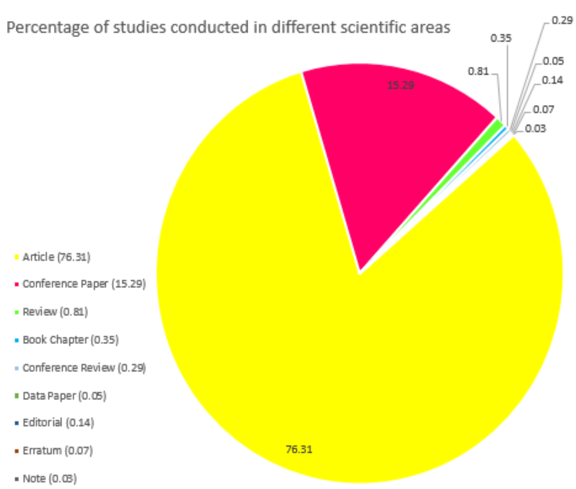

e

<table>
<tr><th colspan="3">KEY WORD:</th></tr>
<tr><td rowspan="3">a</td><td colspan="2">("Vegetation classification")</td></tr>
<tr><td colspan="2">("Crop classification" OR "Crop mapping" OR " Agriculture classification")</td></tr>
<tr><td colspan="2">("Garden classification" OR "Orchard classification " OR "Orchard mapping" OR "Tree crop classification" OR "Fruit tree monitoring")</td></tr>
<tr><td>b</td><td>("Vegetation classification") AND</td><td rowspan="3">1-("Sentinel imagery" OR "Sentinel-2" OR "Sentinel-1" OR "Sentinel satellite")
2-("Landsat imagery" OR "Landsat-8" OR "Landsat time-series")
3-("MODIS imagery" OR "MODIS NDVI" OR "MODIS EVI" OR "MODIS time-series")
4-("Satellite imagery" OR "Remote sensing") AND ("WorldView" OR "GeoEye" OR "Pleiades" OR "SPOT" OR "SAR"(</td></tr>
<tr><td>c</td><td>("Crop classification" OR "Crop mapping" OR " Agriculture classification") AND</td></tr>
<tr><td>d</td><td>("Garden classification" OR "Orchard classification " OR "Orchard mapping" OR "Tree crop classification" OR "Fruit tree monitoring") AND</td></tr>
</table>

f

Figure 9: Comparison chart, a) Three types of classification, b) Unclassified vegetation cover, c) Crops, d) Garden species, e) Percentage of studies in different scientific fields, f) used Keywords.

5. Conclusion

This study provides a comprehensive and systematic review of the progress of vegetation classification by extensively examining remote sensing data and methods over a specified time period. The increasing developments in the world of agriculture indicate the increasing importance of precision agriculture in ensuring global food security. Precision agriculture has a significant impact on increasing production, improving product quality, and reducing waste. This approach strengthens the assurance of global food security and makes it necessary to provide new methods with higher accuracy in the field of classifying vegetation cover, including cropland. In recent decades, researchers have been classifying vegetation cover due to the high importance of nutrition in human life. Initially, traditional methods and censuses were used in small areas, but with the advancement of science, methods based on features such as index, spectrum, texture type, elevation data, and various satellite images have been used. The science of remote sensing and the use of various satellite images have created a significant development in this field. For greater accuracy and error reduction, ground data has been used as a controller and multiple satellite images have been combined. Each classification method has its advantages and limitations, and no one method is perfect for all applications. However, for a specific purpose and the same area, different methods can be compared and the most suitable method can be selected. Recent studies have shown that the use of high-resolution satellite images and deep learning algorithms can improve classification accuracy. Also, the combination of object-based analysis and RF algorithms in mapping agricultural crops during the growing season has yielded positive results. The use of high-resolution digital maps has also been effective in extracting tree species and classifying land use. In addition, the use of multi-source data and combining them with advanced artificial intelligence techniques has improved the accuracy and precision of classification, for example, the use of Sentinel-2 and Landsat-8 data for long-term monitoring of citrus orchards has yielded successful results. In general, it can be stated that 30 percent of the studies conducted in vegetation classification were based on features such as indices, texture, and elevation data, and the rest were used in the classification using various classification methods. Also, for classification based on the use of various classification methods, it can be stated that 6 percent of the studies conducted in this research belonged to unsupervised methods and the remaining 94 percent belonged to supervised methods, of which 46 percent were for hierarchical models, 24 percent for mathematical models, and the remaining 24 percent for layered models. From another perspective, it can be stated that in the studies conducted in the field of vegetation, 31% of the studies were related to horticultural crops, 27% were related to agricultural crops, and another 42% were for other vegetation. Ultimately, this research can help develop appropriate and reliable infrastructure for agricultural and horticultural lands and improve food security in cities. By integrating diverse data sources and advancing algorithmic techniques, we can achieve more accurate and actionable insights that support sustainable agriculture and increased food security. For future research, it is suggested that more data be used to train models to achieve greater accuracy. Deep learning techniques should also be investigated to provide greater capabilities in identifying complex patterns. Interdisciplinary collaboration between researchers in the fields of agricultural sciences and data mining is also suggested to be strengthened to achieve better results.

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