Review of Satellite Remote Sensing-Based Crop Cover Classification Studies over Europe

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Abstract

Crop maps play an important role in a variety of applications, from calculating crop areas and forecasting food production quantities to the analysis of agri-environmental interactions, highlighting the necessity of timely and accurate information on agricultural land use. The availability of remote sensing data has permitted numerous crop classification studies, which have investigated a variety of methods to improve classification performance, such as the selection of remote sensing sources, classification algorithms, and preprocessing methods. This paper compares these approaches with respect to classification accuracy in a European context. The study also investigates aspects such as classification level, study area division, and class granularity. The review shows that optical products provide more information for crop identification than radar products, however, combining optical data with radar backscatter increases accuracy. Classification accuracy benefits from specific features such as red-edge and spectral indices for optical products and Haralik textures for radar. When compared to traditional machine learning and distance-based classification approaches, deep learning algorithms are shown to outperform traditional machine learning methods. Nevertheless, random forest's comparative accuracy at relatively low computational cost makes it a viable alternative for large-scale applications. Finally, preprocessing methods and data on topography, climate, and crop growth patterns appear to improve classification accuracy.

Keywords: Crop Mapping, Classification Accuracy, Supervised Classification, Meta-Analysis

1. Introduction

Timely, reliable, and comprehensive information on agricultural land use is critical for promoting sustainable land management practices and assessing the ecological, economic, and societal effects of climate change on agriculture (Asam et al., 2022). Many agricultural applications, such as estimating crop areas, forecasting yields, assessing crop conditions, and determining land use intensity, heavily rely on the utilization of crop maps. (Kussul et al., 2018). Satellite remote sensing is a pivotal tool for creating crop maps, crop health evaluation, and yield prediction, providing essential insights into agricultural land use and production (Dhumal et al., 2013). Currently, satellite data with global coverage is readily accessible to the public at no cost, featuring enhanced temporal and spatial resolutions, alongside growing computational capabilities (Blickensdörfer et al., 2022). The availability of satellite remote sensing (RS) data, in the following simply called "remote sensing data", has enabled numerous crop classification studies, revealing a wide range of possible methodologies driven by technical improvements. These studies employ different strategies that vary regarding the selection of RS sources, classification algorithms, and preprocessing techniques, to continuously improve classification performance.

This study aims to review existing literature and provide a systematic comparison of how different RS sources, classification algorithms, and preprocessing techniques compare in terms of classification performance. The review is restricted to studies providing crop classifications for Europe. We identify how methods and RS sources have evolved over the last two decades. Furthermore, this study emphasizes other elements that influence classification accuracy, such as the number of classes, study area definition, and classification granularity. Wherever possible, comparisons are made to determine their respective contributions to categorization accuracy.

Existing literature already provides reviews of crop classification studies. For example, Fan et al. (2021) conducted a comprehensive review of research progress in farmland vegetation identification and classification using remote sensing over the last 25 years. They summarized several classification methods, such as using vegetation indices, spectral bands, multi-source data fusion, machine learning, and drone remote sensing. Teixeira et al. (2023) conducted a comprehensive study of deep learning (DL) algorithms for crop classification based on remote sensing data. Emphasizing the importance of different fusion techniques, Orynbaikyzy et al. (2019) provide a comprehensive review of studies concentrating on crop type categorization using a fusion of optical and radar data. Their review looks into alternative fusion methodologies, categorization strategies, and the feasibility of mapping specific crop types. In their study, Almalki et al. (2022) investigate the characteristics of dry and semi-arid vegetation cover and their link to remote sensing and they review the methods for mapping and monitoring changes in vegetation cover using RS data in arid and semi-arid areas. Pluto-Kossakowska, (2021) conducted a review of multitemporal classification approaches for automatically identifying agricultural and arable land using optical satellite imagery. Emphasizing the advancements in RS platforms and machine learning, Potgieter et al. (2021) evaluate the current state of digital technology in broad-acre cropping systems worldwide. In their thorough literature review study, Alami Machichi et al. (2023) trace the historical evolution of crop mapping using remote sensing methods and assess recent advances in the topic, with a special emphasis on machine and deep learning models. Our study contributes to the existing literature in terms of thoroughly examining multiple aspects that may be encountered during remote sensing-based crop classification including data sources, preprocessing, classification algorithms, and postprocessing techniques without a special focus on certain algorithms or data sources. Our aim of providing a systematic comparison of different methods in terms of crop classification performance is useful as a reference for future crop categorization research in terms of methodology and data selection. This review also provides a benchmark in terms of what has been achieved in classification performance as well as regional and temporal coverage.

In the following, we first present the methodology of the review process. Then we summarize the reviewed research in terms of regional coverage, ground truth data type, data availability, and the number of crop types. In the third section, various aspects affecting the classification performance such as the types of remote sensing data used, classification algorithms, classification level, additional features, and additional post-processing methods are scrutinized. Each subsection provides detailed descriptions of methods and data, along with their contributions to accuracy, comparisons with other methods where possible, and their contributions to the reviewed studies.

2. Methodology

The studies included in the review were searched through Google Scholar and the Web of Science. The main inclusion criteria are that satellite remote sensing imagery is the main source of classification data the study area is located over Europe (including Turkey), the publication year is later than 2000, and the publication language is English. The full list of reviewed studies can be found in the Appendix A1.

For the search on Google Scholar only the publication date filter is applied while for the search done over the Web of Science, more available filters are utilized for the efficiency of the process. Those filters are:

- Research areas: *environmental sciences and ecology, remote sensing, imaging science photographic technology, geology, engineering, physical geography, agriculture, water resources, plant sciences, computer science, science technology other topics, optics, instruments instrumentation, biodiversity conservation*
- Excluded micro citation: *glacier, ocean color, aerosols, tectonics, mars, asteroids, earthquakes, archaeology*
- Type: *article*
- Excluded meso citation: *marine biology, ocean dynamics, astronomy*
- In the marked fields: *crop, classification, remote sensing*

After these filters, 730 studies are identified. Further, the authors went through each study to eliminate any that didn't meet the requirements for inclusion. Following the exclusion of irrelevant studies, 136 relevant papers remain, including 13 conference papers and 123 journal articles collected from both research platforms.

For each study, we then systematically noted study area location, study area size, mapping and publication years, classification algorithm, classification accuracy, preprocessing methods, postprocessing methods, classification level, crop classes, ground truth, and satellite data sources used in the studies. For studies with multiple study areas, only the results and methods of the ones in Europe are considered and for studies over multiple years, the results of the year with the highest overall performance are included in the comparison.

Based on the recorded information, a systematic performance comparison is conducted. Firstly, accuracy comparisons are done within each study to avoid biased conclusions when comparing the performance across studies which might differ for example in terms of area covered, ground truth data, or number of classes. After within-study comparison, the accuracy of the methods is compared by analyzing the overall success of the method between the studies. In addition to performance comparison of commonly used methods, advantages of methods and data sources that are not commonly compared within the studies are also discussed in relevant sections of the study.

3. Types of Crop Cover Classification Map

3.1. Regional Coverage

Figure 1 shows the study areas of the reviewed papers and maps. Each country is color-coded according to the number of total studies over the country. The number of national-scale studies is also shown in numbers inside the country's borders. In addition to these, small study areas are shown with red dots on the map. While crop classification studies are available for many European countries, comprehensive countrywide classification maps are lacking in most regions. Most studies focus on France and Germany, with multiple countrywide crop maps available. Germany is the leader in terms of both the overall quantity of studies and studies conducted at the national level. Notably, there is a shortage of studies in Eastern and Northern Europe. Figure 2 displays a histogram depicting the area covered by the study areas in the reviewed studies. The number of large-scale studies is currently limited.

d'Andrimont et al. (2021) provide the broadest study area covering the EU-28 countries at 10-m resolution, presenting the first continental crop map. Based on Sentinel-1 (Attema et al., 2010) data and the 2018 LUCAS Copernicus survey, the study identifies 19 crop types using Random Forest (RF) (Breiman, 2001) classification.

Luo et al. (2022) classified the second-largest study area using RF, trained in select locations with diverse growing conditions and land covers, to map the rest of the area with limited ground data. From 2018 to 2019, they analyzed over 130,000 Sentinel-2 (European Space Agency, 2018) images using the Google Earth Engine (GEE) (Gorelick et al., 2017) platform to create 10 m crop maps for four important crops in ten EU nations.

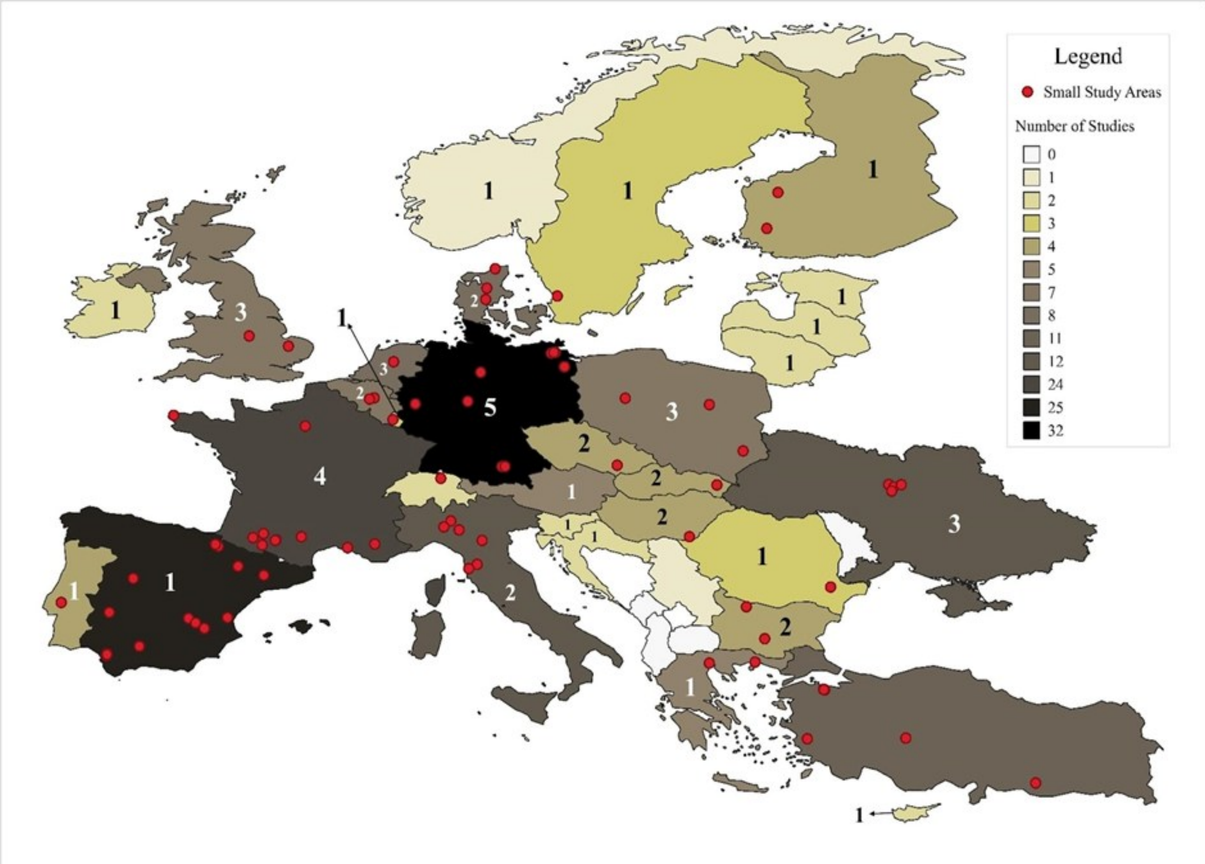

Figure 1. Study areas of the reviewed papers and maps. Each country is color-coded according to the number of total studies over the country. The number of national-scale studies is also shown in numbers inside the country's borders.

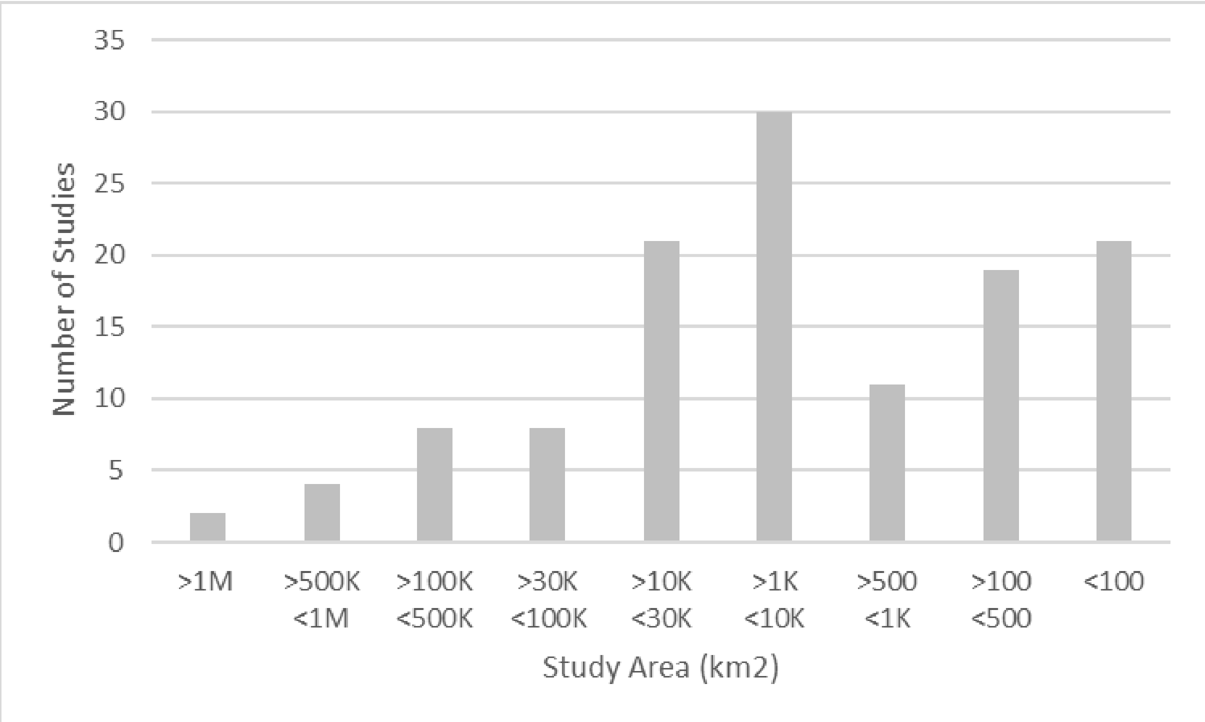

Figure 2. Histogram of the extent of the study areas of the reviewed studies

3.2. Ground Truth

To train a supervised classification requires reference data, also called “ground-truth” data. In addition to training data, an independent dataset should be available to test the performance of the classification. In the case of remote sensing-based crop classification ground-truth data is crop-type information over a coordinat. One way to gather ground truth data, that is used in the reviewed studies (e.g., Kussul et al., 2015; Shelestov et al., 2017; Xie & Quiel, 2000), is to perform surveys to collect land-use information across the study area. In addition to surveys, ground truth information is available through farmer’s declarations (e.g., Debella-Gilo & Gjertsen, 2021; Heupel et al., 2018; Sitokonstantinou et al., 2018). In the EU this is the Integrated Administration and Control System (IACS) which is used to payout subsidies under the Common Agricultural Policy (CAP). Administrative checks and on-the-spot inspections of this information ensure a relatively high level of data quality (Snevajs et al., 2022). IACS, with its geographical module Land-Parcel Identification System (LPIS), is a tool to manage direct payment support at the national level (European Commission. Joint Research Centre. Institute for the Protection and the Security of the Citizen., 2008). LPIS data is commonly used for training and validation purposes in the reviewed studies, especially for country-wise crop maps (e.g., Planque et al., 2021; Teimouri et al., 2019; Woźniak et al., 2022). Another EU-based data set is The Land Use/Cover Area Frame Survey (LUCAS), which is a survey that collects harmonized and comparable data on land use and cover across the entire EU area. Due to the wide-range availability of the data over EU countries, LUCAS data is utilized to create large-scale crop cover maps over the EU (e.g., d’Andrimont et al., 2021; Esch et al., 2014).

Existing land-use maps are also used as a source for training and validation data. In the study of Inglada et al. (2017), the approach chosen is to use existing databases to create reference datasets required for supervised classification and subsequent validation of land cover maps. The study combines four different data sources, including Corine Land Cover (CLC) and LPIS. Luo et al. (2022) obtained reference data from established nationwide crop field datasets or land cover maps. The first dataset Crop Map of England (CROME) encompasses over 20 main crop types, grassland, and non-agricultural land covers. The second dataset consisted of 10 m land cover maps for France (https://www.theia-land.fr/en/product/land-cover-map) and the third dataset, obtained from the Base Registration Crop Parcels (BRP) in the Netherlands, provided cultivated crop information at the parcel level. Additionally, the study utilized LUCAS in situ data to directly validate classification results for all EU countries in 2018.

In addition to the mentioned datasets, benchmark datasets for crop cover classification applications are proposed by some of the reviewed studies. These benchmark datasets contain ground truth data made more accessible and ready-to-use for classification by incorporating spectral information from selected satellite data. Turkoglu et al. (2021) provide the ZueriCrop dataset, which is produced from Swiss farm census data and includes annotated field polygons from Zurich and Thurgau in 2019. This dataset has 48 diverse classes, as well as a labeled hierarchical tree for improved training. Sykas et al. (2022) provide Sen4AgriNet, a multicounty, multiyear dataset covering Catalonia and France from 2016 to 2020. The dataset consists of 42.5 million plots compiled from farmer declarations collected through LPIS, is larger than any other accessible archive, and includes all spectral information. Lastly, Selea (2023) introduces AgriSen-COG, a large-scale crop-type mapping dataset that uses Sentinel-2 and LPIS data and spans five European nations (Austria, Belgium, Spain, Denmark, and the Netherlands).

3.3. Data Availability

Following the trend of open-source science, some authors shared either their dataset, source code, or the output of their work publicly for other researchers or organizations to explore. Table 1 shows those studies and their data availability information. Out of 136 studies, only 14 provided open-source data, code, or results, which does not meet the expectations of today's open-access scientific standard. To enhance reproducibility and facilitate comparisons, future research should prioritize sharing data more consistently.

Table 1. Studies that shared data and/or source codes

Study	Study Area	Crop map	Reference Dataset	Source Code
Rußwurm & Körner, 2018	Munich, Germany			X
Van Tricht et al., 2018	Belgium	X		
Griffiths et al., 2019	Germany	X		
Preidl et al., 2020	Germany	X		
Turkoglu et al., 2021	Zurich and Thurgau, Switzerland		X	X
d'Andrimont et al., 2021	Europe	X		
Metzger et al., 2021	Munich, Germany & Zurich and Thurgau, Switzerland			X
Asam et al., 2022	Germany	X		
Blickensdörfer et al., 2022	Germany	X		
Luo et al., 2022	England, Netherlands, Germany, Denmark, France, Italy, Poland, Hungary, Slovakia, Czech Republic	X		
Snevajs et al., 2022	South Moravia, Czech Republic	X		X
Campos-Taberner et al., 2023	Castelló & Valencia, Spain	X		X
Gallo et al., 2023	Lombardy, Italy		X	X
Rusňák et al., 2023	Danubian Lowland & Slovakian Lowlands, Slovakia		X	
Rußwurm et al., 2023	Brittany, France & Bavaria, Germany			X

3.4. Class Granularity

Classes on crop maps can have different granularity levels, or thematic levels, depending on the ground truth data availability and the detail needed by the user of the map. A common practice is to merge certain types of crops according to their spectral profiles or similarity in species family, season, or similarity of the use of the crop. Grouping all legumes or all grains in aggregated classes are example of this approach. When the detail level of the map can be compromised depending on the requirements for the planned use of the resultant map, merging certain classes can increase the overall accuracy (OA) of the classification. Table 2 summarizes studies comparing classification accuracy across different numbers of classes, hierarchical levels, and grouping strategies. The results indicate that grouped classes generally achieve higher accuracy compared to individual classes or finer-grained levels. Consequently, a fair comparison between approaches requires consideration of the aggregation level of the crop types classified. Class granularity, along with regional coverage and ground truth data, significantly affects the performance of classification maps. Therefore, in Chapter 4, the performance of various crop classification approaches is compared within the study, ensuring these variables remain consistent for a fair evaluation of methods.

Table 2. Accuracies from studies that compared the performance of multiple class number

Study	Class number	Accuracy
Bargiel & Herrmann, 2011	4 classes	76.22%
	3 classes	89.69%
	2 classes	94.77%
Fontanelli et al., 2014	Level 2	~88,5%
	Level 1	~92,5%
Villa et al., 2015	Level 1	85.3%
	Level 0	96.7%
Sitokonstantinou et al., 2018	type	0.87 (κ)
	family	0.91 (κ)
	season	0.91 (κ)
Piedelobo et al., 2019	15 crops	87%
	7 grouped crops	92%

4. Performance of different approaches for crop classification

4.1. Remote Sensing Sources

There are two main types of remote sensing satellites: optical and radar. Optical satellites generate signals at multiple wavelengths and capture multispectral images with various bands of data while radar satellites produce signals at a single wavelength and interact with land features to extract information on surface roughness and moisture content (Joshi et al., 2016). The study's assessment of both product types and features extracted from the products is provided in this section.

4.1.1. Optical Remote Sensing products and features

Optical remote sensing products are passive remote sensing products that receive reflected sunlight from the target (Di & Yu, 2023). They provide reflectance values at visible, near-infrared (NIR), and short-wave infrared (SWIR) ranges of the electromagnetic spectrum, which are important for the identification of crops. Most optical products do not require excessive pre-processing since they are available in levels that are radiometrically and geometrically corrected. Another advantage of optical products for crop classification is that they enable the calculation of spectral indices utilizing differences in characteristic band reflectance of each land/crop cover. One disadvantage of optical products is that due to them being passive sensors, they are affected by the cloud cover over the study area. It is important to take this disadvantage into account when the study area has a humid and cloudy climate and suffers from excessive cloud cover (Francis et al., 2019).

As is seen in Figure 4, Sentinel-2 and Landsat are the most commonly used optical products in crop cover classification. Landsat's first mission was released in 1984 and since then revised and more advanced versions are being released with better resolutions. The last mission of Landsat, Landsat 8 is the most popular mission as its functioning time interval coincides with the popularization of remote sensing-based land cover classification studies. Landsat 8 has 30 m spatial, 16-day temporal, and 8-bit radiometric resolution. It has a 185 km swath width and a global coverage. After its release, Sentinel-2 increasingly replaced Landsat as the main source. One of the reasons that Sentinel-2 is more popular in crop classification studies is the advantage of better resolutions with 10-meter spatial (for visible and NIR bands) and 5-day temporal resolution (European Space Agency, 2018). Shorter re-visit times also come with the advantage of more frequent non-cloudy days and consequently more frequent temporal information on vegetation growth. It also includes red-edge bands unlike Landsat 8, and these bands are shown to be beneficial for accurate crop classification. One disadvantage of Sentinel-2 is the temporal coverage since it is a rather new satellite that was only released in 2015.

The number of studies that utilize the different RS sources over time is shown in Figure 3. One of the first conclusions is that Sentinel and Landsat are the most commonly used remote sensing data sources. It can be seen that Landsat gradually lost its popularity to Sentinel after 2018. After the Sentinel mission started, the use of RapidEye and Satellite pour l'Observation de la Terre (SPOT) (European Space Agency, n.d.) decreased like Landsat. Another observation is that optical satellites are preferred over radar satellites in almost all years. The intense use of remote sensing sources in crop map classification since 2012 may be an indication that the utilization of this technology in this field will increase with more available data sources and advanced techniques in the future.

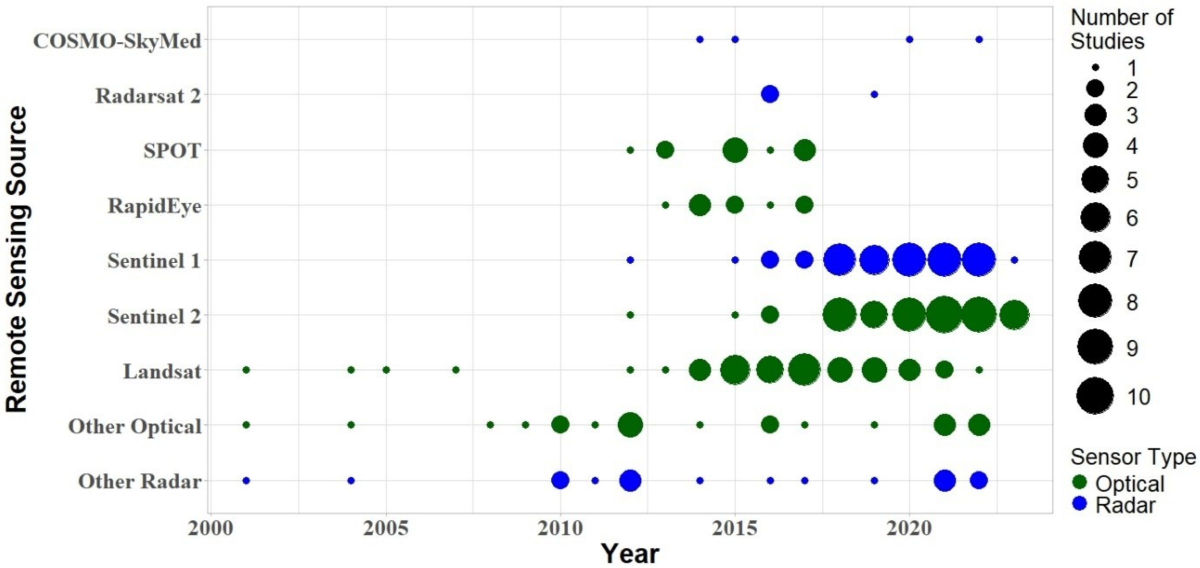

Figure 3. Use of popular remote sensing products over time

Optical Features

Optical remote sensing products have multiple bands with varying along the electromagnetic spectrum from 400 nm to 1 mm covering the visible, infrared, and thermal wavelengths. Each of these bands contributes differently to the identification of crop classes. In the following part of this section, optical bands that are found to be more or less beneficial in the reviewed studies are reviewed.

The red-edge spectral characteristic is identified by the wavelength range of 690–740 nm, which corresponds to the highest gradient found in the reflectance profile of green vegetation (Kim & Yeom, 2014). The absorption of chlorophyll and the scattering of light between leaf cells are the causes of the low reflectance at red wavelengths (~690 nm) and the high reflectance in the near-infrared (~740 nm), respectively (Kim & Yeom, 2014). Most of the commonly used optical satellites include the red-edge band (Sentinel-2, RapidEye, etc.) as this channel improves the separability of crop types (Ustuner et al., 2015) with its capability of capturing the chlorophyll content of the target vegetation. In the reviewed studies, Ustuner et al. (2015) observed that by including the red-edge band in the classification, the OA increases by up to 4.6%, and Griffiths et al. (2019) showed that in all cases, the OA achieved when red-edge bands are included was higher than when those bands were left out. Immitzer et al. (2016) showed in their study that when the spectral bands based on the importance measure Mean Decrease in Accuracy (MDA) obtained from the RF are ranked, red-edge has the highest importance. In addition to that, in the studies of Asam et al. (2022) and Luo et al. (2022), red-edge was shown to be the most valuable band among all features after the used vegetation indices.

The short-wave infrared channel falls into the range of 1 nm to 2.5 nm wavelength on the electromagnetic spectrum. The SWIR band is particularly important due to its strong relation with the water content in the vegetation (Panigrahy et al., 2009). Many of the studies that are reviewed emphasize the importance of SWIR bands for crop classification. Immitzer et al. (2016) showed that the SWIR band was among the five most important bands in their classification, two were located in the SWIR spectral region, and Luo et al. (2022) showed that SWIR was in the top most important features. However, Matton et al. (2015) discarded the SWIR band, as it was found to not provide valuable enough information after the pre-selection step. Even though the band's value was emphasized in many studies, as opposing results are also obtained, the SWIR band can be recommended to be used after a preselection procedure when faced with limited feature space and computational resources.

Near-infrared light refers to light between wavelengths 800 and 2500 nm. The most important feature of this channel is that healthy vegetation reflects prominently more lights falling into the NIR region as opposed to unhealthy vegetation (Kogan & Kogan, 2019), and thus the NIR bands of optical satellites can be used to distinguish crops. The benefit of the NIR is shown by some of the studies reviewed. As an example, in their study, Blickensdörfer et al. (2022) showed that among 19 environmental spectral and radar features, the NIR band has the 3rd highest performance. Based on principal component analysis (Wold et al., 1987), Schmedtmann & Campagnolo (2015) observed that the NIR spectral region was always selected to be used in the classification. Similarly, Crnojevic et al. (2014) observed that the NIR band has a significant influence on classifiers' performance after analyzing the significance of individual spectral bands. In addition to that, Matton et al. (2015) reported that the NIR reflectance was selected for the final features after being one of the best-performing 5 features out of twenty including four spectral bands of the five crop growth characteristics, after their preselecting procedure. One study that did not observe the benefit of NIR in the classification was by Immitzer et al. (2016), reporting that the NIR bands of Sentinel-2 interestingly did not score high in the MDA obtained from the RF model.

Utilizing the spectral reflectance difference between red and NIR wavelengths, one often used measure is the Normalized Difference Vegetation Index (NDVI) (Bremer et al., 2011). A green leaf's maximum absorption of chlorophyll occurs at roughly 690 nm or red wavelength; absorption significantly decreases at the NIR wavelength interval, which is between 650 and 850 nm (Myneni et al., 1995). It is appropriate to use this spectral difference to distinguish vegetation from other classes. Additionally, in the classification of land cover, vegetation classes can be distinguished from one another using the magnitude and/or time interval of the maximum NDVI. The benefit of using NDVI is demonstrated by many crop classification studies. In their study, Asam et al. (2022) reported that the NDVI band is identified as being the most important Sentinel-2 feature among the feature set consisting of NDVI and all bands of Sentinel-2. And August NDVI was consistently ranked as the feature with the highest contribution among bands Sentinel-2 bands B5, B6, B7, B8, B11, B12, NDVI, Normalized Difference Yellow Index (NDYI), and Red Edge Position (REP) (Filella & Penuelas, 1994) while classifying the major crop types across EU countries in the classification of Luo et al. (2022). Similarly, the five most important predictors were based on NDVI observations among combined Sentinel-1 and Sentinel-2 features when the Gini importance of features is compared in the study of Van Tricht et al. (2018). Lastly in the study of Blickensdörfer et al. (2022), NDVI has performed the second best among 19 environmental spectral and radar features. In their study, the best-performing indices are found to be the Soil-Adjusted Vegetation Index (SAVI), which is a vegetation index that uses a soil brightness and color factor to reduce the influence of soil color and brightness (Huete, 1988). Due to its advantage over soil-covered surfaces, it is also found to be beneficial by Palchowdhuri et al. (2018) while classifying the crops in an early stage of growth, where the underlying soil is a lot more visible through the growing vegetation canopy. Another observation made by the authors was that since the green band makes up the Green Normalized Difference Vegetation Index (GNDVI) (Gitelson et al., 1996) ratio rather than the red band, it is more sensitive to the amount of chlorophyll in the plant. Consequently, GNDVI is likely to be more effective for plants with larger leaves or those that are phenologically more advanced or mature. Another optical index found to be beneficial for an accurate crop classification is Normalized Difference Red Edge Index (NDRE) (Barnes et al., 2000), which is shown to outperform NDVI and GNDVI by Ustuner et al. (2014) when the classification performance of the indices is compared through multiple cases with different combinations of the indices. Lastly, Sitokonstantinou et al. (2018) showed that the Plant Senescence Reflectance Index (PSRI) (Peñuelas et al., 1994) is the most consistent of the VIs, having high weights of feature importance among PSRI, NDVI, and Normalized Difference Water Index (Gao, 1996) for nearly all scenes they used for the classification.

Handling Cloud Cover

To avoid misclassifications caused by missing pixels, pixels contaminated with cloud cover should be removed from the data, in other words, they should be masked. The most commonly used cloud masking method in the reviewed papers is setting a cloud probability for each image. Cloud probability information embedded in most Level 2 optical satellite products, which have undergone atmospheric correction, can be used to limit the probability of clouds in the images that will be used for crop classification. The limit set for the probability of the cloud cover over an image does not have concrete rules or formulations in the literature and it is more dependent on the decision of the user, the availability of cloudless images over the region, and the performance expected from the classification. In the reviewed studies, 10% is mostly set for the satellite images. It is also a practice to use completely cloud-free images (e.g., Campos-Taberner et al., 2023) or set a higher probability limit such as 20% (e.g., (Dimitrov et al., 2021; Sitokonstantinou et al., 2018).

Another commonly used, but more sophisticated cloud masking algorithm is the Function of mask (Fmask) (Zhu & Woodcock, 2012). The method uses the physical characteristics of clouds to distinguish between pixels with clear skies and those that could become clouds.

Temperature, brightness probabilities, and spectral variability are used to create distinct cloud masks for land and ocean locations. To accomplish precise cloud and cloud shadow detection in Landsat images, Fmask uses these masks with probable cloud pixels to identify cloud layers, produce shadow layers, and forecast cloud shadow locations (Zhu & Woodcock, 2012). Since the algorithm is available in commonly utilized software and its performance is satisfactory, it is utilized by many studies that are reviewed (e.g., Blickensdörfer et al., 2022; Ghazaryan et al., 2018; Orynbaikyzy et al., 2020; Shelestov et al., 2017; Skakun et al., 2016; Teke & Cetin, 2021).

Multi-Mission Atmospheric Correction and Cloud Screening (MACCS) tool is a method for cloud detection and atmospheric correction developed by Hagolle et al. (2015) in the process of preparing the Level 2A processors for Sentinel-2 satellites and VENµS (Vegetation and Environment monitoring on a Micro Satellite). With an optional processing step available to correct topography-induced illumination distortions, the algorithm used in MACCS gains robustness by using temporal information to distinguish between rapidly varying elements like clouds and slowly changing landscape features (Petrucci et al., 2015). As a consequence of the algorithm's robustness, Defourny et al., (2019), Matton et al. (2015) and Pelletier et al., (2016, 2017) utilized the algorithm for cloud masking.

After cloud masking, when no data is available for some parts of an image used for classification, it is not possible to classify those parts properly with most classification algorithms. So, those data gaps should be filled for a proper classification map. Temporal interpolation is a gap-filling method widely used when multitemporal data is available. The most popular method of temporal interpolation is linear interpolation, which is performed by averaging the reflectance values of the previous and next images in the time series, assuming equal time intervals between each image. When time intervals are not equal or consecutive images are contaminated with clouds, time-weighted averaging can be used for temporal gap filling. Due to the simplicity and the efficiency of the method, it is the most commonly used way of cloud-gap filling among the reviewed studies (e.g., Debella-Gilo & Gjertsen, 2021; Giordano et al., 2020; Inglada et al., 2015, 2016; Orynbaikyzy et al., 2020; Pageot et al., 2020; Pelletier et al., 2016; Teke & Cetin, 2021; Valero et al., 2021; Weilandt et al., 2023). Spatial interpolation is another method for simple cloud gap filling. It can be performed over the object (pixel groups) by interpolating the values of the object pixels for the gaps in that object.

Another commonly used, but more sophisticated gap-filling way is utilizing Self-Organizing Maps (Kohonen, 1990) (e.g., Kussul et al., 2016; Shelestov et al., 2017; Skakun et al., 2016). Kohonen's self-organizing map (SOM) technique is used to correct weather-related inaccuracies in data, such as those brought on by clouds or shadows. Incorrect values are not immediately addressed by SOM; rather, it is handled as missing data (Abdel Latif et al., 2008). It operates by initially training on clean data that isn't affected by clouds. Then, it treats incorrect values as missing and finds and eliminates them. Ultimately, SOM estimates the accurate reflectance values by filling up these missing data. This method has proven effective in managing weather-related data (Abdel Latif et al., 2008).

4.1.2. Radar Remote Sensing products and features

Active remote sensing products receive reflected pulses sent by the instrument and operate in the microwave region of the electromagnetic spectrum, allowing them to penetrate through clouds, thus overcoming limitations caused by the cloud cover over the target (Lee & Pottier, 2017). This capability ensures imagery even in challenging atmospheric conditions. These products provide valuable information on the structure and geometry of the observed target. However, proper use of active remote sensing products requires pre-processing due to its inherently noisy nature. Although extensive processing is required, the data from active remote sensing greatly aids in the comprehension and characterization of the target.

Sentinel-1

The Sentinel-1 mission consists of a pair of polar-orbiting satellites (Sentinel-1A was launched in 2014 and Sentinel-1B launched in 2016) that operate in the C-band synthetic aperture radar imaging mode day and night, allowing them to obtain imagery in any weather (sentinels.copernicus.eu). The product has a 6-day temporal and up to 5-meter spatial resolution. It is the most commonly used radar product in the reviewed studies and it is mostly used together with Sentinel-2. Fine resolution of the product and the capability of overcoming any climatic challenges due to the nature of radar products, it is becoming more popular in remote sensing-based land cover classification studies.

Polarization (VV-VH-HH)

Arbitrary electromagnetic wave polarizations can be described by ellipses determined by two geometrical parameters, the ellipticity angle and the ellipse orientation angle (Evans et al., 1988). Zero degrees ellipticity angle represents linear polarization. For the linear case, orientation angles of 0" and 180" indicate horizontal polarization and 90" indicates vertical polarization (Evans et al., 1988). Radar sensors can operate in different types and combinations of polarization modes. As an example, Sentinel-1 can transmit a signal in either horizontal (H) or vertical (V) polarization, and receive in both V and H polarisations. Radar polarization modes commonly used in crop cover classification can be summarized as HH - for horizontal transmit and horizontal receive, VV - for vertical transmit and vertical receive, HV - for horizontal transmit and vertical receive, and VH - for vertical transmit and horizontal receive. The performance of different polarization modes, their combinations, and their ratios are tested by multiple reviewed studies. When the performance of VV and VH is compared, VV was found to yield higher accuracies (e.g., Arias et al., 2018; Clemente et al., 2020; Karjalainen et al., 2008; Mestre-Quereda et al., 2020; Tomppo et al., 2019). In their study, Mestre-Quereda et al. (2020) attribute this better performance of VH to the higher signal-to-noise ratio (SNR) and smaller temporal decorrelation of VV compared to VH. In the comparison between VV and HH polarizations, studies of Bargiel & Herrmann (2011) and Fontanelli et al. (2022) show that VV polarization yields superior performance compared to HH, and Busquier et al. (2020) noted that the overall performance of the coupled use of HH and VV is equal to VV alone only with some improved accuracies for a few numbers of crop types. On the other hand, Skriver et al. (2011) reported HH-polarization performed slightly better. In addition to separate use of the channels, Demarez et al. (2019) showed that VH/VV yields better results than separate use of the modes and d'Andrimont et al. (2021) showed that the combination of VV and VH gives the highest accuracy when it is compared with for the polarization backscattering coefficients themselves and, the cross-ratio index (VH/VV) along with their combinations.

Haralik textures

Haralick et al. (1973) proposed quantifying the spatial relationship between neighboring pixels in an image by utilizing a gray-level co-occurrence matrix (GLCM). Since they are easy to understand and can be computed from the GLCM, Haralick texture features are frequently utilized in remote sensing applications (Löfstedt et al., 2019). Haralik textures include measures such as energy, entropy, correlation, and inertia, all referring to different texture characteristics of the image. Studies that are using radar images as remote sensing sources while performing crop classification, leveraged Haralik textures. In their study, Demarez et al. (2019) showed that Haralik textures, especially the entropy of channel VV, overperformed the raw VV and VH channel features in terms of variable importance together with the VV/VH ratio. In addition to that, an analysis of the most relevant features derived from SAR imagery performed by Inglada et al. (2016) revealed that among Haralik, local statistics, ratios, and raw images, Haralik textures (entropy, inertia), the polarization ratio, the local mean, and VV imagery contain the majority of the information required for accurate classification.

4.1.3. Multisource Classification

The utilization of classification features derived from multiple remote sensing sources can be referred to as multisource classification. This method aims to combine and benefit from the information offered by multiple sources. Multisource classification can be performed using multiple optical, multiple radar, or a combination of both types of sources. Studies investigating different remote sensing sources are given in Figure 4 with the comparison of the accuracies of those sources and their combinations, where the mapping year is given in parentheses for the studies that mapped multiple years. The figure shows once again how Landsat 8 lost its popularity after 2020 and Sentinel products fill that gap. Another point concerning the use of products, only 3 studies utilized Sentinel-2 with Landsat, but the number of multisource studies combining radar and optical products is 17, which shows that this combination was found to bring more information to the classification than the combination of two optical satellites. When the overall performance of individual satellites is inspected, it can be seen that Sentinel-1 does not perform well when it is used alone. Sentinel-2 overperforms Sentinel-1 in all cases where their accuracies are compared except for two cases. For the majority of the cases, multisource classification yields better results than single-source classification. It is an expected conclusion since different sources bring more information for the differentiation of each crop class. Especially when a radar source is combined with an optical product, crops can be distinguished by both their textural and spectral features. Another advantage of using a combination of optical and radar data is that it is possible to fill potential optical data gaps occurring due to cloud cover.

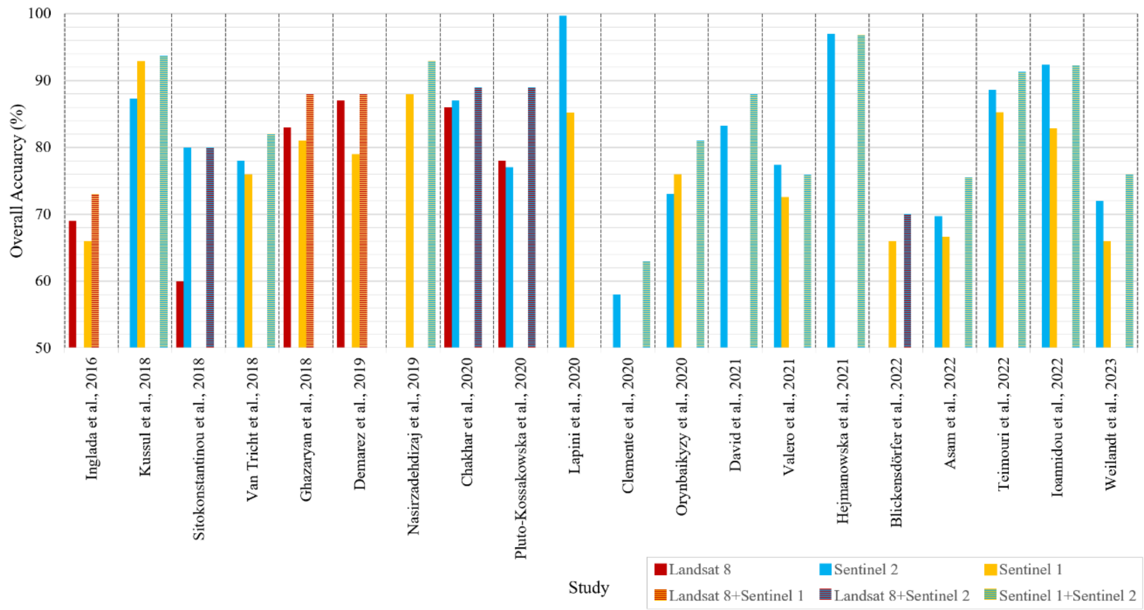

Figure 4. Accuracies from studies that compared the performance of multiple remote sensing sources

4.1.4. Multitemporal Classification

Multitemporal classification is performed by using features from remote sensing products acquired over multiple dates. Since temporal information is available using remote sensing, it is possible to explicitly examine the correlations between multiple temporal phases of a given crop (Ji et al., 2018). Using images from multiple dates allows us to analyze time series and/or perform harmonic analysis of the reflectance changes over time. It is particularly important for crop cover classification since reflectance changes over time can help the algorithm distinguish certain crop classes from each other. Studies investigating multitemporal classification are given in Figure 5 and Figure 6 with the comparison of the accuracies over time. The figures depict similar types of information, but for better clarity, the accuracy results are categorized based on the degree of accuracy increase over time. Both figures indicate that accuracy does not exhibit significant increases after the day of the year (DOY) 220 (mid-August), corresponding to the end of the crop season when most fields are either harvested. The peaks of accuracy increase occur between DOY 120 and 150 (May) and DOY 180 to 210 (July), suggesting substantial variations in spectral and scatter signatures during these months for major crops.

In Figure 6, it is notable that some studies did not observe an increase in accuracy with added temporal data. For instance, Matton et al. (2015) noted a minimal increase in accuracy at the Belgium study site, possibly because the time series starts after May. Conversely, a significant accuracy boost was observed at the France test site from the start after May. The discrepancy in accuracy increases between Ukraine and France, despite similar start dates, could be attributed to climate and cropping season variations across these countries. In the study of David et al. (2021), a different accuracy profile was observed. They found that early results (until April) were inferior to middle results (until July), with late results (until November) not showing significantly superior performance compared to middle. The authors suggest that the differences in accuracy across different stages may be attributed to variations in phenological stages or the emergence of another crop type in November. In contrast to other studies, Teimouri et al. (2022) conducted tests over single-date images throughout the season, rather than time series, as represented with lines with markers in Figure 6. Their study revealed the best accuracy results during May, with optical time series significantly improving crop classification accuracy by at least 3.9%. Demarez et al. (2019) demonstrate that images acquired from April to the end of June notably enhance accuracy, corresponding to the onset of the irrigation campaign, which holds significant importance for water management. However, the accuracy gain becomes less significant after this period.

An explanation for the difference between these two figures may be found in the fact that, in most of the studies represented in Figure 5 (except for Matton et al. (2015) and Tomppo et al. (2019)), which show a significant increase in accuracy, barley and wheat crops are classified as two separate classes. These two common crops, which exhibit similarities in their spectral signatures, appear as distinct classes in only five studies within the second group shown in Figure 6. In other studies, such as those by Valero et al. (2021) and Ghazaryan et al. (2018), these two classes of cereal crops are combined under a single heading to mitigate the disadvantage of similar spectral characteristics that could lead to decreased accuracy. Alternatively, in the work of Teimouri et al. (2022), only one of these crops is represented among the classes in the study area. The differences in accuracy changes can be a result of better separation of crops with similar spectral characteristics due to the use of more temporal data. This is especially relevant since these crops can show minimal differences in their growth stages, which can only be detected through frequent observations throughout the cropping season

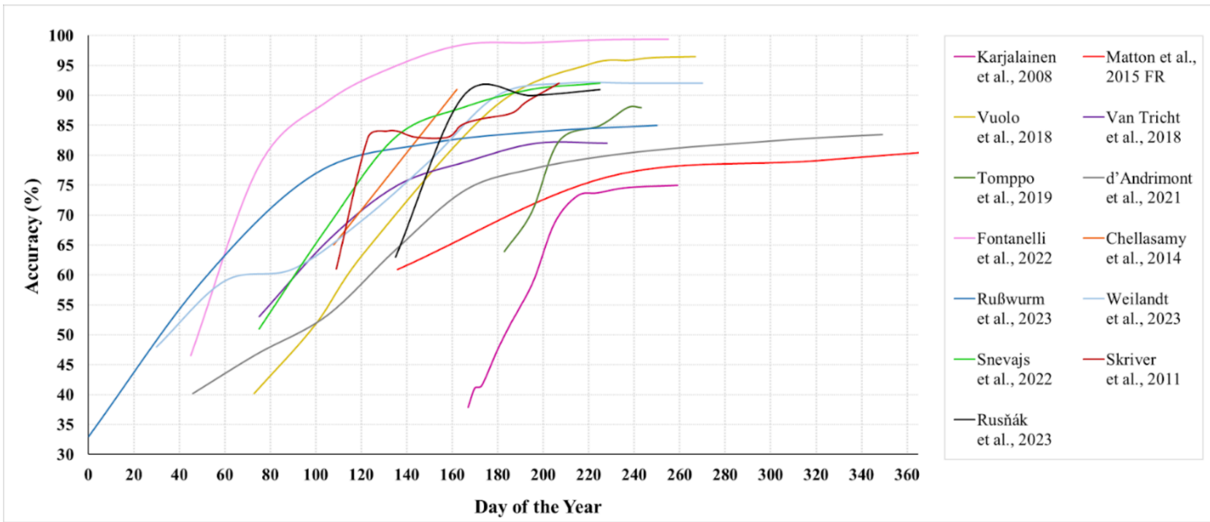

Figure 5. Accuracies from studies that compared the performance of multitemporal information and observed more than 15% accuracy increase with added temporal data

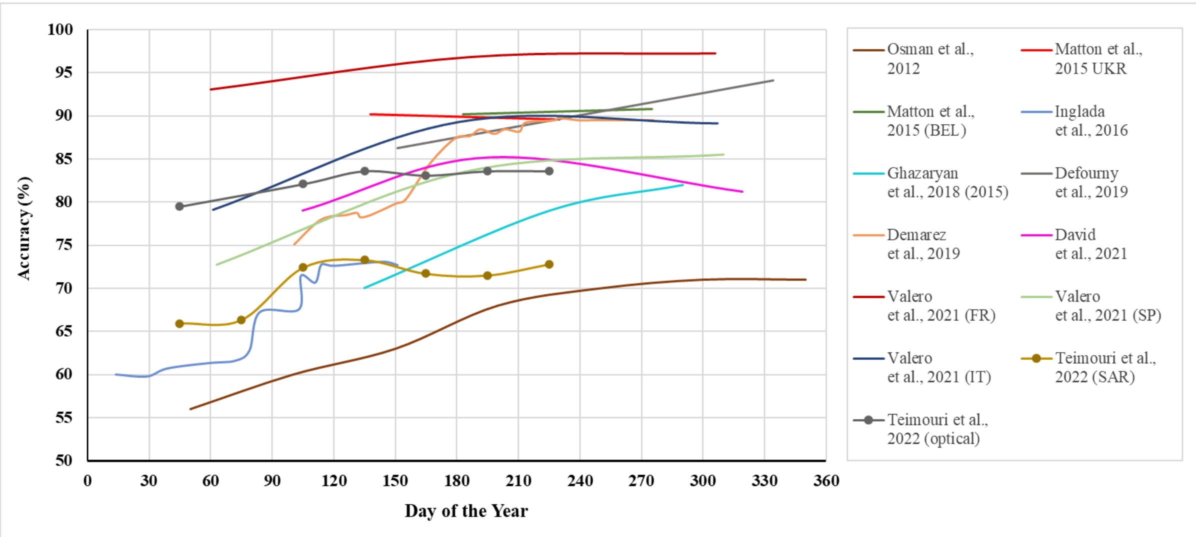

Figure 6. Accuracies from studies that compared the performance of multitemporal information and observed less than 15% accuracy increase with added temporal data

4.1.5. Temporal Compositing

Temporal compositing is the merging of the information of remote sensing images acquired on multiple dates over the same region. It can be performed by summarizing the pixel value using statistical methods like taking the mean/min/max/median of existing multiple pixel values. While observing time series data, using all possible images can result in abundant data and cause storage and computational cost problems. When compromising little reflectance changes over consequent images, temporal information can be summarized with this method. It is also helpful for eliminating data gaps due to excessive cloud cover as the gaps will be filled with the information in the time series. Studies investigating different temporal compositing units are given in Table 3, and the accuracies of different temporal resampling units are compared. It can be concluded from the table that using more frequent images increases classification accuracy. Griffiths et al. (2019) attribute this improvement in accuracy to the importance of high temporal repetition observations for mapping dynamic phenomena like agricultural cultivation, with short interval composites maintaining most of the necessary temporal information. Even though more frequent data brings more information to the classification and yields better performance, computation time should also be a measure for efficiency assessment for resampling units. Debella-Gilo & Gjertsen (2021) discuss another challenge related to frequent data, specifically the difficulty of obtaining cloud-free optical images. They use temporal interpolation to solve this problem, demonstrating its efficiency in preserving accuracy even when the dataset contains cloudy images.

Table 3. Accuracies from studies that compared the performance of multiple temporal resampling units

Study	Resampling Unit	Accuracy (%)
Griffiths et al., 2019	10-day	81
	Monthly	79
	Seasonal	75
Mestre-Quereda et al., 2020	6-day	77.5
	12-day	73.8
	18-day	69.7
Debella-Gilo & Gjertsen, 2021	7-day	94
	14-day	93
	21-day	92
	28-day	90
Busquier et al., 2021	8 images over 240 days	59.7
	40 images over 240 days	76.1

4.2. Classification Algorithms

4.2.1. Overview of Classification Algorithms

Decision Trees

The decision tree classifier classifies an unknown sample step-by-step using a set of decision functions, and this classification strategy can be represented by a tree diagram (Swain & Hauska, 1977). An attribute of the data is chosen at each node of the tree to best divide its set of samples into subsets enriched in one or more classes. The C5.0 decision tree technique, a popular option for supervised learning, was utilized by Esch et al. (2014) with a collection of input characteristics that included spectral bands from five input scenes, NDVI, and seasonality layers. They point out that as long as the chosen classes are well represented in the training dataset, the algorithm will choose pertinent features and appropriate thresholds for class assignment automatically. As more advanced algorithms develop, decision trees are gradually losing popularity in remote sensing-based crop classification research. Simón Sánchez et al. (2022) evaluated the performance of decision trees compared to more complex categorization algorithms serve as an example of this trend. According to their findings, decision trees underperformed the more sophisticated techniques of Multi-Layer Perceptrons (MLPs), convolutional neural networks (CNNs), and RF, demonstrating their shortcomings as reliable models for crop categorization training.

Random Forests

RF, developed by Breiman (2001), are an ensemble of decision trees that produce predictions by choosing the most popular prediction results of grown trees for classification tasks. The power of RF comes from the randomization of split features for each tree resulting in uncorrelated trees, thus making the algorithm more robust to overfitting (Hastie et al., 2009; James et al., 2013). RF is also robust to outliers and noise (Rodriguez-Galiano et al., 2012), which can occur in remote sensing images often due to their nature.

Due to its aforementioned advantages, RF is the most common classification algorithm used in the reviewed crop classification studies. A study by Hütt et al. (2020) demonstrates its robustness on high dimensional data that is not normally distributed. RF is also shown to be more robust to random class label noise by Pelletier et al. (2017) when performance is compared to support vector machines (Cortes & Vapnik, 1995). Another advantage of RF is the ease of use and low computational cost of the algorithm, which make the algorithm more popular for large-scale applications when compared to more complex classification algorithms such as neural networks and SVM. Stefanski et al. (2013) emphasize its simple handling and fast training times with high-dimensional feature spaces even with limited training samples. Woźniak et al. (2022) confirm the efficiency of RF in large-scale applications, reporting the highest with a short computing time. Furthermore, Ok et al. (2012) emphasize the consistency of the RF, by testing the performance of the algorithm with varying hyperparameter combinations and yielding similar performance with these combinations.

Support Vector Machines

As a supervised non-parametric statistical learning method, support vector machines (SVMs) do not make any assumptions about the underlying data distribution (Mountrakis et al., 2011). The SVM training algorithm seeks to identify a hyperplane that divides the dataset into a definite specified number of classes in a way that is consistent with the training examples (Mountrakis et al., 2011). SVM splits the problem into binary classification subproblems, utilizing one SVM learner per subproblem, for multiclass classification with three or more classes (Rusňák et al., 2023). Hyperparameters to be tuned throughout the optimization process include the type of kernel functions, box constraint level, kernel scale, and multiclass strategy (Rusňák et al., 2023).

In the reviewed crop classification papers, SVMs are the second most used approach among commonly used classification algorithms, and their advantages are demonstrated in these studies. Rusňák et al. (2023) used SVMs for classification, leveraging the algorithm’s capacity to map training examples in high-dimensional space and identify the best-separating hyperplanes, which effectively reduced overfitting and produced well-separated classes. They also emphasized how SVM can handle large feature spaces and can adapt to a variety of data distributions. While Rusňák et al. (2023) found SVMs beneficial for handling large feature spaces, Ustuner et al. (2015) highlighted SVM's effectiveness in achieving high classification accuracy with small training datasets. Ustuner et al. (2015) noted that SVM outperformed conventional techniques for agricultural classification across a range of model types, including linear, polynomial, radial basis function, and sigmoid. They concluded that SVM outperformed the conventional Maximum Likelihood Classification (MLC) (Otukei & Blaschke, 2010) technique in terms of performance. Additionally, Camps-Valls et al. (2004) highlighted how effectively SVM performed in classification and regression tasks, even in situations with a lot of potentially relevant input characteristics and unclear patterns and it is also observed to be effective at recognizing noisy features. In terms of recognition and misrecognition rates, they observed that SVM outperformed neural networks, and it was also successful in identifying noisy bands in a variety of categorization settings. Additionally, Camps-Valls et al. (2004) showed how the method can handle the existence of confusing patterns and features in datasets and proposed that SVMs offer an advantage in areas where feature selection is not practical given technological specifications. Additionally, they emphasized how SVMs can produce simple solutions with a low rate of support vectors, which may make it easier to compress hyperspectral images while preserving important information.

Maximum Likelihood Classifier

One of the well-known parametric classification algorithms used for supervised classification is the maximum likelihood approach. For each class, second-order statistics of a Gaussian probability density function (pdf) are used by the maximum-likelihood classifier (MLC) (Paola & Schowengerdt, 1995). If the class pdfs are Gaussian, then it is the best classifier, which is why it is frequently used as a benchmark for classifier comparison (Paola & Schowengerdt, 1995). Using multi-temporal Landsat 8 OLI data from 2013, Azar et al. (2016) showed that MLC was the most accurate algorithm compared to distance-based classifiers Euclidean Minimum Distance (EMD), Spectral Angle Mapper (SAM), and NN. They reported that this result is consistent with earlier research that shows MLC's ability to map different crop kinds utilizing satellite data with a medium resolution. Similarly, for crop classification, Fontanelli et al. (2014) looked into a number of supervised techniques, such as MLC, Energy Minimization Distance, and SAM. They concluded that MLC outperformed its competitors and continuously demonstrated higher OA performance in each thematic level, time step, and using both optical and SAR input data. Furthermore, a comparative study of classifiers for pan-sharpened and multispectral imaging was carried out by Castillejo-González et al. (2009) and the results showed that MLC was the best classifier for all land uses. The robustness and dependability of MLC in crop classification tasks across various datasets and environmental situations are highlighted by these collective outcomes.

K-Nearest Neighbor

Another method explored in the reviewed studies is the K-nearest neighbour (kNN) algorithm. The main principle behind a conventional kNN approach is to predict a test data point's label using the majority rule, which is to say, using the major class of its k most similar training data points in the feature space to predict the test data point's label (Cheng et al., 2017). To classify crops, Chakhar et al. (2020) evaluated a set of 22 classification methods, such as decision trees, ensemble classifiers, SVM, closest neighbour, and discriminant analysis. Out of all the approaches they assessed, they observed that the subspace ensemble method with nearest neighbour learners stood out as the most robust algorithm. This was followed by the nearest neighbour classifier with fine kNN, which provided the best balance between processing time and accuracy.

Neural Networks

To identify patterns in data, neural networks (NN) use a chain of interconnected input, hidden, and output layers. The architecture of NN is customized based on the complexity of the data and the desired performance (Rusňák et al., 2023). Rusňák et al. (2023) describe how NNs, which are well-known for their adaptability, can be optimized for certain data kinds and distributions varying hyperparameters like layer sizes and activation functions.

Skakun et al. (2016) and Shelestov et al. (2017) used committees of neural networks, specifically MLPs with hyperbolic tangent activation function for neurons in the hidden layer and logistic activation function in the output layer, to improve classification accuracy in crop classification application. Skakun et al. (2016) highlighted the benefits of the committee approach, emphasizing its capacity to resolve classification problems and produce probabilistic results. Shelestov et al. (2017) also emphasized how ensemble NNs, in particular, MLP, are more effective than single classifiers like SVM, DT, and RF at enhancing classification performance. While acknowledging the potential of other classifiers, Shelestov et al. (2017) suggested that variations in performance when compared to other techniques could be explained by the fact that NNs' full potential in remote sensing is still to be discovered.

As an alternative to MLPs, the Radial Basis Function (RBF) is also explored for crop classification. Foody (2004) conducted the study to compare the performance of MLP and RBF, suggesting that the presence of untrained classes poses a significant challenge in classifications resulting in a notable decrease in accuracy. The study highlights the RBF network's potential for partitioning local feature space and eliminating unusual cases from further analysis, indicating that it is a better option than MLP for some remote sensing applications and deserves more research.

The most popular deep learning algorithm for spatial pattern analysis, convolutional neural networks (CNNs), are made to identify the spatial features—such as edges, corners, textures, or more abstract shapes—that best characterize a target class or quantity (Kattenborn et al., 2021). Convolutions, or multiple and sequential transformations of the input data on various spatial scales (such as via pooling operations), are the fundamental building blocks for learning these characteristics because they make it easier to recognize and combine both high-level concepts and low-level information (Kattenborn et al., 2021). In their 2017 study, Kussul et al. highlighted the advantages of CNNs in remote sensing applications over more conventional techniques like RF and MLPs. Their research showed that hierarchical representations of spectral and temporal information may be created using CNNs, leading to more precise classification. In particular, they discovered that 2-D CNNs performed better than 1-D CNNs, despite certain restrictions in managing small objects that were smoothed and incorrectly classified in the final classification maps.

To classify crops and distinguish between irrigated and non-irrigated areas, Simón Sánchez et al., (20229 suggested a novel method that makes use of CNNs. Using convolution-based algorithms to make multispectral temporal patterns explicit, they were able to improve classification accuracy by organizing pixel information as a 2D yearly fingerprint. They also added oversampling methods to handle phenological changes and improve the classification process' resilience. The study highlighted how well CNNs performed in comparison to other models, with CNNs providing a good balance between classification accuracy and computational efficiency. Teimouri et al. (2022) noted that CNNs have a high computational cost in addition to the demand for large training datasets in CNN-based crop classification. They also emphasized the significance of precisely creating virtual training samples from real data in order to effectively meet this requirement. Studies comparing CNNs with other classifiers, like MLPs, were carried out by Debella-Gilo & Gjertsen (2021) and Mazzia et al. (2020). CNNs are better at learning than MLPs, according to their research, and the decision between 1-D and 2-D CNN designs is based on certain trade-offs between generalization performance and training time.

Recurrent Neural Networks (RNNs) are a class of deep learning algorithms that account for dependence between sequential inputs (Sharma et al., 2018). RNNs are often employed to account for variations in crop stages over time, as time-series analysis plays a significant role in crop cover classification. The advantage of RNN models in making use of temporal relationships in remote sensing data was emphasized by Ndikumana et al. (2018). Their study showed that RNNs are useful for identifying and taking advantage of temporal correlations, especially in classes that show consistent temporal patterns over extended periods. Because of this feature, RNN models are superior to popular classification strategies that do not leverage temporal correlations directly. Furthermore, RNN-based methods excelled in identifying temporal relationships in remote sensing data, which improved classification precision for a variety of agricultural classes. Mazzia et al. (2020) conducted a comparison between the suggested Pixel R-CNN model (RNN in combination with CNN) and conventional machine learning techniques, including kernel SVM, RF, gradient boosting machine (XGBoost), and SVM. The results of the study showed that the Pixel R-CNN methodology outperformed these popular techniques in terms of OA and kappa values, highlighting its usefulness in using time-series data for multi-temporal classification problems. Another comparison was made by Farmonov et al. (2023) between conventional machine learning algorithms RF and SVM and their proposed CNN-based method for crop-type mapping. They presented a novel wavelet attention 2-D-CNN that outperformed RF and SVM in terms of classification accuracy and robustness. Their study, which made use of hyperspectral data from the DLR Earth Sensing Imaging Spectrometer sensor (German Aerospace Center, 2019), showed how well the suggested CNN architecture could learn characteristics for the classification of images, especially when it came to adding fine-grained details of features in the high-frequency domain.

Another study utilizing RNN and CNN in combination is conducted by Turkoglu et al. (2021) with the ms-convSTAR technique. This technique encodes a convolutional recurrent neural network (convRNN) with a three-level label hierarchy. This method helps the model acquire joint feature representations for rare classes at higher levels, like orchards, by predicting three labels for each pixel at different granularities. The ms-convSTAR approach uses a CNN-based label-refinement component to provide consistency throughout the classification process, in addition to a hierarchical tree structure of labels to achieve simultaneous classification across several hierarchy levels.

Furthermore, a deep learning technique tailored for multitemporal remote sensing images, the Pixel-Set Encoder–Temporal-Attention Encoder (PSETAE) model (Garnot et al., 2019) is utilized by Weilandt et al. (2023). They demonstrated the method’s superiority over an RF algorithm in terms of F1 score (0.91 for PSE-TAE versus 0.72 for RF). Their results are consistent with earlier studies, although their study employed far larger datasets, and they found that deep learning models perform better since they can handle vast volumes of data iteratively. While the RF algorithm can still be further optimized, preliminary findings suggest that its efficacy might not be on par with the deep learning method.

Distance-based classifiers

Two distance-based classifiers are used in the reviewed studies before ML algorithms become more popular. One of these classifiers is the Spectral Angle Mapper (SAM). SAM is defined by (Boardman, 1993) as a tool enabling swift mapping of spectral similarity between image spectra and reference spectra. By computing the angle between them in a space whose dimensions match the number of bands, SAM compares the spectral similarity between the image and reference spectra, which are obtained from either laboratory or field measurements or extracted from the image, assuming data transformation into 'apparent reflectance' without biases (Kruse et al., 1993). The second most popular distance-based classifier used in the reviewed studies is the Euclidean-based minimum distance classification algorithm (EMD). The primary goal of the technique is to classify an unclassified pixel to the nearest class, where the nearest is established using Euclidean distance in N-band space (Hodgson, 1988). Azar et al. (2016) used a variety of techniques to classify crop cover and found that non-parametric and statistical algorithms, such as MLC and NN, performed better than the distance-based classifiers, EMD, and SAM. The authors explained this underperformance by pointing to the fact that SAM and EMD were originally designed to rely on spectrum information rather than multi-temporal information and that they were also limited in their ability to handle intra-class variance within classification decision rules (Kruse et al., 1993; South et al., 2004).

The number of studies that utilized each classification algorithm annually is depicted in Figure 7. As seen in the figure, MLC became less common after 2018 although its use was more common during the 2010s. The most popular classifier from 2016 to 2022 is RF, but the most popular classification technique in 2023 is NN, which may indicate that deep learning potentially might replace other machine learning techniques in the future. Since machine learning algorithms became more widely utilized, SAM has not been employed.

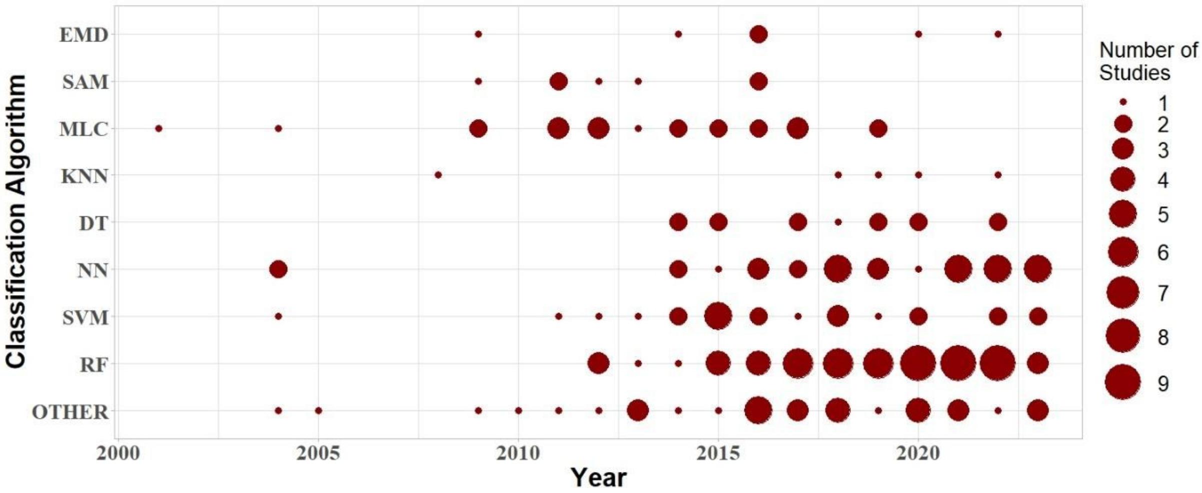

Figure 7. Use of popular classification algorithms over time. (EMD: euclidean-based minimum distance, SAM: spectral angle mapper, MLC: Maximum likelihood classifier, KNN, k-nearest neighbor, DT: decision trees, NN: neural networks, SVM: support vector machines, RF: random forests)

4.2.2. Accuracies obtained by the classification algorithms

The performance comparison of various classification algorithms across studies is illustrated in Figure 8, which also includes the sizes of the study areas. The figure illustrates the relationship between classification algorithms and their accuracy, taking into account the influence of study area size on the choice of algorithm. It shows a trend of increasing study area sizes over time, likely due to advancements in technology and computational resources. Although high accuracies were achieved in the early 2000s, the study areas were more limited. One thing that draws attention is that the maximum likelihood classifier was a promising option for crop classification before machine learning algorithms became popular. The potential of yielding more than 90% accuracy shows that a parametric algorithm can also give satisfactory classification results. However, when machine learning methods started to be used, MLC could not outperform those algorithms and lost its popularity. It can also be observed that the performance of kNN and DT were tested from time to time between 2016-2022 but they never yielded the best accuracy among the options. Similarly, SAM never yields the best results when it is compared to the other methods. Meanwhile, except for one case, NN yielded the best results showing the potential of deep learning techniques. The use of NNin large-scale studies, despite their complexity, indicates their strong performance potential for handling complex tasks. The most commonly used algorithms were RF and SVM, yielding close accuracies. The number of reviewed studies covering areas larger than 30,000 km² demonstrates the widespread use of RF for large-scale classification, with 13 out of 23 large-scale studies utilizing RF. This demonstrates that RF's efficiency for large data sets makes it an ideal tool for mapping crop cover. Considering this close performance and the simplicity of the algorithm, RF can be a favourable choice when +90% accuracy is not aimed.

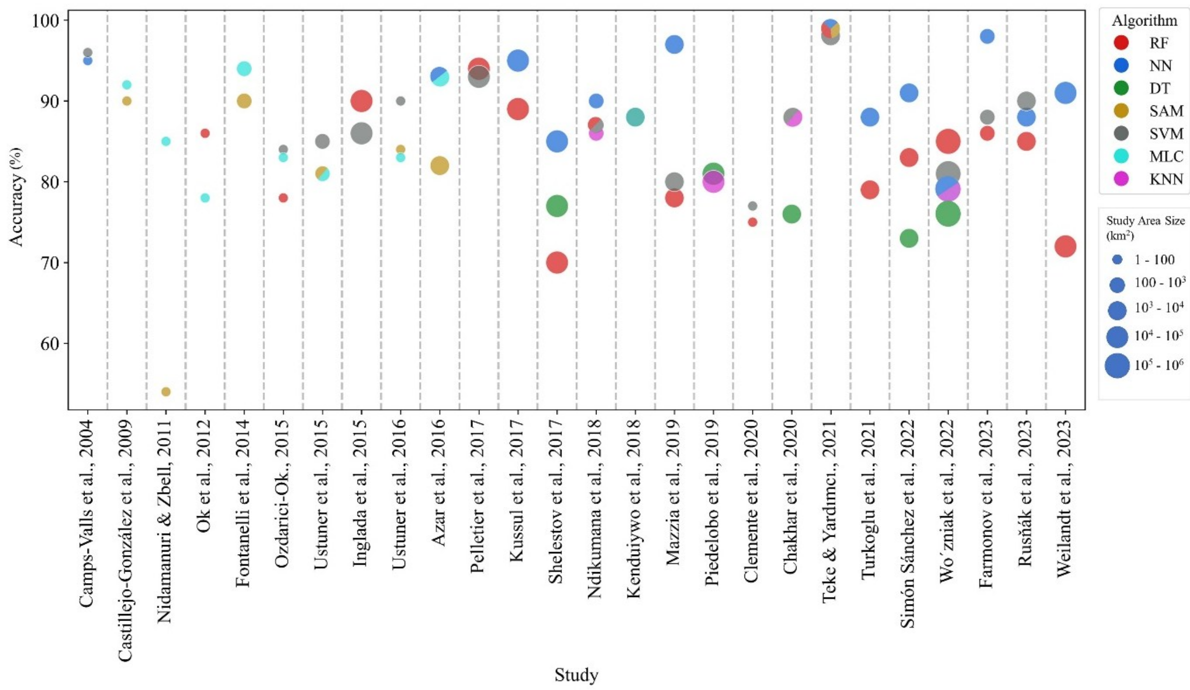

Figure 8. Accuracies from studies that compared the performance of multiple classification algorithms with study area sizes. The colors of the bubbles indicate the type of algorithm used with similar accuracy values grouped in the same bubble, while their size corresponds to the area of the study in square kilometers

4.3. Classification Level

There are two main possible levels of classification units; pixel-level and object-level.

4.3.1. Pixel level classification

With pixel-level classification, each pixel has its input features and each pixel is classified separately. It is simpler and less sophisticated than object-based methods. One of the disadvantages of pixel-level classification is that the images and hence the product map can suffer from salt and pepper noise, and the process of classification can be more computationally costly because of the larger number of units that are classified.

4.3.2. Object level classification

To obtain a crop cover map consisting of objects, pixels can be grouped as single-class objects after the classification. With this method, after the classification is done at the pixel level, majority voting (e.g., Kussul et al., 2016; Vaudour et al., 2015) or taking the mode of all classes within the object (e.g., Turker & Ozdarici, 2011) can be implemented on the pixel's classes over a specified area. To do this, coordinates or areas should be pre-defined such as field boundaries. If the field boundary information is available, then each field can be assigned to a crop class by majority voting of the pixel classes within the field boundary. (e.g., David et al., 2021). If not, classified pixels can be grouped considering spatial relations to eliminate the salt and pepper effect (e.g., Griffiths et al., 2019).

Another way of performing object-based classification is to create the object, in other words, create the pixels groups, image pixels that are similar according to their features can be assigned as a single object to be classified. After grouping, each group (segment, cluster) of pixels is treated as a single object, and the classification is performed at the object level. For crop classification applications, one way of doing this is using available field (parcel) boundary data. Features of the pixels in each field can be represented by single or multiple values for each feature (by taking the mean, median, etc. of the pixels inside the field) and these values can be used as classification inputs to assign a crop class to each field. This method can reduce the computational cost and increase the classification accuracy significantly.

LPIS (or IACS), which supplies the geospatial data for crop delineation and local farmers' declarations as part of their CAP subsidy applications, provided ground truth data and/or object boundary information in many of the reviewed studies (e.g., Sitokonstantinou et al., 2018; Tomppo et al., 2019; Sykas et al., 2022; Ioannidou et al., 2022; Arias et al., 2020; Kyere et al., 2019). These studies calculated parcel-wise statistics to summarize the optical or scattering information of each pixel inside the parcels, like other studies that employed object-based classification with available parcel boundary data through different sources (e.g., Foerster et al., 2012; Larrañaga & Álvarez-Mozos, 2016; Teke & Cetin, 2021).

Object-based classification is also feasible when field data is not available, in this case different segmentation and boundary detection algorithms can be used to create pixel groups and decrease the computational cost of the classification while potentially increasing the classification accuracy by eliminating the salt and pepper effect and minor heterogeneities of the land cover. Studies using segmentation algorithms for before-classification object-based crop classification use statistical measures, most typically the mean value of the pixel features inside of the objects, similar to the studies with parcel boundary information. (e.g., Immitzer et al., 2016; Belgiu & Csillik, 2018; Esch et al., 2014).

Segmentation/Boundary Detection Techniques for Object Level Classification

Segmentation in the context of remote sensing imagery is grouping pixels of the region of interest considering common features of the pixels, according to similarities of those features. Castillejo-González et al. (2009) utilized the Fractal Net Evolution Approach (FNEA) segmentation algorithm on Quickbird imagery before performing segmentation. They highlighted the benefit of the method, emphasizing that users can modify the segmentation output by varying factors like the size, color, and form of the generated image objects in addition to weighing the input data specifications. Hoekman et al. (2011) introduced a new method for unsupervised and supervised image classification that is capable of handling various types of data, including full-polarimetric data, partial-polarimetric data, and multitemporal observations. The method includes several steps. The first step involves (reverse) transforming the full polarimetric radar information into nine backscatter intensity values. Subsequently, the process proceeds to unsupervised clustering, which includes a simple region-growing segmentation, allowing for incomplete and over-segmented regions. Following this, model-based agglomerative clustering and expectation maximization are applied to the pixels within these segments. Classification is then performed using Markov random field filtering applied to the original data. They observed that the unsupervised strategy had significantly more thematic detail while the supervised approach had higher accuracy scores.

To segment Sentinel-2 photos into homogenous objects, Belgiu & Csillik (2018) utilized the multi-resolution segmentation (MRS) algorithm, one of the well-known segmentation approaches in Object-Based Image Analysis (OBIA). They found that segmenting multitemporal images was a useful technique for defining crop fields—particularly those impacted by irrigation systems—which highlights the efficacy of this strategy. The MRS algorithm is also used by Stefanski et al. (2013) to compare the novel method they introduced in their paper. Using a novel segmentation technique and RF for object-based classification of multitemporal data, Stefanski et al. (2013) present a semi-automatic optimization strategy. Several segmentation levels are produced by the Superpixel Contour (SPc) (Mester et al., 2011) method by parameter adjustments within a user-specified range. The best set of parameters is then selected using the RF-provided out-of-bag (OOB) error. They observed that the SPc algorithm produces segmentation maps that are accurate and as good as those of the commonly used MRS, and it is easy to handle with just two primary parameters. The approach suggested by the authors, which selects parameters based on the OOB error rate, is reported to work well and produce better classification accuracy and optimized image segmentation.

The Sequential Maximum a Posteriori (SMAP) (Bouman & Shapiro, 1992) technique was used for segmentation by Xie & Quiel (2000), who emphasized the advantages of this algorithm. The Gaussian mixture distribution spectral class model is used by the SMAP image segmentation technique to process multispectral images. SMAP divides the image into areas by utilizing the fact that neighboring pixels are likely to have the same class, as opposed to segmenting each pixel separately. It works at different resolutions or scales, using coarser segmentations to guide finer ones. In addition to lowering misclassifications, SMAP, according to the authors, also produces more connected regions within a class, which may be useful in some situations.

Esch et al. (2014) used the Definiens Developer software (version 8.7) to segment images before the classification step. They highlighted that the method first presented by Esch et al. (2008) has the goal of minimizing over- and under-segmentation to obtain more accurate results that are especially suited to spatially heterogeneous landscapes. Another way to create objects for object-based classification is edge detection. Some of the reviewed studies preferred this technique instead of segmentation. Inglada et al. (2015) stated that the reason for choosing this technique is that tuning of segmentation approaches is difficult to automatize for different crops and field types, which causes errors. For this reason, the authors used edge-preserving smoothing filtering in the first phase of the mean-shift approach. Another study by Lavreniuk et al. (2018) also used edge detection to approximate the derivatives based on the Sobel operator for each pixel, one for changes in the horizontal direction and another for changes in the vertical direction.

4.3.3. Accuracy comparison

The results of studies that performed classification at both the object and pixel level on the same work area and compared the accuracy at these two levels are given in Figure 9. It can be seen that object-level classification yields better accuracy except for 3 cases: Belgiu & Csillik (2018) over Italy and Matton et al. (2015) over France and Belgium.

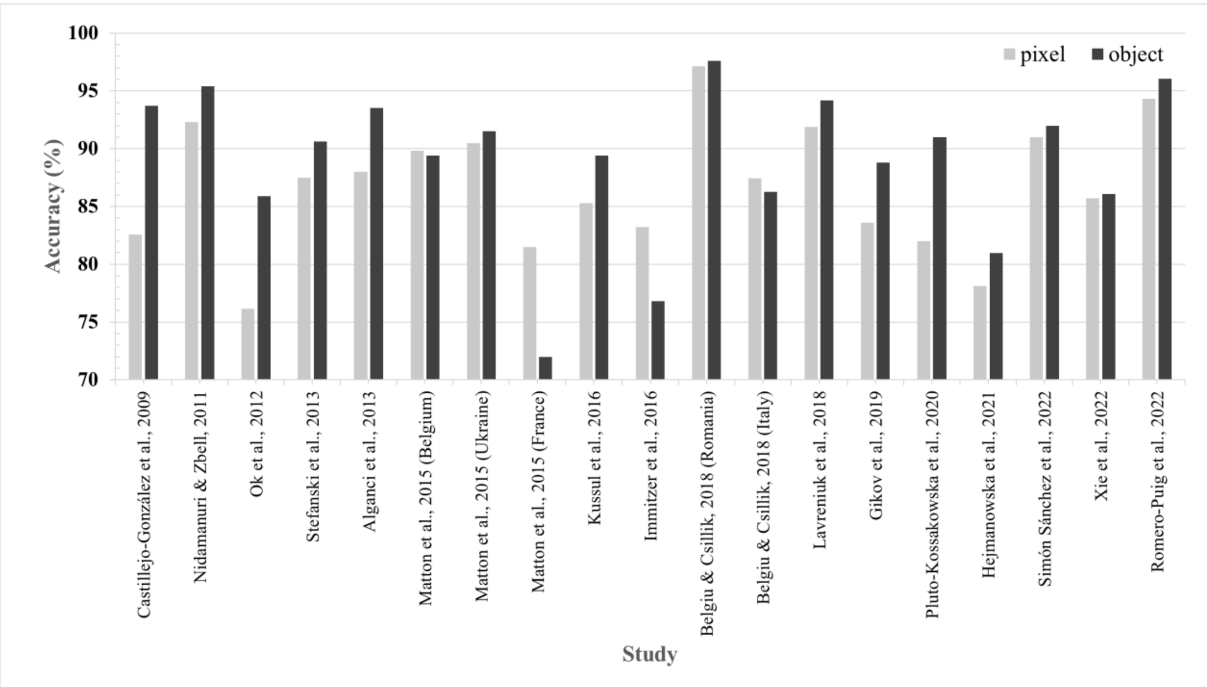

Figure 9. Accuracies from studies that compared the performance of multiple classification levels

4.4. Additional features

Features retrieved from sources other than optical and radar satellites can be used to improve classification accuracy. The most common types of additional features used in crop classification studies are climatic and topographic features. Balzter et al. (2015) analyzed the first two Sentinel-1A SAR image acquisitions over Thuringia, Germany. They used a Digital Terrain Model (DTM), a Canopy Height Model (CHM), and slope and aspect maps from the Shuttle Radar Topography Mission (SRTM) as input bands to analyze the landscape's geomorphological properties. They found that including SRTM-based inputs, such as slope and aspect, improved the classification accuracy by 20.9%. Another study investigating the added utility of topographic features to crop classification was conducted by Demarez et al. (2019), investigating the impact of Sentinel-1 images combined with Landsat 8 optical imagery and DEM. The study is conducted in a temperate zone in southwest France and focuses on irrigated maize crops using the RF classifier. Integrating radar, optical, and SRTM data improved early crop classifications (k = 0.89) as compared to using each data source separately (k = 0.84). While the digital elevation model was useful in the early phases, its effectiveness reduced as crops matured. Kyere et al. (2020) incorporated elevation and slope data from the SRTM-DEM in their study. They utilized multi-temporal Harmonized Landsat Sentinel-2 (HLS) data and a target-oriented cross-validation modeling approach with the RF algorithm to classify 13 crop types. In contrast with the other studies that evaluated the performance of SRTM, they reported that the addition of topographic information to the spectral predictors did not enhance the overall classification performance. Pageot et al. (2020) proposed a method to identify irrigated and rainfed plots in a temperate region (southwestern France) by combining Sentinel-2, Sentinel-1, and SAFRAN (Durand et al., 1993) meteorological time series data using RF classification algorithm. Using monthly cumulative indices obtained from these satellite data, the study used two years of data with various meteorological characteristics to evaluate the performance of the method over different climatic conditions. The authors reported that combining data from radar, optical, and weather sources improved irrigated crop categorization accuracy compared to individual data sources. Blickensdörfer et al. (2022) used predictor factors such as terrain, temperature, and precipitation to address agro-ecological gradients across Germany, as well as extensive time series data from Sentinel-2 and Landsat 8, paired with monthly Sentinel-1 composites. Topographic variables like elevation, hillslope, and aspect were calculated using a DEM given by the German Federal Agency for Cartography and Geodesy, as well as the Topographic Wetness Index (TWI) (Gruber & Peckham, 2009). Climate parameters such as temperature and precipitation were studied using high-resolution climatological data, with special attention paid to deviations from average climatology for the years 2017-2019. Meteorological and soil moisture data has been obtained from the German weather service. 39 environmental factors were developed to capture regional and seasonal changes in growing conditions. Integrating optical, SAR and environmental data improved total accuracy by 6% to 10% over single-sensor strategies. Seasonal and long-term environmental variables were included in the model to account for variability, resulting in enhanced parcel homogeneity and less regional-specific class confusion identified through visual interpretation of the maps.

4.5. Additional Methods

Some extra steps can be implemented to increase the accuracy or to decrease the computational cost of the classification. In this section, additional methods used in the reviewed studies enhancing the classification either by increasing accuracy or decreasing computational time are presented.

4.5.1. Hierarchical Classification

Hierarchical classification performs classification multiple times on different granularities. Results of the first classification granularity level with coarser classes can be used to mask irrelevant classes before the classification with more detailed classes (i.e., the first classification divides the study area as cropland & non-cropland, then performing classification over cropland for different crop types). This method can potentially decrease the computational cost by reducing the study area of the detailed classification. It can also potentially increase classification accuracy by eliminating classes that can be confused with detailed classes beforehand (e.g., Chen et al., 2009; Turkoglu et al., 2021). Asam et al. (2022) performed a two-phase hierarchical classification to first distinguish the cropland area and classify the crop cover in the second phase. Similarly, Van Tricht et al. (2018) and d'Andrimont et al. (2021) first performed a classification with broad land cover classes and performed a second level of classification for crop classes. With the hierarchical approach Van Tricht et al., (2018) reported improved accuracy (+1.5% OA) compared to the non-hierarchical approach in which classification is performed in one single step. As a different approach to the implementation of hierarchical classification, Foerster et al. (2012) first classified the whole data into three groups consisting of summer crops, winter crops, and perennial field grass/fallow land, and in the second phase, single crops are classified with their NDVI temporal profiles.

4.5.2. Feature Selection

For a more efficient classification, the number of classification features can be decreased by performing feature selection or feature reduction. Feature selection is a way of decreasing the number of the classification of features according to their contribution to classification performance. This way features that have less contribution to the accuracy are eliminated from the input dataset. The most widely used feature selection method in the reviewed papers is random forest importance (e.g., Inglada et al., 2016; Sitokonstantinou et al., 2018; Van Tricht et al., 2018; Crnojevic et al., 2014; Kenduiywo et al., 2017; Loosvelt et al., 2012; Kyere et al., 2020) that offers an equitable method of comparison that can assist in determining the predictor variables that are actually meaningful (Strobl et al., 2008). On the other hand, feature reduction is reducing the number of features to keep only the most relevant information, but not necessarily keeping the original features. A common method used in the reviewed paper is principal component analysis (PCA). PCA is used to fit a low-dimensional subspace to a set of data points in a high-dimensional space (Vidal et al., 2005). PCA is used for feature space reduction in two of the reviewed studies; Mazzia et al. (2020) and Schmedtmann & Campagnolo (2015). Performing feature selection instead of reduction can be more useful in terms of understanding the contribution of certain features to the classification.

Separability Analysis can be performed to be informed and take action about how the algorithm's capability of discriminating each class combination. Dabboor et al. (2014) describe the Jeffries-Matusita (JM) distance as a frequently used statistical separability criterion with a parametric nature, as well as its typical application for separability assessment using the normal distribution. They point out that it takes into account the distance and distribution values of class means by including covariance matrices, implying that it may be used to assess dataset eligibility for classification and highlight areas that require more features. Arias et al. (2020) use the JM distance, calculating a mean value across the study period to compare the significance of various polarizations and statistical features.

4.5.3. Division of the Study Area

When classification is performed over large areas, the study area can be divided into sub-areas for several reasons; decreasing the computational time by parallel computing considering the spatial variations of features, and compensating for the different data availability over the study area. Studies with divided study areas are given in Table 4 with the comparison of the accuracies of different division units. It can be concluded that dividing the study area considering the climatic information increases the accuracy while only using administrative units does not.

Table 4. Accuracies from studies that compared the performance of multiple division units

Study	Division units	Accuracy
Inglada et al., 2017	tile	82%
	climatic	86%
Arias et al., 2020	no division	72%
	agroclimatic regional	77%
Asam et al., 2022	no division	75.5%
	landscape regions	74.7%
Campos-Taberner et al., 2023	no division	≥ 11.0 pp
	regional	≥ 3.0 pp

5. Conclusion

The primary goal of this study is to evaluate crop classification studies across Europe and report the impact of various methodologies and data sources on classification accuracy. It aims to determine the advantages of each method for constructing a crop map with the aim of high accuracy. The report also serves as a review of crop classification efforts over the last 23 years in Europe, as well as the types of data sources available. The reviewed studies' limitations include a lack of reliable and long-term ground truth datasets, as well as computational capacity. It is also observed that - probably due to these factors - large-scale and country-scale crop maps are rarely provided. A comparison of the accuracy contributions of remote sensing methods reveals that optical products provide more information for crop identification than radar products while integrating optical information with radar backscatter improves classification accuracy. Future research should focus on cloud masking and gap-filling algorithms to use the information provided by optical products, as there is no one-size-fits-all solution for dealing with cloud cover. Red-edge and spectral indices for optical products, as well as VV channels with Haralik textures for radar products, are demonstrated to be useful crop classification features. The incorporation of multitemporal image data was found to improve classification accuracy when the image dates were chosen according to crop growth patterns in the study area. Temporal composites of multiple date images are a possible solution when computational efficiency is a concern or data gaps exist due to cloud cover over the study area.

When comparing the accuracy contributions of classification methods, deep learning algorithms stand out due to their specialized features for spatial and temporal data, as well as their superior performance compared to other ML and distance-based classification algorithms. As it becomes more common to use and adjust DL algorithms for crop classification, future studies might entirely rely on DL algorithms. Even though DL outperforms other ML methods, RF stands out as a simple and efficient method for large-scale crop mapping due to its comparatively high accuracy and low computational cost. Object-based classification produces higher accuracies and more homogeneous crop maps than pixel-based techniques. Despite their clear advantages, field boundary data is difficult to obtain, and segmentation algorithms require additional focus. Topographic and climatic factors have been demonstrated to improve classification accuracy, but they are not sufficient alone for effective crop classification. It is also recommended to employ topographic and climatic data to divide the study area to increase classification accuracy.

Limitations encountered throughout the evaluation process included a lack of reporting of computing cost in the crop classification literature, resulting in a lack of discussion and conclusion concerning the efficiency of the approaches. Moving forward, more research and resources are needed across various aspects of crop mapping, including refining cloud cover techniques, enhancing segmentation algorithms, and augmenting the availability of ground truth data to achieve greater accuracy and practicality in crop classification studies and applications.

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Appendix

Table S1. Reviewed studies with mapping year and study areas

Study / Map	Mapping Year	STUDY AREA
Alganci et al., 2013	2010	Hilvan, Turkey
Arias et al., 2018	2016	Pamplona, Spain
Arias et al., 2020	2016	Navarre, Spain
Asam et al., 2022	2018	Germany
Azar et al., 2016	2013	Lombardy, Italy
Balzter et al., 2015	2014	Thuringia, Germany
Bargiel & Herrmann, 2011	2009	Fuhrberger Feld, Germany Gorajec, Poland
Bargiel, 2017	2015- 2016	Northern Germany
Belgiu & Csillik, 2018	2016	Bărăgan Plain, Romania southern Lombardy and northern Emilia-Romagna, Italy
Benevides et al., 2021	2018	Alentejo region, Portugal
Blickensdörfer et al., 2022	2017-2020	Germany
Busquier et al., 2020	2009	Near the city of Hanover, Germany
Busquier et al., 2021	2020	Iberian Peninsula in the Castilla y León region, Spain
Busquier et al., 2022	2017	BXII sector, Seville, Spain
Campos-Taberner et al., 2023	2019–2020 agronomic year	Castell´o & Valencia & Alacant, Spain
Camps-Valls et al., 2004	1999	Barrax, Spain
Castillejo-González et al., 2009	2004	Córdoba, Spain
Chakhar et al., 2020	2017	a semiarid region in the southeast of Spain
Clemente et al., 2020	2019	south of Empoli and west of Florence, Tuscany region, Italy
Crnojevic et al., 2014	2013	Vojvodina, Serbia
d'Andrimont et al., 2021	2018	EU

David et al., 2021	2017	France
De Wit & Clevers, 2004	1999	Netherlands
Debella-Gilo & Gjertsen, 2021	2019	Norway
Defourny et al., 2019	2016	Ukraine Occitanie, France
Demarez et al., 2019	2015	near Toulouse, France
Dey et al., 2021	2015	Seville, Spain
Dimitrov et al., 2021	2019	Bulgaria
Durgun et al., 2016	2015	Flanders Belgium, Kyiv Ukraine
Farmonov et al., 2023	2021	Mez˝ohegyes, Békés County, Hungary
Foerster et al., 2012	growing seasons 1994-1995	Havel River catchment, Germany
Fontanelli et al., 2014	2013	Lombardy region, framed within the Po river plain and the Ticino river basin, Italy
Fontanelli et al., 2022	2020-2021	Ponte a Elsa, Italy
Foody, 2004		Feltwell, UK
G. Xie & Niculescu, 2022	2019	Finistère, France
Gallo et al., 2023	2016–2018	Lombardy, Italy
Gella et al., 2021	2018	eastern Netherlands Over Ijssel province
Ghazaryan et al., 2018	2015-2016	Vasilkovsky, Ukraine
Gikov et al., 2019		Zlatia and Belozem, Bulgaria
Giordano et al., 2020	2016	the Seine et Marne and the Alpes de Haute-Provence, France
Griffiths et al., 2019		Germany
Hejmanowska et al., 2021	2018	near Pozna´n, Poland
Heupel et al., 2018	growing seasons 2015-2016	DEMMIN test area, Germany
Hoekman et al., 2011	1991 Netherlands 2006 Germany	Flevoland, Netherlands DEMMIN test area, Germany

Hütt et al., 2020	2017	Rur basin, Germany
Immitzer et al., 2016	2015	Marchfeld, Austria
Inglada et al., 2015	2012	test sites in France, Belgium, Ukraine
Inglada et al., 2016	2015	near Toulouse, France
Inglada et al., 2017	2014	France
Ioannidou et al., 2022	2018	Navarre district, Spain
Karjalainen et al., 2008	2003	near the city of Seinäjok, Finland
Kenduiywo et al., 2017	2009	Fuhrberg, Germany
Kenduiywo et al., 2018	2015	Hannover, Germany
Kluger et al., 2021	2017	Occitanie, France
Kussul et al., 2015	2013	Kyiv, Ukraine
Kussul et al., 2016	Kyiv 2013–2015 Odessa 2014–2015	Kyiv & Odessa, Ukraine
Kussul et al., 2017	2015	Kyiv, Ukraine
Kussul et al., 2018	2013-2016	Bilotserkivskiy, Ukraine
Kyere et al., 2019	2005-2015	Nothern Hesse, Germany
Kyere et al., 2020	2016-2017-2018?	Northern Hesse, Germany
Lapini et al., 2020	2019	Val d’Elsa, Italy
Larrañaga & Álvarez-Mozos, 2016	2010	Pamplona, Spain
Lavreniuk et al., 2019	2016	
Lavreniuk, Kussul, & Novikov, 2018	2016-2017	JECAM test site, Kyiv, Ukraine
Lavreniuk, Kussul, Shelestov, et al., 2018	2017	JECAM test site, Kyiv, Ukraine
Lin et al., 2022	2018, 2019	Hauts-de-France, France
Loosvelt, Peters, Skriver, De Baets, et al., 2012	1998	Foulum test site, Denmark
Loosvelt, Peters, Skriver, Lievens, et al., 2012	1998	Foulum test site, Denmark

Luo et al., 2022	2018, 2019	England, Netherlands, Germany, Denmark, France, Italy, Poland, Hungary, Slovakia, Czech Republic
M. Teimouri et al., 2022	2018	Catalonia, Spain
Martínez-Casasnovas et al., 2005	1993, 1994, 1996-2000	Flumen irrigation district, Ebro Valley, Spain
Matton et al., 2015	2013	JECAM test sites in Belgium, France, Ukraine
Mazzia et al., 2020	2016	Carpi, Italy
Mestre-Quereda et al., 2020	2017	Sevilla, Spain
Metzger et al., 2021	2016Germany 2019 Zurich	north of Munich, Germany Swiss cantons of Zurich and Thurgau
N. Teimouri et al., 2019	2017	Several regions in Denmark
Nasirzadehdizaji et al., 2019	2016	Konya basin, Turkey
Ndikumana et al., 2018	2017	Camargue, France
Nidamanuri & Zbell, 2011a	2003,2004	Dedelow, Germany
Nidamanuri & Zbell, 2011b	1999	Dedelow, Germany
Nidamanuri & Zbell, 2011c	1999	Dedelow, Germany
Nidamanuri & Zbell, 2012	1999	Dedelow, Germany
Ntouros et al., 2009	2003	Kavala, Greece
Ok et al., 2012	2004	Karacabey, Turkey
Orynbaikyzy et al., 2020	2017	Brandenburg, Germany
Osman et al., 2012	2009	Toulouse, France
Ozdarici-Ok et al., 2015	2004,2008	Karacabey, Turkey
Pageot et al., 2020	2017-2018	Adour Amont watershed, France
Palchowdhuri et al., 2018	2016	Coalville, UK
Pelletier et al., 2016	2013	south of France
Pelletier et al., 2017	2013	south of France
Piedelobo et al., 2019	2017	Duero river basin, Spain
Planque et al., 2021	2018	Wales, UK

Pluto-Kossakowska et al., 2020	2016	Lublin Upland, Poland
Preidl et al., 2020	2016	Germany
Romero-Puig et al., 2022	2015	Sevilla, Spain
Rusňák et al., 2023	2018-2022	Danubian Lowland and eastern Slovakian lowland, Slovakia
Rußwurm & Körner, 2018	2016,2017	north of Munich, Germany
Rußwurm et al., 2023	2017	Brittany, France near Hollfeld, Germany
Schmedtmann & Campagnolo, 2015	2012	Ribatejo, Portugal
Selea, 2023	2019–2020	Austria, Belgium, Spain, Denmark, and the Netherlands
Shelestov et al., 2017	2013	JECAM test site in Ukraine
Siachalou et al., 2015	2010	Thessaloniki, Greece
Siachalou et al., 2017	2010	Thessaloniki, Greece
Siesto et al., 2021	2017-2020	Mérida and Don Benito, Spain
Simón Sánchez et al., 2022	2018	Albacete, Spain
Sitokonstantinou et al., 2018	2016	Navarra, Spain
Skakun et al., 2016	2015	JECAM test site, Ukraine
Skriver et al., 2011	2006	Demmin agricultural test site, Germany
Skriver, 2011	1998	Foulum agricultural test site, Denmark
Snevajs et al., 2022	2020	Rostenice farm,in South Moravia, Czech Republic
Stefanski et al., 2013	2011	Luxembourg Bonn, Germany
Sykas et al., 2022	2019-2020	Catalonia France
Teke & Cetin, 2021	2013-2015	Harran Plain, Turkey
Tomppo et al., 2019	2017	southwestern part of Finland
Turker & Arikan, 2005	2000	Karacabey, Turkey
Turker & Ozdarici, 2011	2004	Karacabey, Turkey
Turkoglu et al., 2021	2019	Zurich and Thurgau, Switzerland

Ustuner et al., 2014		Aegean region, Turkey
Ustuner et al., 2015	2012	Aydin, Turkey
Ustuner et al., 2016	2012	Aydin, Turkey
Valcarce-Diñeiro et al., 2019	2015	Castilla y Leon, Spain
Valero et al., 2021	2016, 2017	near Toulouse, France
Van Tricht et al., 2018		Belgium
Vaudour et al., 2015	2013	Alluets plateau Yvelines, France
Villa et al., 2015	2013, 2014	Lombardy, Italy
Vuolo et al., 2018	2016, 2017	Marchfeld, Austria
Waldhoff et al., 2012	2008-2010	Rur catchment, Germany
Waldhoff et al., 2017	2015	Rur catchment, Germany
Weilandt et al., 2023	2018-2020	Brandenburg, Mecklenburg-Vorpommern, and Thuringia, Germany
Woźniak et al., 2022	2019, 2020	Poland
X. Xie & Quiel, 2000	1998, 1999	near the city of Halmstad, Sweden
CORINE	1990, 2000, 2006, 2012, 2018	Europe and Turkey
CROME	2016-2021	England
THEIA	2016-2022	France

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