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Satellite remote sensing-based crop cover classification over Europe: accuracy of different methodological approaches

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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 Haralick textures for radar. Compared to traditional machine learning and distance-based classification methods, deep learning algorithms have been shown to achieve superior performance. 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 accuracy.

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KEYWORDS
Crop mapping; classification accuracy; supervised classification; meta-analysis; preprocessing; postprocessing

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

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use and production (Dhumal, YogeshRajendra, and Mehrotra 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, Gessner, and Conrad (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 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 colour, 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, 148 relevant papers remain, including 13 conference papers and 135 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. First, 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 a within-study comparison, the accuracy of the methods is compared by analysing 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 illustrates the study areas covered in the reviewed papers and maps. Each country is colour-coded based on the total number of studies conducted within its borders, while the number of national-scale studies is indicated numerically inside each country. In addition, smaller study areas are marked with red dots on the map. Although crop classification studies exist for many European countries, comprehensive, countrywide classification maps remain scarce in most regions. Most studies focus on France and Germany, with multiple countrywide crop maps available. In particular, Germany stands out as the leading country in terms of both the overall number of studies and those conducted at the national level. Conversely, there is a noticeable lack of studies in Eastern and Northern Europe.

Figure 2 presents a histogram showing the extent of the areas covered by the reviewed studies, revealing that large-scale studies are still relatively limited. Among them, d'Andrimont et al. (2021) offer the broadest coverage, producing the first continental-scale crop map at a 10-metre resolution across the EU-28 countries. This study leverages Sentinel-1 data (Attema et al. 2010) and the 2018 LUCAS Copernicus

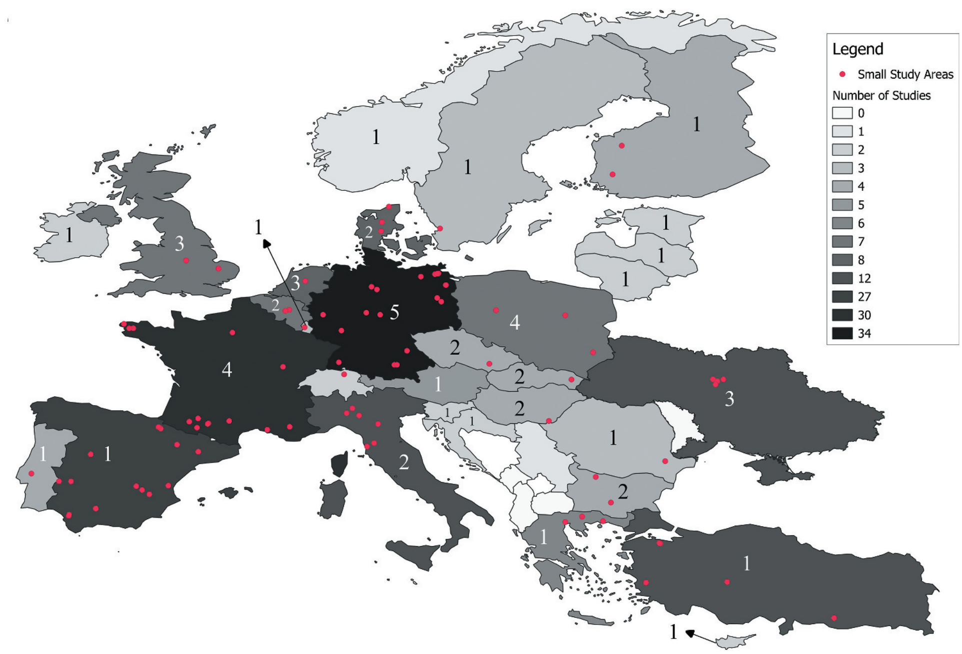

Figure 1. Study areas of the reviewed papers and maps. Each country is colour-coded according to the number of total studies over the country. The number of national-scale studies is also shown in numbers inside the country's borders.

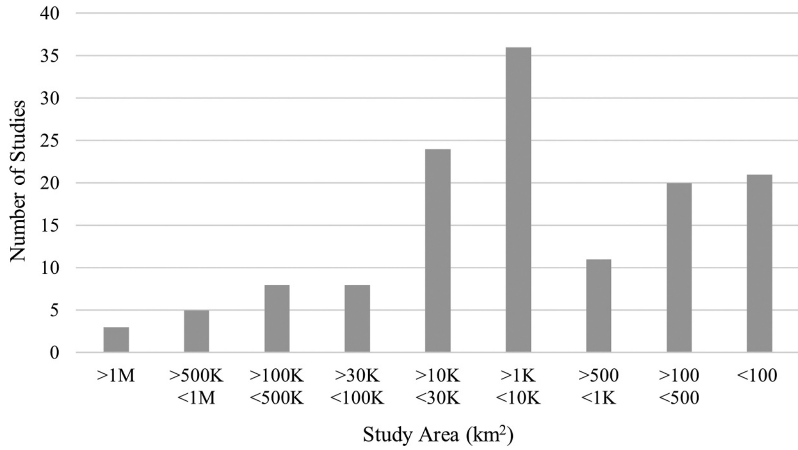

Figure 2. Histogram of the extent of the study areas of the reviewed studies.

survey to identify 19 crop types using Random Forest (RF) classification (Breiman 2001). Using the same ground truth data and covering the same spatial extent, Ghassemi et al. (2022a) produced the second remote sensing – based crop-type map of EU countries, this time relying on Sentinel-2 imagery (European Space Agency 2018).

3.2. Ground truth

Supervised classification requires reference data, often referred to as 'ground-truth' data, to train the model. In addition to this training data, a separate, independent dataset is essential for evaluating the classification's performance. In the context of remote sensing-based crop classification, ground-truth data typically consists of crop type information linked to specific geographic coordinates. One way to gather ground truth data, that is used in the reviewed studies (e.g. Kussul et al. 2015; Shelestov et al. 2017; X. Xie and 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 and Kristian Gjertsen 2021; Heupel, Spengler, and Itzerott 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; N. Teimouri, Dyrmann, and Nyholm Jørgensen 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; Ghassemi et al. 2022).

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 nation-wide 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. As an alternative or complementary approach, M. M. Teimouri et al. (2023) proposed generating virtual training labels by subdividing existing training samples into subclasses using self-organizing maps and assigning labels to unlabelled pixels based on their distance to these subclasses in feature space. This method reduces the need for extensive manual labelling and can improve classification accuracy by effectively expanding the training dataset, addressing a common challenge in supervised crop mapping.

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 labelled 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. Additionally, Weikmann, Paris, and Bruzzone (2021) contribute TimeSen2Crop, a pixel-based dataset containing over one million Sentinel-2 time-series samples for 16 crop types across Austria. And 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 and Körner (2018)	Munich, Germany			X
Tricht et al. (2018)	Belgium	X		
Griffiths, Nendel, and Hostert (2019)	Germany	X		
Preidl, Lange, and Doktor (2020)	Germany	X		
Turkoglu et al. (2021)	Zurich and Thurgau, Switzerland		X	X
d'Andrimont et al. (2021)	Europe	X		
Martini et al. (2021)	Brittany, France		X	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		
Fare Garnot, Vivien, and Chehata (2022)	France		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
Han et al. (2023)	Brandenburg, Germany		X	X
Rusňák et al. (2023)	Danubian Lowland & Slovakian Lowlands, Slovakia		X	
Rußwurm et al. (2023)	Brittany, France & Bavaria, Germany			X

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

Study	Class number	Accuracy
Bargiel and 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%
Ghassemi et al. (2022)	21 individual classes	77.6%
	8 grouped classes	82.5%

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.

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 and 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, Sidiropoulos, and Muller 2019).

As is seen in Figure 3, 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-metre spatial (for visible and NIR bands) and 5-day temporal resolution (European Space Agency 2018). Shorter re-visit times also come

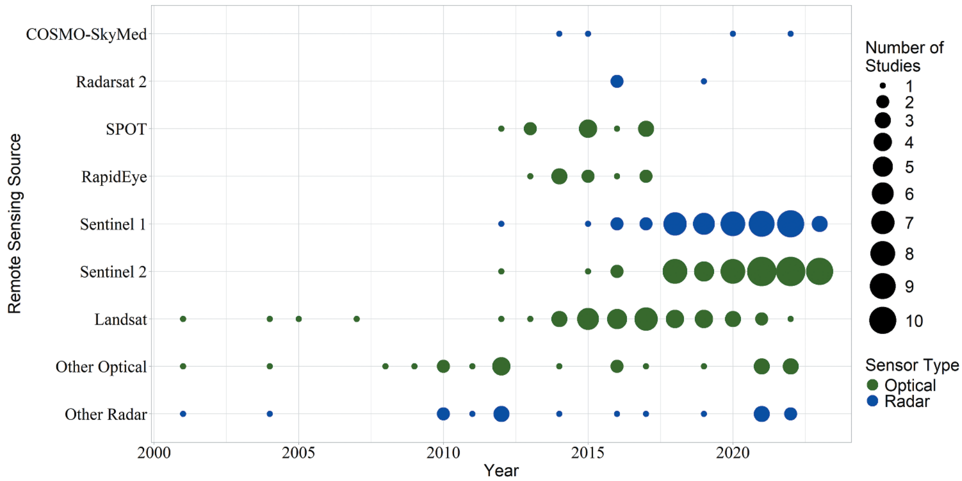

Figure 3. Use of popular remote sensing products over time.

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.

4.1.1.1. 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 and 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 and 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, Balik Sanli, and Dixon 2015) with its capability of capturing the chlorophyll content of the target vegetation. In the reviewed studies, Ustuner, Balik Sanli, and Dixon (2015) observed that by including the red-edge band in the classification, the OA increases by up to 4.6%, and Griffiths, Nendel, and Hostert (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, Vuolo, and Atzberger (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, and Ray 2009). Many of the studies that are reviewed emphasize the importance of SWIR bands for crop classification. Immitzer, Vuolo, and Atzberger (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 the 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 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, Esbensen, and Geladi 1987), Schmedtmann and 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 analysing 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 20, 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, Vuolo, and Atzberger (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 and 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 Tricht et al. (2018). Beyond its strong performance in classification, NDVI also offers computational advantages. According to Lozano-Tello et al. (2023) neural network models trained solely on NDVI reduced training time by 59.35% and required less storage compared to models using all 12 Sentinel-2 bands, while maintaining nearly equivalent accuracy. Finally, 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 colour factor to reduce the influence of soil colour 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, Merzlyak, and Lichtenthaler 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. Finally, Sitokonstantinou et al. (2018) showed that the Plant Senescence Reflectance Index (PSRI) (Filella and Peñuelas 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.

4.1.1.2. 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 and 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 and 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 and Cetin 2021).

Multi-Mission Atmospheric Correction and Cloud Screening (MACCS) tool is a method for cloud detection and atmospheric correction developed by Petrucci 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 and Kristian Gjertsen 2021; Giordano et al. 2020; Inglada et al. 2015, 2016; Orynbaikyzy et al. 2020; Pageot et al. 2020; Pelletier et al. 2016; Teke and 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 (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). As another sophisticated method to mitigate the cloud cover – related limitations on optical-based crop classification efforts, Zhou et al. (2023) applied contrastive learning to fill cloud-induced gaps by transforming spectral data into complete time-series feature representations. Their method uses temporal consistency augmentation and spectral band masking, combined with crop-type information, to learn robust feature embeddings that reconstruct missing data. This approach improves gap filling and enhances classification accuracy without relying on traditional interpolation techniques.

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 and 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.

4.1.2.1. 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-metre 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.

4.1.2.2. 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, Campo-Bescós, and Álvarez-Mozos 2018; Clemente et al. 2020; Karjalainen, Kaartinen, and Hyyppä 2008; Mestre-Quereda et al. 2020; Tomppo, Antropov, and Praks 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 and Herrmann (2011) and Fontanelli et al. (2022) show that VV polarization yields superior performance compared to HH, and Busquier, Lopez-Sanchez, and Bargiel (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.

4.1.2.3. Haralick textures. Haralick et al. (1973) proposed quantifying the spatial relationship between neighbouring 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). Haralick 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 Haralick textures. In their study, Demarez et al. (2019) showed that Haralick textures, especially the entropy of channel VV, outperformed 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 Haralick, local statistics, ratios, and raw images, Haralick 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

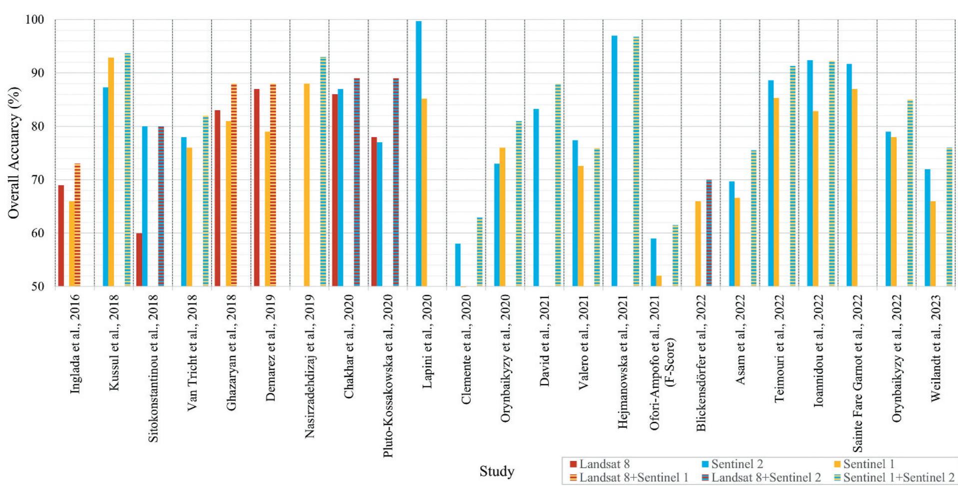

Figure 4. Accuracies from studies that compared the performance of multiple remote sensing sources.

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 three 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 outperforms 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.

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 analyse time series and/or perform harmonic analysis of the reflectance changes over time. By integrating temporal patterns of reflectance and backscatter, these methods allow more accurate discrimination of crop types, particularly those with similar spectral properties at individual time points.

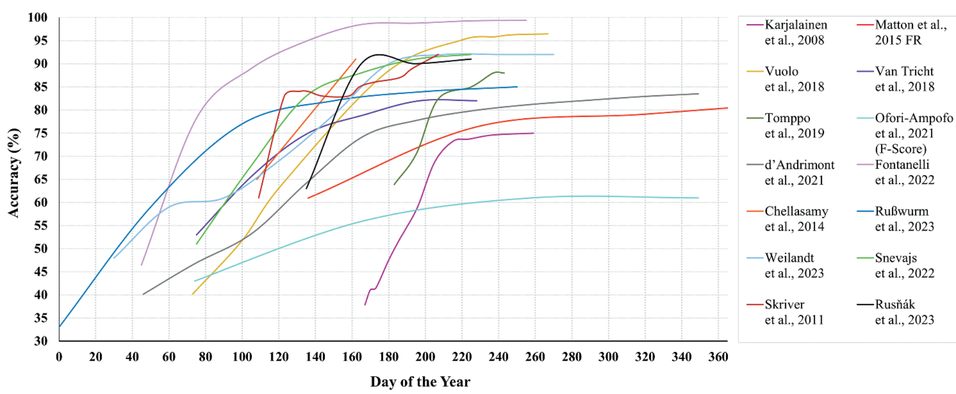

Figure 5. Accuracies from studies that compared the performance of multitemporal information and observed more than 15% accuracy increase with added temporal data.

Studies investigating multitemporal classification are given in Figures 5 and 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 the 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, Giordano, and Mallet (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, M. 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 the 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, Antropov, and Praks (2019)), which show a significant increase in accuracy, barley and

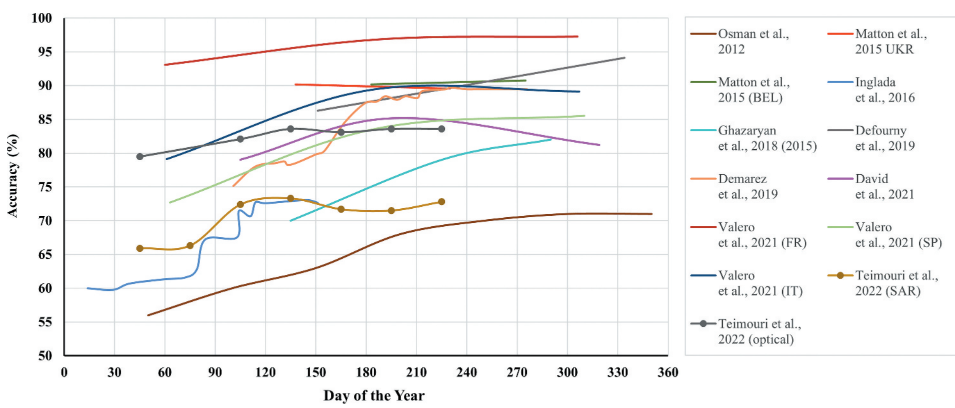

Figure 6. Accuracies from studies that compared the performance of multitemporal information and observed less than 15% accuracy increase with added temporal data.

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 M. 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.

The figures also show that from 2008 to 2023 there has been a consistent and growing interest in multitemporal classification methods. Early work in the late 2000s and early 2010s has already explored these approaches, and since then, the frequency and variety of research using multitemporal remote sensing data have increased significantly. The continued rise in publications over recent years indicates that multitemporal classification has become a standard and essential practice in crop monitoring studies. This trend highlights the increasing recognition of the value of temporal dynamics in remote sensing for accurately distinguishing crop types and understanding growth patterns, which single-date classifications often fail to achieve.

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, Nendel, and Hostert (2019) attribute this

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

Study	Resampling Unit	Accuracy (%)
Griffiths, Nendel, and Hostert (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 and Kristian 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

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 and Kristian 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.

4.2. Classification algorithms

4.2.1. Overview of classification algorithms

In this section of the study, the most commonly used classifiers are briefly explained, and their advantages and limitations in comparison to other methods are highlighted based on the reviewed studies.

4.2.1.1. 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 and 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.

4.2.1.2. 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, Waldhoff, and Bareth (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 and Vapnik 1995). Another advantage of RF is the ease of use and low computational cost of the algorithm, which makes the algorithm more popular for large-scale applications when compared to more complex classification algorithms such as neural networks and SVM. Stefanski, Mack, and Waske (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, Akar, and Gungor (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.

4.2.1.3. 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, Im, and Ogole 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, Im, and Ogole 2011). SVM splits the problem into binary classification subproblems, fclasses (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, Balik Sanli, and Dixon (2015) highlighted SVM's effectiveness in achieving high classification accuracy with small training datasets. Ustuner, Balik Sanli, and Dixon (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 and 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.

4.2.1.4. 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 and 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 and 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.

4.2.1.5. 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.

4.2.1.6. Neural Networks. To identify patterns in data, neural networks (NN) use a chain of interconnected input, hidden, and output layers. The architecture of the 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 a 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. (2022) 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. M. 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 and Kristian Gjertsen (2021) and Mazzia, Khaliq, and Chiaberge (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, Liu, and Yang 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, Khaliq, and Chiaberge (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. In line with recent advances in spatio-temporal modelling, a novel approach called Spatio-Temporal Multi-level Attention (STMA) was proposed by Han et al. (2023) to improve crop classification using time-series SAR imagery. Unlike traditional DL-based models that operate with limited spatio-temporal receptive fields, STMA integrates multi-scale spatio-temporal features through a multi-level attention mechanism. Additionally, it employs a learnable spatial attention position encoding to adaptively generate position priors, enhancing the extraction of multi-granularity features.

Furthermore, a deep learning technique tailored for multitemporal remote sensing images, the Pixel-Set Encoder – Temporal-Attention Encoder (PSETAE) model (V. S. F. 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.

4.2.1.7. 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. 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, Jiaguo, and Lusch 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.

4.2.2. Accuracies obtained by the classification algorithms

RF is the most frequently used classification method in crop classification studies due to its robustness, simplicity, and efficiency. It handles high-dimensional and non-normally

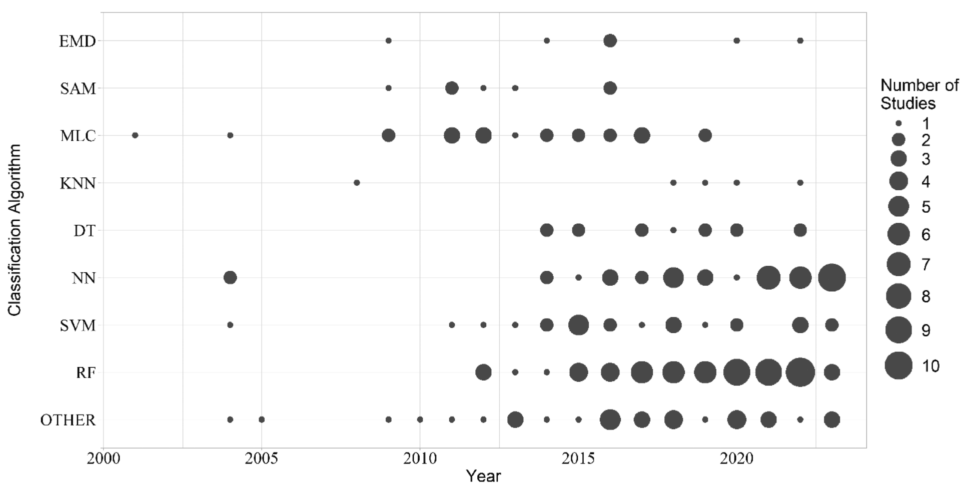

Figure 7. Use of popular classification algorithms over time. (EMD: Euclidean-based minimum distance, SAM: spectral angle mapper, MLC: maximum likelihood classifier, KNN, k-nearest neighbour, DT: decision trees, NN: neural networks, SVM: support vector machines, RF: random forests).

distributed data effectively (Hütt, Waldhoff, and Bareth 2020) and remains resilient to label noise (Pelletier et al. 2017). Its ease of use and low computational cost make it well-suited for large-scale applications (Woźniak et al. 2022), and it performs reliably across varying hyperparameter settings (Ok, Akar, and Gungor 2012). However, despite these strengths, RF can be outperformed by more advanced models when temporal or spatial complexity is high.

Support Vector Machines (SVM) are the second most applied technique, valued for their ability to manage high-dimensional feature spaces and define optimal separating hyperplanes. SVMs perform well even with small training datasets (Ustuner, Balik Sanli, and Dixon 2015), adapt to various data distributions (Rusňák et al. 2023), and effectively filter noisy features (Camps-Valls et al. 2004). Their performance often surpasses conventional approaches like Maximum Likelihood Classification (MLC) and neural networks in specific scenarios. However, SVMs can be computationally expensive and sensitive to kernel and parameter choices, especially with large datasets.

Maximum Likelihood Classification (MLC), though more traditional, continues to show strong performance, especially with medium-resolution, multi-temporal satellite data. Several studies have shown MLC outperforming distance-based classifiers such as Euclidean Minimum Distance (EMD) and Spectral Angle Mapper (SAM) (Azar et al. 2016; Castillejo-González et al. 2009; Fontanelli et al. 2014). Its strengths lie in statistical modelling, but it is less effective when intra-class variability is high or when spectral information alone is insufficient for discrimination.

Neural networks (NNs), including multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), offer powerful tools for handling complex, high-dimensional, and temporally rich data. MLP ensembles have been shown to outperform RF, SVM, and decision trees in some cases (Shelestov et al. 2017). CNNs are particularly effective at learning spatial and spectral hierarchies (Kussul et al. 2017), with 2-D architectures generally offering better accuracy than 1-D CNNs. RNNs further enhance performance by modelling temporal dependencies, improving classification of crop types with consistent seasonal patterns (Mazzia, Khaliq, and Chiaberge 2020). Hybrid architectures like Pixel R-CNN and attention-based CNNs (Farmonov et al. 2023) achieve superior accuracy and robustness but come with increased computational demands and often require large, well-annotated datasets.

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 decision trees (DT) were tested from time to time between 2016 and 2022, but they never yielded the best accuracy among the options. Similarly, SAM never yields the best results

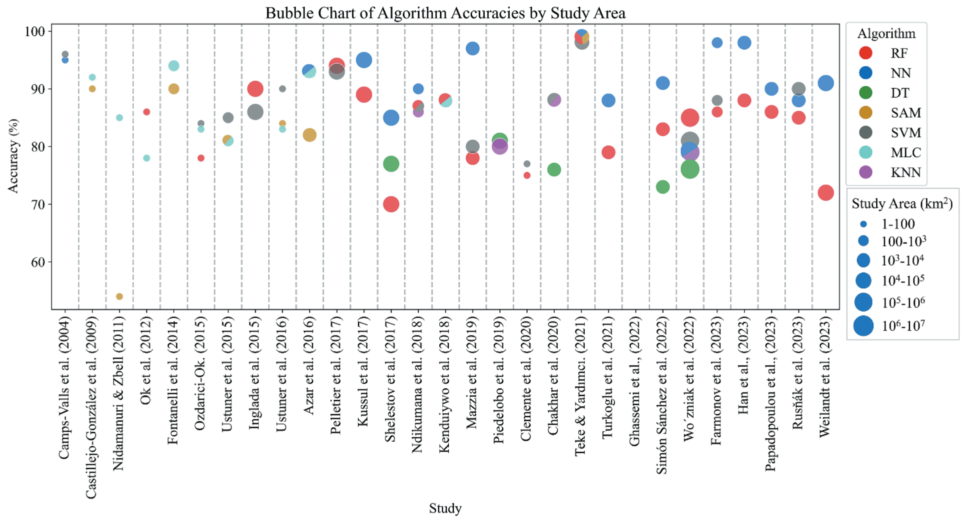

Figure 8. Accuracies from studies that compared the performance of multiple classification algorithms with study area sizes. The colours of the bubbles indicate the type of algorithm used with similar accuracy values grouped in the same bubble, while their size corresponds to the area of the study in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

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 NN in 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 km^2 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.

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, Noirot-Cosson, and Membrive 2015) or taking the mode of all classes within the object (e.g. Turker and 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, Giordano, and Mallet 2021). If not, classified pixels can be grouped considering spatial relations to eliminate the salt and pepper effect (e.g. Griffiths, Nendel, and Hostert 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. Arias, Ángel Campo-Bescós, and Álvarez-Mozos 2020; Ioannidou et al. 2022; Kyere et al. 2019; Sitokonstantinou et al. 2018; Sykas et al. 2022; Tomppo, Antropov, and Praks 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 and Álvarez-Mozos 2016; Teke and 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. Belgiu and Csillik 2018; Esch et al. 2014; Immitzer, Vuolo, and Atzberger 2016).

4.3.2.1. 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, colour, and form of the generated image objects in addition to weighing the input data specifications. Hoekman, Vissers, and Tran (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 and 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, Mack, and Waske (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, Mack, and Waske (2013) present a semi-automatic optimization strategy. Several segmentation levels are produced by the Superpixel Contour (SPc) (Mester, Conrad, and Guevara 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 and Shapiro 1992) technique was used for segmentation by X. Xie and 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 neighbouring 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, Kussul, Shelestov, 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.

A more recent approach is panoptic segmentation, which combines classification and segmentation by simultaneously detecting parcel boundaries and classifying each parcel's crop type without relying on predefined field boundaries (Kirillov et al. 2019). This method was tested by Fare Garnot, Vivien, and Chehata (2022) for crop classification using the publicly available PASTIS-R – Panoptic Segmentation of Radar and Optical Satellite image Time Series dataset. Although it underperformed compared to object-based methods using known parcel boundaries, it still outperformed pixel-based approaches, demonstrating strong potential when parcel boundary information is unavailable.

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 three cases: Belgiu and Csillik (2018) over Italy and Matton et al. (2015) over France and Belgium.

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) analysed 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 analyse the landscape's geomorphological properties. They found that including

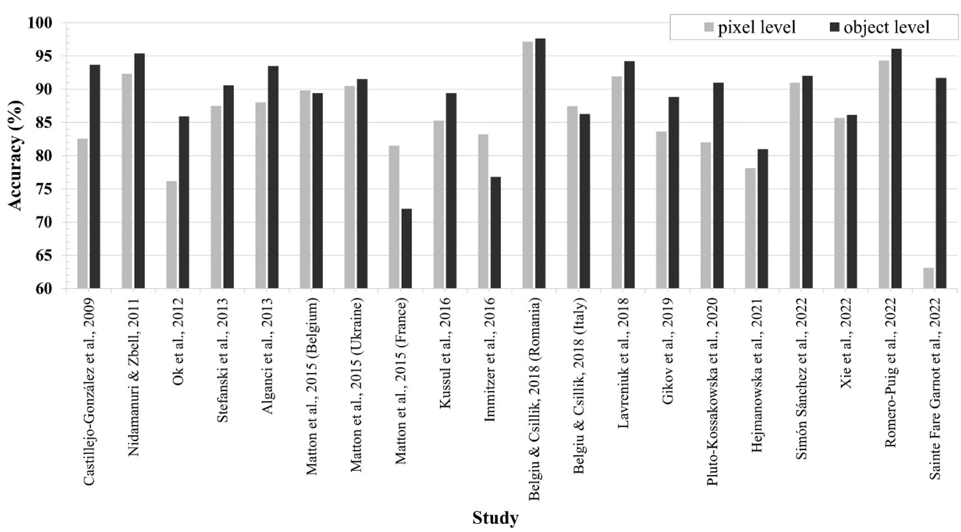

Figure 9. Accuracies from studies that compared the performance of multiple classification levels.

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 the 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 modelling 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 meteorological time-series data using an RF classification algorithm. Using monthly cumulative indices obtained from these satellite data, the study used 2 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 and Peckham 2009). Climate parameters such as temperature and precipitation were studied using high-resolution climatological data, with special attention paid to deviations from the average climatology for the years 2017–2019. Meteorological and soil moisture data has been obtained from the German weather service. Thirty-nine environmental factors were developed to capture regional and seasonal changes in growing conditions. Integrating optical, SAR and environmental data improved the 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, 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 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. Lastly Ya'nan et al. (2024) implemented hierarchical crop classification with a first level grouping crops by growing season (summer, winter, spring, and other) at the coarse level, followed by individual crop classification at the fine level. Their method employs a tree hierarchical loss (THL) to enforce consistency between levels and a temporal proposal block (TPB) to focus on important time segments for detailed classification.

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); Tricht et al. (2018); Crnojevic et al. (2014); Kenduiywo, Bargiel, and Soergel (2017); 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. PCA is used for feature space reduction in two of the reviewed studies; Mazzia, Khaliq, and Chiaberge (2020) and Schmedtmann and 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)

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, Ángel Campo-Bescós, and Álvarez-Mozos (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
Donmez, Yilmaz, and Yucel (2024)	no divison	91.54%
	temperature zones	92.35%

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, Ángel Campo-Bescós, and Álvarez-Mozos (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 subareas 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.

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, and integrating optical information with radar backscatter improves classification accuracy. To maximize the potential of optical remote sensing, future research should prioritize developing advanced cloud masking and gap-filling algorithms, since no universal solution exists for handling cloud cover. Among optical features, red-edge bands and spectral indices contribute most significantly to classification accuracy, with studies consistently highlighting NDVI as one of the top-performing spectral indicators for crop classification. Additionally, SAVI, which reduces the influence of soil brightness and colour, proves especially beneficial when classifying crops at early growth stages where the underlying soil is still visible through the sparse vegetation canopy. Another important index, the GNDVI, which uses the green band instead of the red, is more sensitive to chlorophyll content and is thus likely more effective for plants with larger leaves or more advanced phenological stages. For radar data, VV channels combined with Haralick texture features have proven useful for crop classification. When comparing the performance of VV and VH polarizations, VV generally yields higher accuracy. This is attributed to VV's higher signal-to-noise ratio (SNR) and smaller temporal decorrelation compared to VH. However, studies have shown that using the ratio VH/VV improves results beyond using each polarization separately. Furthermore, combining VV and VH polarizations provides the highest classification accuracy compared to using individual backscatter coefficients or the cross-ratio index (VH/VV) alone or in combination.

The incorporation of multitemporal image data was found to improve classification accuracy when image acquisition dates were selected according to crop growth patterns in the study area. Peaks in accuracy typically occur between DOY 120 and 150 (May) and DOY 180 to 210 (July), indicating substantial variations in spectral and scatter signatures during these periods for major crops. However, accuracy improvements vary depending on study design, climatic conditions, and cropping systems. Combining spectrally similar crops like barley and wheat into single classes tends to reduce accuracy gains from temporal data, while separating them can lead to higher classification improvements. Frequent temporal observations are particularly valuable for distinguishing crops with similar growth stages. When computational efficiency or cloud cover limits the use of frequent observations, temporal composites of multiple-date images offer a practical alternative to maintain classification accuracy.

When comparing the accuracy contributions of different classification methods, DL algorithms consistently stand out. Recent advancements in DL, including CNNs, RNNs, and transformer-based architectures, enable the extraction of complex spatial and temporal features from multi-source remote sensing data. These models can capture subtle phenological variations and spatial patterns across crop types, which traditional ML algorithms often fail to detect. Moreover, developments in transfer learning, data augmentation, and attention mechanisms have further improved DL performance, allowing models to generalize better across regions and seasons. As a result, DL-based approaches have increasingly demonstrated superior accuracy in crop classification, suggesting that future studies may progressively rely on DL as the primary method. Despite the clear advantages of DL, classical ML methods, particularly RF, remain highly relevant. RF continues to offer a robust combination of high accuracy, low computational cost, and ease of implementation, making it suitable for large-scale crop mapping where processing resources are limited. Recent improvements in RF, such as optimized hyperparameter tuning, ensemble strategies, and integration with feature selection techniques, have further enhanced its efficiency and performance, ensuring it remains a practical alternative when DL is not feasible.

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 insufficient 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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References

Abdel Latif, B., R. Lecerf, G. Mercier, and L. Hubert-Moy. 2008. "Preprocessing of Low-Resolution Time Series Contaminated by Clouds and Shadows." *IEEE Transactions on Geoscience & Remote Sensing* 46 (7): 2083–2096. https://doi.org/10.1109/TGRS.2008.916473.

Alami, M. M., L. E. Mansouri, Y. Imani, O. Bourja, O. Lahlou, Y. Zennayi, F. Bourzeix, I. Hanadé Houmma, and R. Hadria. 2023. "Crop Mapping Using Supervised Machine Learning and Deep Learning: A Systematic Literature Review." *International Journal of Remote Sensing* 44 (8): 2717–2753. https://doi.org/10.1080/01431161.2023.2205984.

Alganci, U., E. Sertel, M. Ozdogan, and C. Ormeci. 2013. "Parcel-Level Identification of Crop Types Using Different Classification Algorithms and Multi-Resolution Imagery in Southeastern Turkey." *Photogrammetric Engineering & Remote Sensing* 79 (11): 1053–1065. https://doi.org/10.14358/PERS.79.11.1053.

Almalki, R., M. Khaki, P. M. Saco, and J. F. Rodriguez. 2022. "Monitoring and Mapping Vegetation Cover Changes in Arid and Semi-Arid Areas Using Remote Sensing Technology: A Review." *Remote Sensing* 14 (20): 5143. https://doi.org/10.3390/rs14205143.

Andrimont, R. D., A. Verhegghen, G. Lemoine, P. Kempeneers, M. Meroni, and M. van der Velde. 2021. "From Parcel to Continental Scale – A First European Crop Type Map Based on Sentinel-1 and LUCAS Copernicus In-Situ Observations." *Remote Sensing of Environment* 266 (December): 112708. https://doi.org/10.1016/j.rse.2021.112708.

Arias, M., M. Ángel Campo-Bescós, and J. Álvarez-Mozos. 2020. "Crop Classification Based on Temporal Signatures of Sentinel-1 Observations Over Navarre Province, Spain." *Remote Sensing* 12 (2): 278. https://doi.org/10.3390/rs12020278.

Arias, M., M. A. Campo-Bescós, and J. Álvarez-Mozos. 2018. "Crop Type Mapping Based on Sentinel-1 Backscatter Time Series." *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium* 6623–6626. https://doi.org/10.1109/IGARSS.2018.8519005.

Asam, S., U. Gessner, R. Almengor González, M. Wenzl, J. Kriese, and C. Kuenzer. 2022. "Mapping Crop Types of Germany by Combining Temporal Statistical Metrics of Sentinel-1 and Sentinel-2 Time Series with LPIS Data." *Remote Sensing* 14 (13): 13. https://doi.org/10.3390/rs14132981.

Attema, E., C. Cafforio, M. Gottwald, P. Guccione, A. Monti Guarnieri, F. Rocca, and P. Snoeij. 2010. "Flexible Dynamic Block Adaptive Quantization for Sentinel-1 SAR Missions." *IEEE Geoscience & Remote Sensing Letters* 7 (4): 766–770. https://doi.org/10.1109/LGRS.2010.2047242.

Azar, R., P. Villa, D. Stroppiana, A. Crema, M. Boschetti, and P. Alessandro Brivio. 2016. "Assessing In-Season Crop Classification Performance Using Satellite Data: A Test Case in Northern Italy." *European Journal of Remote Sensing* 49 (1): 361–380. https://doi.org/10.5721/EuJRS20164920.

Balzter, H., B. Cole, C. Thiel, and C. Schmullius. 2015. "Mapping Corine Land Cover from Sentinel-1A SAR and SRTM Digital Elevation Model Data Using Random Forests." *Remote Sensing* 7 (11): 14876–14898. https://doi.org/10.3390/rs71114876.

Bargiel, D. 2017. "A New Method for Crop Classification Combining Time Series of Radar Images and Crop Phenology Information." *Remote Sensing of Environment* 198 (September): 369–383. https://doi.org/10.1016/j.rse.2017.06.022.

Bargiel, D., and S. Herrmann. 2011. "Multi-Temporal Land-Cover Classification of Agricultural Areas in Two European Regions with High Resolution Spotlight TerraSAR-X Data." *Remote Sensing* 3 (5): 859–877. https://doi.org/10.3390/rs3050859.

Barnes, EM, TR Clarke, SE Richards, P.D. Colaizzi, J. Haberland, M. Kostrzewski, P. Waller, et al. 2000. "Coincident Detection of Crop Water Stress, Nitrogen Status and Canopy Density Using Ground Based Multispectral Data." 1691 (6).

Belgiu, M., and O. Csillik. 2018. "Sentinel-2 Cropland Mapping Using Pixel-Based and Object-Based Time-Weighted Dynamic Time Warping Analysis." *Remote Sensing of Environment* 204 (January): 509–523. https://doi.org/10.1016/j.rse.2017.10.005.

Benevides, P., H. Costa, F. D. Moreira, D. Moraes, and M. Caetano. 2021. "Annual Crop Classification Experiments in Portugal Using Sentinel-2." *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, Brussels, Belgium. Vol. 11, 5838–5841. July. https://doi.org/10.1109/IGARSS47720.2021.9555009.

Blickensdörfer, L., M. Schwieder, D. Pflugmacher, C. Nendel, S. Erasmi, and P. Hostert. 2022. "Mapping of Crop Types and Crop Sequences with Combined Time Series of Sentinel-1, Sentinel-2 and Landsat 8 Data for Germany." *Remote Sensing of Environment* 269 (February): 112831. https://doi.org/10.1016/j.rse.2021.112831.

Bouman, C., and M. Shapiro. 1992. "Multispectral Image Segmentation Using a Multiscale Model." 3:565–568.

Breiman, L. 2001. "Random Forests." *Machine Learning* 45:5–32. https://doi.org/10.1023/A:1010933404324.

Bremer, D. J., H. Lee, K. Su, and S. J. Keeley. 2011. 'Relationships between Normalized Difference Vegetation Index and Visual Quality in Cool-Season Turfgrass: II. Factors Affecting NDVI and Its Component Reflectances'. Crop Science 51 (5): 2219–2227. https://doi.org/10.2135/cropsci2010.12.0729.

Busquier, M., J. M. Lopez-Sanchez, and D. Bargiel. 2020. "Added Value of Coherent Copolar Polarimetry at X-Band for Crop-Type Mapping." *IEEE Geoscience & Remote Sensing Letters* 17 (5): 819–823. https://doi.org/10.1109/LGRS.2019.2933738.

Busquier, M., J. M. Lopez-Sanchez, F. Ticconi, and N. Floury. 2022. "Combination of Time Series of L-, C-, and X-Band SAR Images for Land Cover and Crop Classification." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 15:8266–8286. https://doi.org/10.1109/JSTARS.2022.3207574.

Busquier, M., R. Valcarce-Diñeiro, J. M. Lopez-Sanchez, J. Plaza, N. Sánchez, and B. Arias-Pérez. 2021. "Fusion of Multi-Temporal PAZ and Sentinel-1 Data for Crop Classification." *Remote Sensing* 13 (19): 3915. https://doi.org/10.3390/rs13193915.

Campos-Taberner, M., F. Javier García-Haro, B. Martínez, S. Sánchez-Ruiz, Á. Moreno-Martínez, G. Camps-Valls, and M. Amparo Gilabert. 2023. "Land Use Classification Over Smallholding Areas in the European Common Agricultural Policy Framework." *ISPRS Journal of Photogrammetry & Remote Sensing* 197 (March): 320–334. https://doi.org/10.1016/j.isprsjprs.2023.02.005.

Camps-Valls, G., L. Gomez-Chova, J. Calpe-Maravilla, J. D. Martin-Guerrero, E. Soria-Olivas, L. Alonso-Chorda, and J. Moreno. 2004. "Robust Support Vector Method for Hyperspectral Data Classification and Knowledge Discovery." *IEEE Transactions on Geoscience & Remote Sensing* 42 (7): 1530–1542. https://doi.org/10.1109/TGRS.2004.827262.

Castillejo-González, I. L., F. López-Granados, A. García-Ferrer, J. M. Peña-Barragán, M. Jurado-Expósito, M. S. de la Orden, and M. González-Audicana. 2009. "Object- and Pixel-Based Analysis for Mapping Crops and Their Agro-Environmental Associated Measures Using quickbird Imagery." *Computers and Electronics in Agriculture* 68 (2): 207–215. https://doi.org/10.1016/j.compag.2009.06.004.

Chakhar, A., D. Ortega-Terol, D. Hernández-López, R. Ballesteros, J. F. Ortega, and M. A. Moreno. 2020. "Assessing the Accuracy of Multiple Classification Algorithms for Crop Classification Using Landsat-8 and Sentinel-2 Data." *Remote Sensing* 12 (11): 11. https://doi.org/10.3390/rs12111735.

Cheng, D., S. Zhang, X. Liu, K. Sun, and M. Zong. 2017. "Feature Selection by Combining Subspace Learning with Sparse Representation." *Multimedia Systems* 23 (3): 285–291. https://doi.org/10.1007/s00530-015-0487-0.

Clemente, J. P., G. Fontanelli, G. G. Ovando, Y. L. B. Roa, A. Lapini, and E. Santi. 2020. "Google Earth Engine: Application of Algorithms for Remote Sensing of Crops in Tuscany (Italy)." In *2020 IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS)*, Santiago, Chile. 195–200. https://doi.org/10.1109/LAGIRS48042.2020.9165561 .

Cortes, C., and V. Vapnik. 1995. "Support-Vector Networks." *Machine Learning* 20 (3): 273–297. https://doi.org/10.1023/A:1022627411411.

Crnojevic, V., P. Lugonja, B. Brkljac, and B. Brunet. 2014. "Classification of Small Agricultural Fields Using Combined Landsat-8 and RapidEye Imagery: Case Study of Northern Serbia." *Journal of Applied Remote Sensing* 8 (1): 083512. https://doi.org/10.1117/1.JRS.8.083512.

Dabboor, M., S. Howell, M. Shokr, and J. Yackel. 2014. "The jeffries–Matusita Distance for the Case of Complex Wishart Distribution as a Separability Criterion for Fully Polarimetric SAR Data." *International Journal of Remote Sensing* 35 (19): 6859–6873.

David, N., S. Giordano, and C. Mallet. 2021. "Investigating Operational Country-Level Crop Monitoring with Sentinel~1 and~2 Imagery." *Remote Sensing Letters* 12 (10): 970–982. https://doi.org/10.1080/2150704X.2021.1950940.

Debella-Gilo, M., and A. Kristian Gjertsen. 2021. "Mapping Seasonal Agricultural Land Use Types Using Deep Learning on Sentinel-2 Image Time Series." *Remote Sensing* 13 (2): 289. https://doi.org/10.3390/rs13020289.

Defourny, P., S. Bontemps, N. Bellemans, C. Cara, G. Dedieu, E. Guzzonato, O. Hagolle, et al. 2019. "Near Real-Time Agriculture Monitoring at National Scale at Parcel Resolution: Performance Assessment of the Sen2-Agri Automated System in Various Cropping Systems Around the World." *Remote Sensing of Environment* 221 (February): 551–568. https://doi.org/10.1016/j.rse.2018.11.007.

Demarez, V., F. Helen, C. Marais-Sicre, and F. Baup. 2019. "In-Season Mapping of Irrigated Crops Using Landsat 8 and Sentinel-1 Time Series." *Remote Sensing* 11 (2): 2. https://doi.org/10.3390/rs11020118.

De Wit, A. J. W., and J. G. P. W. Clevers. 2004. “Efficiency and Accuracy of Per-Field Classification for Operational Crop Mapping.” *International Journal of Remote Sensing* 25 (20): 4091–4112. https://doi.org/10.1080/01431160310001619580.

Dey, S., U. Chaudhuri, N. Bhogapurapu, J. M. Lopez-Sanchez, B. Banerjee, A. Bhattacharya, D. Mandal, and Y. S. Rao. 2021. “Synergistic Use of Tandem-X and Landsat-8 Data for Crop-Type Classification and Monitoring.” *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 14:8744–8760. https://doi.org/10.1109/JSTARS.2021.3103911.

Dhumal, R. K., K. V. YogeshRajendra, and S. C. Mehrotra. 2013. “Classification of Crops from Remotely Sensed Images: An Overview.” *International Journal of Engineering Research and Applications (IJERA)* 3 (3): 758–761.

Di, L., and E. Yu. 2023. “Remote Sensing.” In *Remote Sensing Big Data,* edited by Liping Di and Eugene Yu, 17–43. Springer International Publishing. https://doi.org/10.1007/978-3-031-33932-5_2.

Dimitrov, P., L. Filchev, E. Roumenina, and G. Jelev. 2021. “Crop Type Mapping in Bulgaria Using Sentinel-1/2 Data.” *Aerospace Research in Bulgaria* 33:40–50. https://doi.org/10.3897/arb.v33.e04.

Donmez, E., M. T. Yilmaz, and I. Yucel. 2024. “Added Utility of Temperature Zone Information in Remote Sensing-Based Large Scale Crop Mapping.” *Remote Sensing Applications: Society & Environment* 35 (August): 101264. https://doi.org/10.1016/j.rsase.2024.101264.

Durgun, Y., A. Gobin, R. Van De Kerchove, and B. Tychon. 2016. “Crop Area Mapping Using 100-m PROBA-V Time Series.” *Remote Sensing* 8 (7): 585. https://doi.org/10.3390/rs8070585.

Esch, T., A. Metz, M. Marconcini, and M. Keil. 2014. “Combined Use of Multi-Seasonal High and Medium Resolution Satellite Imagery for Parcel-Related Mapping of Cropland and Grassland.” *International Journal of Applied Earth Observation and Geoinformation* 28 (May): 230–237. https://doi.org/10.1016/j.jag.2013.12.007.

Esch, T., M. Thiel, M. Bock, A. Roth, and S. Dech. 2008. “Improvement of Image Segmentation Accuracy Based on Multiscale Optimization Procedure.” *IEEE Geoscience & Remote Sensing Letters* 5 (3): 463–467. https://doi.org/10.1109/LGRS.2008.919622.

European Space Agency. 2018. *Sentinel-2 MSI Level-2A BOA Reflectance*. European Space Agency. https://doi.org/10.5270/S2_-6eb6imz.

European Space Agency. n.d. “‘SPOT 1-5 ESA Archive’.” European Space Agency. https://doi.org/10.5270/esa-6mxo3sr.

Evans, D. L., T. G. Farr, J. J. Van Zyl, and H. A. Zebker. 1988. “Radar Polarimetry: Analysis Tools and Applications.” *IEEE Transactions on Geoscience & Remote Sensing* 26 (6): 774–789.

Fan, D., X. Su, B. Weng, T. Wang, and F. Yang. 2021. “Research Progress on Remote Sensing Classification Methods for Farmland Vegetation.” *AgriEngineering* 3 (4): 971–989. https://doi.org/10.3390/agriengineering3040061.

Fare Garnot, S., L. L. Vivien, and N. Chehata. 2022. “Multi-Modal Temporal Attention Models for Crop Mapping from Satellite Time Series.” *ISPRS Journal of Photogrammetry & Remote Sensing* 187 (May): 294–305. https://doi.org/10.1016/j.isprsjprs.2022.03.012.

Farmonov, N., K. Amankulova, J. Szatmari, A. Sharifi, D. Abbasi-Moghadam, S. M. Mirhoseini Nejad, and L. Mucsi. 2023. “Crop Type Classification by DESIS Hyperspectral Imagery and Machine Learning Algorithms.” *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 16:1576–1588. https://doi.org/10.1109/JSTARS.2023.3239756.

Filella, I., and J. Penuelas. 1994. “The Red Edge Position and Shape as Indicators of Plant Chlorophyll Content, Biomass and Hydric Status.” *International Journal of Remote Sensing* 15 (7): 1459–1470. https://doi.org/10.1080/01431169408954177.

Foerster, S., K. Kaden, M. Foerster, and S. Itzerott. 2012. “Crop Type Mapping Using Spectral–Temporal Profiles and Phenological Information.” *Computers and Electronics in Agriculture* 89 (November): 30–40. https://doi.org/10.1016/j.compag.2012.07.015.

Fontanelli, G., A. Crema, R. Azar, D. Stroppiana, P. Villa, and M. Boschetti. 2014. “Agricultural Crop Mapping Using Optical and SAR Multi-Temporal Seasonal Data: A Case Study in Lombardy Region, Italy.” In *2014 IEEE Geoscience and Remote Sensing Symposium*, Quebec City, QC, Canada. 1489–1492. https://doi.org/10.1109/IGARSS.2014.6946719 .

Fontanelli, G., A. Lapini, L. Santurri, S. Pettinato, E. Santi, G. Ramat, S. Pilia, et al. 2022. “Early-Season Crop Mapping on an Agricultural Area in Italy Using *X*-Band Dual-Polarization SAR Satellite Data and Convolutional Neural Networks." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 15:6789–6803. https://doi.org/10.1109/JSTARS.2022.3198475.

Foody, G. M. 2004. "Supervised Image Classification by MLP and RBF Neural Networks with and without an Exhaustively Defined Set of Classes." *International Journal of Remote Sensing* 25 (15): 3091–3104. https://doi.org/10.1080/01431160310001648019.

Francis, A., P. Sidiropoulos, and J.-P. Muller. 2019. "Cloudfcn: Accurate and Robust Cloud Detection for Satellite Imagery with Deep Learning." *Remote Sensing* 11 (19): 2312. https://doi.org/10.3390/rs11192312.

Gallo, I., L. Ranghetti, N. Landro, R. La Grassa, and M. Boschetti. 2023. "In-Season and Dynamic Crop Mapping Using 3D Convolution Neural Networks and Sentinel-2 Time Series." *ISPRS Journal of Photogrammetry & Remote Sensing* 195 (January): 335–352. https://doi.org/10.1016/j.isprsjprs.2022.12.005.

Garnot, V. S. F., L. Landrieu, S. Giordano, and N. Chehata. 2019. "Satellite Image Time Series Classification with Pixel-Set Encoders and Temporal Self-Attention." Version 1. https://doi.org/10.48550/ARXIV.1911.07757.

Garnot, V. S., L. Landrieu, and N. Chehata. 2022. "Multi-Modal Temporal Attention Models for Crop Mapping from Satellite Time Series." *ISPRS Journal of Photogrammetry & Remote Sensing* 187 (May): 294–305. https://doi.org/10.1016/j.isprsjprs.2022.03.0112.

Gella, G. W., W. Bijker, and M. Belgiu. 2021. "Mapping Crop Types in Complex Farming Areas Using SAR Imagery with Dynamic Time Warping." *ISPRS Journal of Photogrammetry & Remote Sensing* 175 (May): 171–183. https://doi.org/10.1016/j.isprsjprs.2021.03.004.

Ghassemi, B., A. Dujakovic, M. Żółtak, M. Immitzer, C. Atzberger, and F. Vuolo. 2022. "Designing a European-Wide Crop Type Mapping Approach Based on Machine Learning Algorithms Using LUCAS Field Survey and Sentinel-2 Data." *Remote Sensing* 14 (3): 541. https://doi.org/10.3390/rs14030541.

Ghazaryan, G., O. Dubovyk, F. Löw, M. Lavreniuk, A. Kolotii, J. Schellberg, and N. Kussul. 2018. "A Rule-Based Approach for Crop Identification Using Multi-Temporal and Multi-Sensor Phenological Metrics." *European Journal of Remote Sensing* 51 (1): 511–524. https://doi.org/10.1080/22797254.2018.1455540.

Giordano, S., S. Bailly, L. Landrieu, and N. Chehata. 2020. "Improved Crop Classification with Rotation Knowledge Using Sentinel-1 and -2 Time Series." *Photogrammetric Engineering & Remote Sensing* 86 (7): 431–441. https://doi.org/10.14358/PERS.86.7.431.

Gitelson, A. A., M. N. Merzlyak, and H. K. Lichtenthaler. 1996. "Detection of Red Edge Position and Chlorophyll Content by Reflectance Measurements Near 700 Nm." *Journal of Plant Physiology* 148 (3–4): 501–508.

Griffiths, P., C. Nendel, and P. Hostert. 2019. "Intra-Annual Reflectance Composites from Sentinel-2 and Landsat for National-Scale Crop and Land Cover Mapping." *Remote Sensing of Environment* 220 (January): 135–151. https://doi.org/10.1016/j.rse.2018.10.031.

Gruber, S., and S. Peckham. 2009. "Chapter 7 Land-Surface Parameters and Objects in Hydrology." In *Developments in Soil sciencedevelopments in Soil Science*, 33. https://doi.org/10.1016/S0166-2481(08)00007-X.

Han, Z., C. Zhang, L. Gao, Z. Zeng, B. Zhang, and P. M. Atkinson. 2023. "Spatio-Temporal Multi-Level Attention Crop Mapping Method Using Time-Series SAR Imagery." *ISPRS Journal of Photogrammetry & Remote Sensing* 206 (December): 293–310. https://doi.org/10.1016/j.isprsjprs.2023.11.016.

Haralick, R. M., K. Shanmugam, and I. Dinstein. 1973. "Textural Features for Image Classification." *IEEE Transactions on Systems, Man, and Cybernetics SMC-3* 3 (6): 610–621. https://doi.org/10.1109/TSMC.1973.4309314.

Hastie, T., R. Tibshirani, J. H. Friedman, and J. H. Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Vol. 2. Springer.

Heupel, K., D. Spengler, and S. Itzerott. 2018. "A Progressive Crop-Type Classification Using Multitemporal Remote Sensing Data and Phenological Information." *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science* 86 (2): 53–69. https://doi.org/10.1007/s41064-018-0050-7.

Hoekman, D. H., M. A. M. Vissers, and T. N. Tran. 2011. "Unsupervised Full-Polarimetric SAR Data Segmentation as a Tool for Classification of Agricultural Areas." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 4 (2): 402–411. https://doi.org/10.1109/JSTARS.2010.2042280.

Huete, A. R. 1988. "A Soil-Adjusted Vegetation Index (SAVI)." *Remote Sensing of Environment* 25 (3): 295–309. https://doi.org/10.1016/0034-4257(88)90106-X.

Hütt, C., G. Waldhoff, and G. Bareth. 2020. "Fusion of Sentinel-1 With Official Topographic and Cadastral Geodata for Crop-Type Enriched LULC Mapping Using FOSS and Open Data." *ISPRS International Journal of Geo-Information* 9 (2): 120. https://doi.org/10.3390/ijgi9020120.

Immitzer, M., F. Vuolo, and C. Atzberger. 2016. "First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe." *Remote Sensing* 8 (3): 3. https://doi.org/10.3390/rs8030166.

Inglada, J., M. Arias, B. Tardy, O. Hagolle, S. Valero, D. Morin, G. Dedieu, et al. 2015. "Assessment of an Operational System for Crop Type Map Production Using High Temporal and Spatial Resolution Satellite Optical Imagery." *Remote Sensing* 7 (9): 12356–12379. https://doi.org/10.3390/rs70912356.

Inglada, J., A. Vincent, M. Arias, and C. Marais-Sicre. 2016. "Improved Early Crop Type Identification by Joint Use of High Temporal Resolution SAR and Optical Image Time Series." *Remote Sensing* 8 (5): 5. https://doi.org/10.3390/rs8050362.

Inglada, J., A. Vincent, M. Arias, B. Tardy, D. Morin, and I. Rodes. 2017. "Operational High Resolution Land Cover Map Production at the Country Scale Using Satellite Image Time Series." *Remote Sensing* 9 (1): 1. https://doi.org/10.3390/rs9010095.

Ioannidou, M., A. Koukos, V. Sitokonstantinou, I. Papoutsis, and C. Kontoes. 2022. "Assessing the Added Value of Sentinel-1 PolSAR Data for Crop Classification." *Remote Sensing* 14 (22): 5739. https://doi.org/10.3390/rs14225739.

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. *An Introduction to Statistical Learning*. Vol. 112. Springer.

Ji, S., C. Zhang, X. Anjian, Y. Shi, and Y. Duan. 2018. "3D Convolutional Neural Networks for Crop Classification with Multi-Temporal *Remote Sensing* Images." *Remote Sensing* 10 (2): 75. https://doi.org/10.3390/rs10010075.

Joshi, N., M. Baumann, A. Ehammer, R. Fensholt, K. Grogan, P. Hostert, M. Jepsen, et al. 2016. "A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring." *Remote Sensing* 8 (1): 70. https://doi.org/10.3390/rs8010070.

Karjalainen, M., H. Kaartinen, and J. Hyyppä. 2008. "Agricultural Monitoring Using ENVISAT Alternating Polarization SAR Images." *Photogrammetric Engineering & Remote Sensing* 74 (1): 117–126. https://doi.org/10.14358/PERS.74.1.117.

Kattenborn, T., J. Leitloff, F. Schiefer, and S. Hinz. 2021. "Review on Convolutional Neural Networks (CNN) in Vegetation Remote Sensing." *ISPRS Journal of Photogrammetry & Remote Sensing* 173 (March): 24–49. https://doi.org/10.1016/j.isprsjprs.2020.12.010.

Kenduiywo, B. K., D. Bargiel, and U. Soergel. 2017. "Higher Order Dynamic Conditional Random Fields Ensemble for Crop Type Classification in Radar Images." *IEEE Transactions on Geoscience & Remote Sensing* 55 (8): 4638–4654. https://doi.org/10.1109/TGRS.2017.2695326.

Kim, H.-O., and J.-M. Yeom. 2014. "Effect of Red-Edge and Texture Features for Object-Based Paddy Rice Crop Classification Using RapidEye Multi-Spectral Satellite Image Data." *International Journal of Remote Sensing, October* 13:1–23. https://doi.org/10.1080/01431161.2014.965285.

Kirillov, A., K. He, R. Girshick, C. Rother, and P. Dollár. 2019. "Panoptic Segmentation." In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, 9404–9413. IEEE.

Kluger, D. M., S. Wang, and D. B. Lobell. 2021. "Two Shifts for Crop Mapping: Leveraging Aggregate Crop Statistics to Improve Satellite-Based Maps in New Regions." *Remote Sensing of Environment* 262:112488. https://doi.org/10.1016/j.rse.2021.112488.

Kogan, F. 2019. "Vegetation Health Method." In *Remote Sensing for Food Security*, edited by F. Kogan. Springer International Publishing. https://doi.org/10.1007/978-3-319-96256-6_4.

Kruse, F. A., A. B. Lefkoff, J. W. Boardman, K. B. Heidebrecht, A. T. Shapiro, P. J. Barloon, and A. F. H. Goetz. 1993. "The Spectral Image Processing System (sips)—Interactive Visualization and Analysis of Imaging Spectrometer Data." *Remote Sensing of Environment* 44 (2–3): 145–163. https://doi.org/10.1016/0034-4257(93)90013-N.

Kussul, N., G. Lemoine, F. Javier Gallego, S. V. Skakun, M. Lavreniuk, and A. Y. Shelestov. 2016. "Parcel-Based Crop Classification in Ukraine Using Landsat-8 Data and Sentinel-1A Data." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 9 (6): 2500–2508. https://doi.org/10.1109/JSTARS.2016.2560141.

Kussul, N., L. Mykola, A. Shelestov, and S. Skakun. 2018. "Crop Inventory at Regional Scale in Ukraine: Developing in Season and End of Season Crop Maps with Multi-Temporal Optical and SAR Satellite Imagery." *European Journal of Remote Sensing* 51 (1): 627–636. https://doi.org/10.1080/22797254.2018.1454265.

Kussul, N., S. Skakun, A. Shelestov, M. Lavreniuk, B. Yailymov, and O. Kussul. 2015. "'Regional Scale Crop Mapping Using Multi-Temporal Satellite Imagery'." *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XL-7/W3 (April): 45–52. https://doi.org/10.5194/isprsarchives-XL-7-W3-45-2015.

Kyere, I., T. Astor, R. Graß, and M. Wachendorf. 2019. "Multi-Temporal Agricultural Land-Cover Mapping Using Single-Year and Multi-Year Models Based on Landsat Imagery and IACS Data." *Agronomy* 9 (6): 309. https://doi.org/10.3390/agronomy9060309.

Kyere, I., T. Astor, R. Graß, and M. Wachendorf. 2020. "Agricultural Crop Discrimination in a Heterogeneous Low-Mountain Range Region Based on Multi-Temporal and Multi-Sensor Satellite Data." *Computers and Electronics in Agriculture* 179 (December): 105864. https://doi.org/10.1016/j.compag.2020.105864.

Larrañaga, A., and J. Álvarez-Mozos. 2016. "On the Added Value of Quad-Pol Data in a Multi-Temporal Crop Classification Framework Based on RADARSAT-2 Imagery." *Remote Sensing* 8 (4): 335. https://doi.org/10.3390/rs8040335.

Lavreniuk, M., N. Kussul, and A. Novikov. 2018. "Deep Learning Crop Classification Approach Based on Sparse Coding of Time Series of Satellite Data." In *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 4812–4815. July. https://doi.org/10.1109/IGARSS.2018.8518263.

Lavreniuk, M., N. Kussul, A. Shelestov, O. Dubovyk, and F. Löw. 2018. "Object-Based Postprocessing Method for Crop Classification Maps." In *IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium*, Valencia, Spain, 7058–7061. IEEE. https://doi.org/10.1109/IGARSS.2018.8519199.

Lavreniuk, M., A. Shelestov, N. Kussul, O. Rubel, V. Lukin, and K. Egiazarian. 2019. "Use of Modified BM3D Filter and CNN Classifier for SAR Data to Improve Crop Classification Accuracy." In *2019 IEEE 2nd Ukraine Conference on Electrical and Computer Engineering (UKRCON)*, Lviv, Ukraine, 1–6. IEEE. https://doi.org/10.1109/UKRCON.2019.8879805.

Lee, J.-S., and E. Pottier. 2017. *Polarimetric Radar Imaging: From Basics to Applications*. CRC press.

Lin, C., L. Zhong, X.-P. Song, J. Dong, D. B. Lobell, and Z. Jin. 2022. "Early-and in-Season Crop Type Mapping without Current-Year Ground Truth: Generating Labels from Historical Information via a Topology-Based Approach." *Remote Sensing of Environment*, 112994 274.

Löfstedt, T., P. Brynolfsson, T. Asklund, T. Nyholm, and A. Garpebring. 2019. "Gray-Level Invariant Haralick Texture Features." *PLOS ONE* 14 (2): e0212110. https://doi.org/10.1371/journal.pone.0212110.

Loosvelt, L., J. Peters, H. Skriver, B. De Baets, and N. E. C. Verhoest. 2012. "Impact of Reducing Polarimetric SAR Input on the Uncertainty of Crop Classifications Based on the Random Forests Algorithm." *IEEE Transactions on Geoscience & Remote Sensing* 50 (10): 4185–4200. https://doi.org/10.1109/TGRS.2012.2189012.

Loosvelt, L., J. Peters, H. Skriver, H. Lievens, F. M. B. Van Coillie, B. De Baets, and N. E. C. Verhoest. 2012. "Random Forests as a Tool for Estimating Uncertainty at Pixel-Level in SAR Image Classification." *International Journal of Applied Earth Observation and Geoinformation* 19 (October): 173–184. https://doi.org/10.1016/j.jag.2012.05.011.

Lozano-Tello, A., G. Siesto, M. Fernández-Sellers, and A. Caballero-Mancera. 2023. “Evaluation of the Use of the 12 Bands vs. NDVI from Sentinel-2 Images for Crop Identification.” *Sensors* 23 (16): 7132. https://doi.org/10.3390/s23167132.

Luo, Y., Z. Zhang, L. Zhang, J. Han, J. Cao, and J. Zhang. 2022. “Developing High-Resolution Crop Maps for Major Crops in the European Union Based on Transductive Transfer Learning and Limited Ground Data.” *Remote Sensing* 14 (8): 8. https://doi.org/10.3390/rs14081809.

Martínez-Casasnovas, J. A., A. Martín-Montero, and M. Auxiliadora Casterad. 2005. “Mapping Multi-Year Cropping Patterns in Small Irrigation Districts from Time-Series Analysis of Landsat TM Images.” *The European Journal of Agronomy* 23 (2): 159–169. https://doi.org/10.1016/j.eja.2004.11.004.

Martini, M., V. Mazzia, A. Khaliq, and M. Chiaberge. 2021. “Domain-Adversarial Training of Self-Attention-Based Networks for Land Cover Classification Using Multi-Temporal Sentinel-2 Satellite Imagery.” *Remote Sensing* 13 (13): 2564. https://doi.org/10.3390/rs13132564.

Matton, N., G. Canto, F. Waldner, S. Valero, D. Morin, J. Inglada, M. Arias, S. Bontemps, B. Koetz, and P. Defourny. 2015. “An Automated Method for Annual Cropland Mapping Along the Season for Various Globally-Distributed Agrosystems Using High Spatial and Temporal Resolution Time Series.” *Remote Sensing* 7 (10): 13208–13232. https://doi.org/10.3390/rs71013208.

Mazzia, V., A. Khaliq, and M. Chiaberge. 2020. “Improvement in Land Cover and Crop Classification Based on Temporal Features Learning from Sentinel-2 Data Using Recurrent-Convolutional Neural Network (R-CNN).” *Applied Sciences* 10 (1): 238. https://doi.org/10.3390/app10010238.

Mester, R., C. Conrad, and A. Guevara. 2011. “Multichannel Segmentation Using Contour Relaxation: Fast Super-Pixels and Temporal Propagation.” 250–261.

Mestre-Quereda, A., J. M. Lopez-Sanchez, F. Vicente-Guijalba, A. W. Jacob, and M. E. Engdahl. 2020. “Time-Series of Sentinel-1 Interferometric Coherence and Backscatter for Crop-Type Mapping.” *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 13:4070–4084. https://doi.org/10.1109/JSTARS.2020.3008096.

Metzger, N., M. Ozgur Turkoglu, S. D’Aronco, J. Dirk Wegner, and K. Schindler. 2021. “Crop Classification Under Varying Cloud Cover with Neural Ordinary Differential Equations.” *IEEE Transactions on Geoscience & Remote Sensing* 60:1–12. https://doi.org/10.1109/TGRS.2021.3101965.

Mountrakis, G., J. Im, and C. Ogole. 2011. “Support Vector Machines in Remote Sensing: A Review.” *ISPRS Journal of Photogrammetry & Remote Sensing* 66 (3): 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001.

Myneni, R. B., F. G. Hall, P. J. Sellers, and A. L. Marshak. 1995. “The Interpretation of Spectral Vegetation Indexes.” *IEEE Transactions on Geoscience & Remote Sensing* 33 (2): 481–486. https://doi.org/10.1109/TGRS.1995.8746029.

Ndikumana, E., D. Ho Tong Minh, N. Baghdadi, D. Courault, and L. Hossard. 2018. “Deep Recurrent Neural Network for Agricultural Classification Using Multitemporal SAR Sentinel-1 for Camargue, France.” *Remote Sensing* 10 (8): 1217. https://doi.org/10.3390/rs10081217.

Nidamanuri, R. R., and B. Zbell. 2011b. “Transferring Spectral Libraries of Canopy Reflectance for Crop Classification Using Hyperspectral Remote Sensing Data.” *Biosystems Engineering* 110 (3): 231–246. https://doi.org/10.1016/j.biosystemseng.2011.07.002.

Nidamanuri, R. R., and B. Zbell. 2011c. “Use of Field Reflectance Data for Crop Mapping Using Airborne Hyperspectral Image.” *ISPRS Journal of Photogrammetry & Remote Sensing* 66 (5): 683–691. https://doi.org/10.1016/j.isprsjprs.2011.05.001.

Nidamanuri, R. R., and B. Zbell. 2012. “Existence of Characteristic Spectral Signatures for Agricultural Crops – Potential for Automated Crop Mapping by Hyperspectral Imaging.” *Geocarto International* 27 (2): 103–118. https://doi.org/10.1080/10106049.2011.623792.

Ntouros, K. D., I. Z. Gitas, and G. N. Silleos. 2009. “Mapping Agricultural Crops with EO-1 Hyperion Data.” In *2009 First Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, Grenoble, France, 1–4. IEEE. https://doi.org/10.1109/WHISPERS.2009.5289057.

Ok, A. O., O. Akar, and O. Gungor. 2012. "Evaluation of Random Forest Method for Agricultural Crop Classification." *European Journal of Remote Sensing* 45 (1): 421–432. https://doi.org/10.5721/EuJRS20124535.

Orynbaikyzy, A., U. Gessner, and C. Conrad. 2019. "Crop Type Classification Using a Combination of Optical and Radar Remote Sensing Data: A Review." *International Journal of Remote Sensing* 40 (17): 6553–6595. https://doi.org/10.1080/01431161.2019.1569791.

Orynbaikyzy, A., U. Gessner, B. Mack, and C. Conrad. 2020. "Crop Type Classification Using Fusion of Sentinel-1 and Sentinel-2 Data: Assessing the Impact of Feature Selection, Optical Data Availability, and Parcel Sizes on the Accuracies." *Remote Sensing* 12 (17): 2779. https://doi.org/10.3390/rs12172779.

Otukei, J. R., and T. Blaschke. 2010. "Land Cover Change Assessment Using Decision Trees, Support Vector Machines and Maximum Likelihood Classification Algorithms." *International Journal of Applied Earth Observation and Geoinformation* 12:S27–31. https://doi.org/10.1016/j.jag.2009.11.002.

Ozdarici-Ok, A., A. Ok, and K. Schindler. 2015. "Mapping of Agricultural Crops from Single High-Resolution Multispectral Images—Data-Driven Smoothing vs. Parcel-Based Smoothing." *Remote Sensing* 7 (5): 5611–5638. https://doi.org/10.3390/rs70505611.

Pageot, Y., F. Baup, J. Inglada, N. Baghdadi, and V. Demarez. 2020. "Detection of Irrigated and Rainfed Crops in Temperate Areas Using Sentinel-1 and Sentinel-2 Time Series." *Remote Sensing* 12 (18): 3044. https://doi.org/10.3390/rs12183044.

Palchowdhuri, Y., R. Valcarce-Diñeiro, P. King, and M. Sanabria-Soto. 2018. "Classification of Multi-Temporal Spectral Indices for Crop Type Mapping: A Case Study in Coalville, UK." *The Journal of Agricultural Science* 156 (1): 24–36. https://doi.org/10.1017/S0021859617000879.

Panigrahy, R. K., S. S. Ray, and S. Panigrahy. 2009. "Study on the Utility of irs-P6 AWiFS SWIR Band for Crop Discrimination and Classification." *Journal of the Indian Society of Remote Sensing* 37 (2): 325–333. https://doi.org/10.1007/s12524-009-0026-6.

Paola, J. D., and R. A. Schowengerdt. 1995. "A Detailed Comparison of Backpropagation Neural Network and Maximum-Likelihood Classifiers for Urban Land Use Classification." *IEEE Transactions on Geoscience & Remote Sensing* 33 (4): 981–996. https://doi.org/10.1109/36.406684.

Pelletier, C., S. Valero, J. Inglada, N. Champion, and G. Dedieu. 2016. "Assessing the Robustness of Random Forests to Map Land Cover with High Resolution Satellite Image Time Series over Large Areas." *Remote Sensing of Environment* 187 (December): 156–168. https://doi.org/10.1016/j.rse.2016.10.010.

Pelletier, C., S. Valero, J. Inglada, N. Champion, C. Marais Sicre, and G. Dedieu. 2017. "Effect of Training Class Label Noise on Classification Performances for Land Cover Mapping with Satellite Image Time Series." *Remote Sensing* 9 (2): 173. https://doi.org/10.3390/rs9020173.

Petrucci, B., M. Huc, T. Feuvrier, C. Ruffel, O. Hagolle, V. Lonjou, and C. Desjardins. 2015. *MACCS : Multi-Mission Atmospheric Correction and Cloud Screening Tool for High-Frequency Revisit Data Processing*. Edited by Lorenzo Bruzzone. https://doi.org/10.1117/12.2194797.

Piedelobo, L., D. Hernández-López, R. Ballesteros, A. Chakhar, S. Del Pozo, D. González-Aguilera, and M. A. Moreno. 2019. "Scalable Pixel-Based Crop Classification Combining Sentinel-2 and Landsat-8 Data Time Series: Case Study of the Duero River Basin." *Agricultural Systems* 171 (May): 36–50. https://doi.org/10.1016/j.agsy.2019.01.005.

Planque, C., R. Lucas, S. Punalekar, S. Chognard, C. Hurford, C. Owers, C. Horton, et al. 2021. "National Crop Mapping Using Sentinel-1 Time Series: A Knowledge-Based Descriptive Algorithm." *Remote Sensing* 13 (5): 846. https://doi.org/10.3390/rs13050846.

Pluto-Kossakowska, J. 2021. "Review on Multitemporal Classification Methods of Satellite Images for Crop and Arable Land Recognition." *Agriculture* 11 (10): 999. https://doi.org/10.3390/agriculture11100999.

Potgieter, A. B., Y. Zhao, P. J. Zarco-Tejada, K. Chenu, Y. Zhang, K. Porker, B. Biddulph, et al. 2021. "Evolution and Application of Digital Technologies to Predict Crop Type and Crop Phenology in Agriculture." *Silico Plants* 3 (1): diab017. https://doi.org/10.1093/insilicoplants/diab017.

Preidl, S., M. Lange, and D. Doktor. 2020. "Introducing APiC for Regionalised Land Cover Mapping on the National Scale Using Sentinel-2A Imagery." *Remote Sensing of Environment* 240 (April): 111673. https://doi.org/10.1016/j.rse.2020.111673.

Rodriguez-Galiano, V. F., B. Ghimire, J. Rogan, M. Chica-Olmo, and J. Pedro Rigol-Sanchez. 2012. "An Assessment of the Effectiveness of a Random Forest Classifier for Land-Cover Classification." *ISPRS Journal of Photogrammetry & Remote Sensing* 67:93–104. https://doi.org/10.1016/j.isprsjprs.2011.11.002.

Rusňák, T., T. Kasanický, P. Malík, J. Mojžiš, J. Zelenka, M. Sviček, D. Abrahám, and A. Halabuk. 2023. "Crop Mapping Without Labels: Investigating Temporal and Spatial Transferability of Crop Classification Models Using a 5-Year Sentinel-2 Series and Machine Learning." *Remote Sensing* 15 (13): 3414. https://doi.org/10.3390/rs15133414.

Rußwurm, M., N. Courty, R. Emonet, S. Lefèvre, D. Tuia, and R. Tavenard. 2023. "End-to-End Learned Early Classification of Time Series for In-Season Crop Type Mapping." *ISPRS Journal of Photogrammetry & Remote Sensing* 196 (February): 445–456. https://doi.org/10.1016/j.isprsjprs.2022.12.016.

Rußwurm, M., and M. Körner. 2018. "Multi-Temporal Land Cover Classification With Sequential Recurrent Encoders." *ISPRS International Journal of Geo-Information* 7 (4): 129. https://doi.org/10.3390/ijgi7040129.

Schmedtmann, J., and M. Campagnolo. 2015. "Reliable Crop Identification with Satellite Imagery in the Context of Common Agriculture Policy Subsidy Control." *Remote Sensing* 7 (7): 9325–9346. https://doi.org/10.3390/rs70709325.

Selea, T. 2023. "'AgriSen-COG, a Multicountry, Multitemporal Large-Scale Sentinel-2 Benchmark Dataset for Crop Mapping Using Deep Learning'." *Remote Sensing* 15 (12): 2980. https://doi.org/10.3390/rs15122980.

Sharma, A., X. Liu, and X. Yang. 2018. "Land Cover Classification from Multi-Temporal, Multi-Spectral Remotely Sensed Imagery Using Patch-Based Recurrent Neural Networks." *Neural Networks* 105 (September): 346–355. https://doi.org/10.1016/j.neunet.2018.05.019.

Shelestov, A., M. Lavreniuk, N. Kussul, A. Novikov, and S. Skakun. 2017. "Exploring Google Earth Engine Platform for Big Data Processing: Classification of Multi-Temporal Satellite Imagery for Crop Mapping." *Frontiers in Earth Science*: 17. https://doi.org/10.3389/feart.2017.00017.

Siachalou, S., G. Mallinis, and M. Tsakiri-Strati. 2015. "A Hidden Markov Models Approach for Crop Classification: Linking Crop Phenology to Time Series of Multi-Sensor Remote Sensing Data." *Remote Sensing* 7 (4): 3633–3650. https://doi.org/10.3390/rs70403633.

Siachalou, S., G. Mallinis, and M. Tsakiri-Strati. 2017. "Analysis of Time-Series Spectral Index Data to Enhance Crop Identification Over a Mediterranean Rural Landscape." *IEEE Geoscience & Remote Sensing Letters* 14 (9): 1508–1512. https://doi.org/10.1109/LGRS.2017.2719124.

Siesto, G., M. Fernández-Sellers, and A. Lozano-Tello. 2021. "Crop Classification of Satellite Imagery Using Synthetic Multitemporal and Multispectral Images in Convolutional Neural Networks." *Remote Sensing* 13 (17): 3378. https://doi.org/10.3390/rs13173378.

Simón Sánchez, A.-M., J. González-Piqueras, L. de la Ossa, and A. Calera. 2022. "Convolutional Neural Networks for Agricultural Land Use Classification from Sentinel-2 Image Time Series." *Remote Sensing* 14 (21): 5373. https://doi.org/10.3390/rs14215373.

Sitokonstantinou, V., I. Papoutsis, C. Kontoes, A. Arnal, A. Armesto Andrés, and J. Garraza Zurbano. 2018. "Scalable Parcel-Based Crop Identification Scheme Using Sentinel-2 Data Time-Series for the Monitoring of the Common Agricultural Policy." *Remote Sensing* 10 (6): 911. https://doi.org/10.3390/rs10060911.

Skakun, S., N. Kussul, A. Yu, M. L. Shelestov, and O. Kussul. 2016. "Efficiency Assessment of Multitemporal C-Band RADARSAT-2 Intensity and Landsat-8 Surface Reflectance Satellite Imagery for Crop Classification in Ukraine." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 9 (8): 3712–3719. https://doi.org/10.1109/JSTARS.2015.2454297.

Skriver, H., F. Mattia, G. Satalino, A. Balenzano, V. R. N. Pauwels, N. E. C. Verhoest, and M. Davidson. 2011. "Crop Classification Using Short-Revisit Multitemporal SAR Data." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 4 (2): 423–431. https://doi.org/10.1109/JSTARS.2011.2106198.

Snevajs, H., K. Charvat, V. Onckelet, J. Kvapil, F. Zadrazil, H. Kubickova, J. Seidlova, and I. Batrlova. 2022. "Crop Detection Using Time Series of Sentinel-2 and Sentinel-1 and Existing Land Parcel Information Systems." *Remote Sensing* 14 (5): 1095. https://doi.org/10.3390/rs14051095.

South, S., Q. Jiaguo, and D. P. Lusch. 2004. "Optimal Classification Methods for Mapping Agricultural Tillage Practices." *Remote Sensing of Environment* 91 (1): 90–97.

Stefanski, J., B. Mack, and O. Waske. 2013. "Optimization of Object-Based Image Analysis with Random Forests for Land Cover Mapping." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 6 (6): 2492–2504. https://doi.org/10.1109/JSTARS.2013.2253089.

Strobl, C., A.-L. Boulesteix, T. Kneib, T. Augustin, and A. Zeileis. 2008. "Conditional Variable Importance for Random Forests." *BMC Bioinformatics* 9 (1): 307. https://doi.org/10.1186/1471-2105-9-307.

Swain, P. H., and H. Hauska. 1977. "The Decision Tree Classifier: Design and Potential." *IEEE Transactions on Geoscience Electronics* 15 (3): 142–147. https://doi.org/10.1109/TGE.1977.6498972.

Sykas, D., M. Sdraka, D. Zografakis, and I. Papoutsis. 2022. "'A Sentinel-2 Multiyear, Multicountry Benchmark Dataset for Crop Classification and Segmentation with Deep Learning'." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 15:3323–3339. https://doi.org/10.1109/JSTARS.2022.3164771.

Teimouri, M., M. Mokhtarzade, N. Baghdadi, and C. Heipke. 2022. "Fusion of Time-Series Optical and SAR Images Using 3D Convolutional Neural Networks for Crop Classification." *Geocarto International* 37 (27): 15143–15160. https://doi.org/10.1080/10106049.2022.2095446.

Teimouri, M., M. Mokhtarzade, N. Baghdadi, and C. Heipke. 2023. "Generating Virtual Training Labels for Crop Classification from Fused Sentinel-1 and Sentinel-2 Time Series." *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science* 91 (6): 413–423. https://doi.org/10.1007/s41064-023-00256-w.

Teimouri, N., M. Dyrmann, and R. Nyholm Jørgensen. 2019. "A Novel Spatio-Temporal FCN-LSTM Network for Recognizing Various Crop Types Using Multi-Temporal Radar Images." *Remote Sensing* 11 (8): 990. https://doi.org/10.3390/rs11080990.

Teixeira, I., R. Morais, J. J. Sousa, and A. Cunha. 2023. "Deep Learning Models for the Classification of Crops in Aerial Imagery: A Review." *Agriculture* 13 (5): 965. https://doi.org/10.3390/agriculture13050965.

Teke, M., and Y. Y. Cetin. 2021. "Multi-Year Vector Dynamic Time Warping-Based Crop Mapping." *Journal of Applied Remote Sensing* 15 (1): 016517–016517. https://doi.org/10.1117/1.JRS.15.016517.

Tomppo, E., O. Antropov, and J. Praks. 2019. "Cropland Classification Using Sentinel-1 Time Series: Methodological Performance and Prediction Uncertainty Assessment." *Remote Sensing* 11 (21): 2480. https://doi.org/10.3390/rs11212480.

Tricht, V., A. G. Kristof, S. Gilliams, and I. Piccard. 2018. "Synergistic Use of Radar Sentinel-1 and Optical Sentinel-2 Imagery for Crop Mapping: A Case Study for Belgium." *Remote Sensing* 10 (10): 1642. https://doi.org/10.3390/rs10101642.

Turker, M., and M. Arikan. 2005. "Sequential Masking Classification of Multi-Temporal Landsat7 ETM + Images for Field-Based Crop Mapping in Karacabey, Turkey." *International Journal of Remote Sensing* 26 (17): 3813–3830. https://doi.org/10.1080/01431160500166391.

Turker, M., and A. Ozdarici. 2011. "Field-Based Crop Classification Using SPOT4, SPOT5, IKONOS and QuickBird Imagery for Agricultural Areas: A Comparison Study." *International Journal of Remote Sensing* 32 (24): 9735–9768. https://doi.org/10.1080/01431161.2011.576710.

Turkoglu, M. O., S. D'Aronco, G. Perich, F. Liebisch, C. Streit, K. Schindler, and J. D. Wegner. 2021. "Crop Mapping from Image Time Series: Deep Learning with Multi-Scale Label Hierarchies." *Remote Sensing of Environment* 264 (October): 112603. https://doi.org/10.1016/j.rse.2021.112603.

Ustuner, M., F. Balik Sanli, and B. Dixon. 2015. "Application of Support Vector Machines for Landuse Classification Using High-Resolution RapidEye Images: A Sensitivity Analysis." *European Journal of Remote Sensing* 48 (1): 403–422. https://doi.org/10.5721/EuJRS20154823.

Ustuner, M., F. B. Sanli, S. Abdikan, M. T. Esetlili, and Y. Kurucu. 2014. “Crop Type Classification Using Vegetation Indices of RapidEye Imagery.” *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XL–7 (September): 195–198. https://doi.org/10.5194/isprsarchives-XL-7-195-2014.

Valcarce-Diñeiro, R., B. Arias-Pérez, J. M. Lopez-Sanchez, and N. Sánchez. 2019. “Multi-Temporal Dual- and Quad-Polarimetric Synthetic Aperture Radar Data for Crop-Type Mapping.” *Remote Sensing* 11 (13): 1518. https://doi.org/10.3390/rs11131518.

Valero, S., L. Arnaud, M. Planells, and E. Ceschia. 2021. “Synergy of Sentinel-1 and Sentinel-2 Imagery for Early Seasonal Agricultural Crop Mapping.” *Remote Sensing* 13 (23): 4891. https://doi.org/10.3390/rs13234891.

Vaudour, E., P. E. Noirot-Cosson, and O. Membrive. 2015. “Early-Season Mapping of Crops and Cultural Operations Using Very High Spatial Resolution Pléiades Images.” *International Journal of Applied Earth Observation and Geoinformation* 42 (October): 128–141. https://doi.org/10.1016/j.jag.2015.06.003.

Villa, P., D. Stroppiana, G. Fontanelli, R. Azar, and P. Brivio. 2015. “In-Season Mapping of Crop Type with Optical and X-Band SAR Data: A Classification Tree Approach Using Synoptic Seasonal Features.” *Remote Sensing* 7 (10): 12859–12886. https://doi.org/10.3390/rs71012859.

Waldhoff, G., C. Curdt, D. Hoffmeister, and G. Bareth. 2012. “Analysis of Multitemporal and Multisensor Remote Sensing Data for Crop Rotation Mapping.” *ISPRS Annals of the Photogrammetry, Remote Sensing & Spatial Information Sciences* 1:177–182. https://doi.org/10.5194/isprsannals-I-7-177-2012.

Waldhoff, G., U. Lussem, and G. Bareth. 2017. “Multi-Data Approach for Remote Sensing-Based Regional Crop Rotation Mapping: A Case Study for the Rur Catchment, Germany.” *International Journal of Applied Earth Observation and Geoinformation* 61 (September): 55–69. https://doi.org/10.1016/j.jag.2017.04.009.

Weikmann, G., C. Paris, and L. Bruzzone. 2021. “‘Timesen2Crop: A Million Labeled Samples Dataset of Sentinel 2 Image Time Series for Crop-Type Classification’.” *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 14:4699–4708. https://doi.org/10.1109/JSTARS.2021.3073965.

Weilandt, F., R. Behling, R. Goncalves, A. Madadi, L. Richter, T. Sanona, D. Spengler, and J. Welsch. 2023. “Early Crop Classification via Multi-Modal Satellite Data Fusion and Temporal Attention.” *Remote Sensing* 15 (3): 799. https://doi.org/10.3390/rs15030799.

Wold, S., K. Esbensen, and P. Geladi. 1987. “Principal Component Analysis.” *Chemometrics and Intelligent Laboratory Systems* 2 (1–3): 37–52. https://doi.org/10.1016/0169-7439(87)80084-9.

Woźniak, E., M. Rybicki, W. Kofman, S. Aleksandrowicz, C. Wojtkowski, S. Lewiński, J. Bojanowski, et al. 2022. “Multi-Temporal Phenological Indices Derived from Time Series Sentinel-1 Images to Country-Wide Crop Classification.” *International Journal of Applied Earth Observation and Geoinformation* 107 (March): 102683. https://doi.org/10.1016/j.jag.2022.102683.

Xie, X., and F. Quiel. 2000. “Crop Classification in Southern Sweden with Multitemporal ERS-2 SAR Data.” In *ERS-ENVISAT Symposium: Looking down to Earth in the New Millennium*, Gothenburg, Sweden.

Ya’nan, Z., Z. Weiwei, F. Li, G. Jianwei, C. Yuehong, Z. Xin, and L. Jiancheng. 2024. “Hierarchical Classification for Improving Parcel-Scale Crop Mapping Using Time-Series Sentinel-1 Data.” *Journal of Environmental Management* 369 (October): 122251. https://doi.org/10.1016/j.jenvman.2024.122251.

Zhou, Y., Y. Wang, N. Yan, L. Feng, Y. Chen, T. Wu, J. Gao, X. Zhang, and W. Zhu. 2023. “Contrastive-Learning-Based Time-Series Feature Representation for Parcel-Based Crop Mapping Using Incomplete Sentinel-2 Image Sequences.” *Remote Sensing* 15 (20): 5009. https://doi.org/10.3390/rs15205009.

Zhu, Z., and C. E. Woodcock. 2012. “Object-Based Cloud and Cloud Shadow Detection in Landsat Imagery.” *Remote Sensing of Environment* 118 (March): 83–94. https://doi.org/10.1016/j.rse.2011.10.028.