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Review on Multitemporal Classification Methods of Satellite Images for Crop and Arable Land Recognition

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Abstract: This paper presents a review of the conducted research in the field of multitemporal classification methods used for the automatic identification of crops and arable land using optical satellite images. The review and systematization of these methods in terms of the effectiveness of the obtained results and their accuracy allows for the planning towards further development in this area. The state of the art analysis concerns various methodological approaches, including selection of data in terms of spatial resolution, selection of algorithms, as well as external conditions related to arable land use, especially the structure of crops. The results achieved with use of various approaches and classifiers and subsequently reported in the literature vary depending on the crops and area of analysis and the sources of satellite data. Hence, their review and systematic conclusions are needed, especially in the context of the growing interest in automatic processes of identifying crops for statistical purposes or monitoring changes in arable land. The results of this study show no significant difference between the accuracy achieved from different machine learning algorithms, yet on average artificial neural network classifiers have results that are better by a few percent than others. For very fragmented regions, better results were achieved using Sentinel-2, SPOT-5 rather than Landsat images, but the level of accuracy can still be improved. For areas with large plots there is no difference in the level of accuracy achieved from any HR images.

Keywords: crop detection; machine learning; satellite image classification

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1. Introduction

The aim of this paper is to systematise the present achievements in the field of crop and arable land recognition with use of multitemporal classification based on machine learning algorithms using optical satellite images. Recognition and classification of different crops in a particular area and environmental conditions involves the accuracy and optimalisation of these processes. Such factors as crop types and agriculture structure, classifier methods, and optical sensors are the focus of this paper. Certain trends as well as indications of further development and research directions, whose aim is to automatise crop identification processes, transpire from the projects and implementation experience described so far.

Research and studies into arable areas could be categorised into three main groups depending on spatial resolution of data. The first category consists in monitoring change and its dynamics in arable land on a continental scale with a resolution of 1 km, with use of data from sensors such as, for instance, NOAA/AVHRR, VEGETATION, MODIS [1,2]. The second category includes studies into identification and classification of crop types, conducted on a regional scale [3]. Currently, this approach is frequently adopted by scientists and developers using widely available data of medium resolution of several dozen metres, which is still called high resolution (for instance SPOT or Sentinel-2 of 10 m to 60 m resolution or Landsat of 30 m resolution). The third category in the context of spatial resolution consideration are studies with use of very high resolution imaging–of 1 m or less resolution, such as WorldView, QuickBird, Ikonos (Table 1), or aerial imaging of several centimetres resolution [4]. Such data are mainly used for the purpose of local-scale application in detection and monitoring of arable land and crop conditions at the detail level, which is used to manage and plan agricultural production in a single farm, often in combination with GIS and GPS technologies in precision agriculture [3]. Research and studies of the second category play a vital role in managing and monitoring vegetation cover in arable land, providing answers to questions of what and where something is cultivated [3]. This means recognition of the crop or land type along with a specification of their location and boundaries. However, it needs to be emphasized that arable land is characterised by high complexity, which means a great diversity of species and types as well as dynamics of change related to the growing season or crop rotation [5]. All of these are particularly important in the areas of the complex mosaic of crops and arable plots of varied geometry and size. These factors, combined with a diversity of crop types, phenological changes, agricultural practices, and environmental and climatic parameters result in a great divergence and variability that need to be allowed for while establishing a model and prove challenging in the automatic classification of images [6]. Hence, the issue of automatic crop detection is a topical one, present in numerous studies undertaken in order to improve quality and reliability. As a matter of fact, that consists in a search for methods allowing high accuracy of intermediate results as well as final cartographic products. Numerous global projects aiming at crop recognition with use of satellite images [7–9] make use of machine learning classification algorithms.

Table 1. Sensors most frequently used to examine vegetation and identify crops in arable lands, based on [3,10].

Sensor	Resolution		Imaging Width
	Panchromatic Mode	Multispectral Mode (Number of Bands)	
LR–category 1			
NOAA AVHRR	-	1 km/8 km (6)	2400 km
(Vegetation]	-	1.15 km (4)	2000 km
MODIS/Terra	-	250 m/500 m/1 km (36)	2330 km
HR–category 2			
SPOT 1–4	10 m	20 m (3–4)	60 km
SPOT 5	2.5 m/5 m	10 m (4)	60 km
SPOT 6–7	1.50 m	6 m (4)	60 km
Landsat 7–8	15 m	30 m (6–8)	185 km
Sentinel 2	-	10 m/20 m/60 m (13)	290 km
Gaofen 1–2	2 m	8 m (4)	93 km
VHR–category 3			
Ikonos	0.82 m	3.20 m (4)	11 km
Quick Bird	0.65 m	2.62 m (4)	16 km
Geo Eye	0.46 m	1.84 m (4)	15 km
World View 1–3	0.46–0.31 m	1.84–1.24 m (8)	13 km
Pleiades/Pleiades Neo	0.50 m/0.30 m	2 m/1.2 m (4/6)	20 km/14 km
Super View	0.50 m	2 m (4)	12 km

The early commonly applied classification methods known as parametric or non-parametric [11] were used to categorize land or crop types on the basis of single images. This resulted mainly from the costliness and rareness of such imaging in the 1980s and 1990s, in addition to IT limits. More recent decades brought the development of methods based on a combination of variability of the spectral reflection value with the crop growth stage during the growing season [5]. This approach requires monitoring of changes in the area during the season and establishing samples called spectro-temporal profiles which are most frequently based directly on reflection values or on processed data e.g., vegetation indices. These indices calculated from two bands (e.g., NDVI from red and infrared) correlate well with biomass [3]. The value of such processed images indicates healthier or more stressed vegetation and can be used to compare conditions of the same species at different times in a year, in different years or growing in different areas in the same region or same field [3].

The further progress in processing was to obtain a multitemporal image dataset, whose timing coincides with changes typical of a specific crop type. It involves numerous specific and variable features of the cultivation calendar as well as individual cases [5,6]. Hence, a difficulty of establishing appropriate patterns arises, not to mention a difficulty of obtaining adequate imaging data or attempts at universalising or extrapolating the model to other regions [5]. And this is where machine learning as an image classification approach can be of help.

The main aim of machine learning (ML) is to create an automated system able to improve with use of the gained experience (here: imagery data) as well as to be able to extrapolate the acquired knowledge [12] in order to crop recognition and classification.

The idea of classification in the context of processing and analysing satellite images implies data categorisation into defined groups. This group process can vary significantly, depending on the various needs, including the need for thematic details, which means the number of classes, or geometric details related to image spatial resolution. Classes that should be classified into the same category exhibit certain physical features, most frequently in the form of a spectral reflection registered in one or many spectral channels [11]. The aim of a systematised and automated process of digital classification is to identify areas of similar features, label them and assign them to a class. Automated classification methods rely on defining the rules of assigning pixels to classes on the basis of their spectral features [13], or in the case of crop detection on spectral and time feature space [14].

The earliest methods of ML that were effectively used for remote sensing were known as unsupervised and supervised classifications. In the supervised approach, the "machine" otherwise algorithm is taught using samples (i.e., the training set) of the desired input and output. The "machine" processes the input data to determine correlations and logic which can be later used to predict results. After the identification of a logical pattern, this can be applied to determine whether a given object belongs to a given class [12]. This spectro-temporal sample as a training set is a key issue of any algorithm [5,6,13]. Moreover, Vieira et al. involved the spectro-temporal response surface (STRS), which provides for the generalization in time of spectral reflectance properties of agricultural areas [14]. For unsupervised training, the analyst employs a computer algorithm that locates concentrations of feature vectors within a heterogenous sample of pixels. These so-called clusters are then assumed to represent classes in the image and are used to calculate class signatures. They remain to be identified (labelled), however, they may not correspond to classes of interest to the analyst [11]. Therefore it is rather rarely used for crop identification, though some studies involved such approaches [5,14].

Another aspect of crop identification, independent of the ML algorithm, concerns the spatial unit, i.e., pixel or object (i.e., single parcel) [5]. Pixel-based methods often fail to identify actual parcel boundaries [15], while spatial filters improve accuracy by removing small inclusions within the dominant class [16].

Although certain algorithms and image data combinations may produce good results in specific land and crop type, they may perform poorly in other related applications [5,17,18]. In this regard, the choice of data sets, sensors, and processing methods depends on the feasibility and objectives of the crop identification study. The main goal of this paper is to compare the results of ML methods used for crop recognition at the parcel level, especially in fragmented areas. To the best of my knowledge, there is no comprehensive assessment of the progress and challenges in crop types studies with a key focus on complex structure agricultural areas. Consequently, there is a need to review the advancements in crop types detection methods, especially using the most popular high resolution (HR) images. The paper also interrogates the results from commonly used ML algorithms with respect to crop types, structure, and parcel size achieved in recent studies.

2. Methods

The multitemporal classification of optical images approach was chosen from among the many described in literature methods since it is reported as the effective one and to make possible the comparison of the results. The major research method was literature review and analysis of the reported outcomes. The databases (e.g., Scopus, Google Scholar, Web of Science, IEEE Xplore, ScienceDirect, MDPI, BazTech) were chosen to search for the relevant literature. This choice was motivated by the extensive numbers of publications as well as advanced tools for literature analysis. Queries covering all possible combinations of terms related to optical satellite sensors, arable land and crop classification methods were used and returned over 50 articles from 1995 to 2021. The majority of the papers (almost 30) are dated from 2014–2018. The most popular journals are Remote Sensing (11 papers), Computers and Electronics in Agriculture (6), International Journal of Applied Earth Observation and Geoinformation (5), and ISPRS publishing (6 papers). A few papers were found in the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (3 papers), the International Journal of Remote Sensing (3), Remote Sensing of Environment (2), and Machine Learning (2 papers). Besides the peer-reviewed papers, in this research some other types of publication were included: one Master's thesis and four reports or information on the internet. Most of the reviewed articles are case studies on the topic of crop type classification using optical and radar data. In addition to the reviewed case studies, literature on remote sensing data and ML algorithms were analysed. These research and review publications were mainly used as information sources to describe the methodological context and background of the above-mentioned topics but were not included in the systematic review.

In the last decade the interest in machine learning (ML) methods in crop detection increased, especially using time-series images [5,6,14,17,18]. Therefore the literature review covers several recent years, mainly but not only the period since 2010. Earlier efforts before 1995, though vital in development of currently used crop and arable land recognition algorithms, are already historical studies and therefore not the subject of this paper. During the last 20 years, the most focus went to study and adjust the classifiers using multitemporal data as much as possible.

A state of the art review indicates main areas of interest for research groups so far concerning the development of algorithmics in automation processes of crop and arable land recognition and the quality increase of these processes (here: increase in accuracy of the products of these processes). The most frequent statistics describing the accuracy of classification are adopted from Congalton [19], and they are estimated based on an error matrix. Overall Accuracy (OA) for classification itself, and User's Accuracy (UA) for particular classes (crops) dominate in the publications, therefore these will be used in the next paragraphs to compare the results of classification. The results were juxtaposed in the tables and displayed in figures as an alluvial chart, box plot and matrix plot.

3. Results

In this chapter, the results of crop detection using multitemporal optical images were compared. The technical issues like classifiers and image sensors were considered as were the environmental issues i.e., crop types and agricultural structure.

Analysis of the bibliography available on the subject indicates considerable interest in some particular supervised algorithms: Random Forests–RF [20], Support Vector Machine–SVM [21] and Artificial Neural Network–ANN [22] successfully used in satellite images classification [23]. A steady increase in interest in supervised methods of multitemporal classification of vegetation classes [5,24] or topographic objects identification

[25,26] can be seen as well. The automated crop and arable land recognition based on multitemporal classification includes methods such as RF [17,27–30], SVM [16,17,28,31–33], ANN [28,34–36]. Other methods, such as maximum likelihood algorithm–MXL [5,24,37] or K-Means algorithm [5] are still used, mostly to compare the classification results. There are a lot of aspects affecting the performance of the classification: chosen classification method, spectral characteristic similarities of the crops [33] or biophysical variables [38] and weather conditions, such as cloudiness [39], temperature and precipitation of the study area [6]. Therefore, an identification method working well in one agro-region, i.e., an area with similar climate, soil and agro-technical conditions, cannot be assumed to work as well in another, different environment [6]. The final result of classification depends not only on the selected method of data processing but also on many other factors such as input satellite data type and acquisition period, quality of the training data, plant species or arable land structure. Therefore it is difficult to discuss the merits of any method in comparison with others. However, the previous mentioned classifier, that is RF, ANN and SVM, yield very good results. Since they are very common in use for multitemporal classification, their accuracy will be discussed, paying special attention to the dominant crops and agricultural structure.

3.1. Approach to Classification

Since both elements input images and the type of classifier establish an approach to classification, their results will be considered together.

Both pixel and object approach for crop classification are frequently used. The choice depends on the availability of software of the OBIA type [40] and the ability to generate reference boundaries for the crops [34]. However, the pixel approach seems to dominate, followed with aggregation of the classification result related to the plot. Extra filters are frequently used in the final processing stage in order to smooth and remove single random pixels [18]. The parcel-based approaches have been found to be more accurate than the pixel-based approaches [41]. The field boundaries can be derived from the digital vector database [42] or by segmentation [43]. The accuracy of the results is also affected by the image processing unit (i.e., pixel or object). In mixed agriculture landscapes, image segmentation methods seem to provide a significant advantage, as different types of land use have different functions and at the same time are similar spectrally [44].

Although the weather can make the crop development start earlier or later, so too are the amount and correct timing images important factors for crop identification [6]. There are also some unique approaches to classification, such as using single date imagery [45] or pre-harvest images [46]. Nevertheless, most of the studies are based on time-series data from the whole growing season.

The most popular satellite images used for crop recognition are Landsat and Sentinel-2 due primarily to the open and easy access to the data. Another reason is the parameters of these systems: spatial and spectral resolution and temporal resolution i.e., time of revisits. Today, the access to this data and processing tools is even faster and less complicated since both data and software are incorporated within single services e.g., DIAS–Data and Information Access Services [47], the Google Earth Engine [48] or even through the open-access software [49,50]. The other remote sensing systems i.e., SPOT, Pleiades, RapidEye, or commercial VHR systems are not so common in use due to the price and small area of acquisition [3]. For instance, Landsat image covers an area 180 km by 180 km, while WorldView-2 is 16 km by 16 km only (Table 1). Again, it is much faster is to process a single image for a big area at once rather than to process mosaics of the images acquired on different dates [13].

Table 2 presents crop classification results obtained with use of RF, SVM, ANN, and MXL, the most popular techniques and diverse satellite data. Countries (as research areas) in bold type are the ones where small-holdings and complex agricultural structure dominate. The results are presented from the lowest to highest accuracy within each method and for each sensor separately. The overall accuracy level of classification results in

Landsat images (TM, ETM+, OLI) ranges from 70% (Tasmania, MXL) to 92% (Iran, SVM), in Sentinel-2 images from 77% (South Africa, SVM) to 98% (China, ANN), and in SPOT-5 or RapidEye images from 74% (Pakistan, RF) to 95% (China, ANN). This range seems relatively stable regardless the method. On Figure 1 one can notice that RF classifier ranges from 74–96%, MXL varies from 70% to 92%, while SVM is from 82% to 92%. The best results are found by the ANN method, which reaches the accuracy of 85–98% for Ukraine and China, respectively, and this method is on top of other classifiers.

Table 2. The best overall accuracy (OA) of crop classification with machine learning methods and the area of research from selected publications. “Small-holdings” in bold type.

Classifier	Landsat TM/ETM/OLI Country [Reference]	Sentinel-2, S2 + L8 Country [Reference]	SPOT5/RapidEye Country [Reference]
RF	**79% Poland** [51]	80% Mali [27]	74% Pakistan [45]
	90% France [45]	**83% Austria** [52] **96% Austria** [53]	86% Uzbekistan [54]
	90% Argentina [30]	84% India [45]	**87% Germany** [55] **87% Luxemburg** [55]
	90% South Africa [30]	**86–91% Poland** [51]	94% France, Belgium, Ukraine [18]
	90% USA [30]	**89% Spain** [31]	
		89% Japan [56]	
SVM	**84% Portugal** [33]	83% South Africa [46]	87% Turkey [57]
	86% France, China [17]	82% India [45]	90% USA [16]
	90% Argentina, South Africa, USA [17]	**91% Spain** [31]	
	92% Iran [32]	91% Japan [56]	
ANN	85% Ukraine [34]	91% Finland [58]	95% China, Gaofen1–2 [59]
	86% Ukraine [60]	96% Italy [61]	
	89% Canada [36]	98% China [62]	
MXL	70% Tasmania [63]	89% China [64]	78% Turkey [65]
	73% Germany [6]		86% USA [16]
	90% Canada [24]		92% Canada [45]

In the research areas characterised by great fragmentation of plots, these values vary from 83% (Austria) to 89% (Spain) for the RF method, while for the SVM method it is slightly higher and reaches 84% (Portugal) to 91% (Spain). Overall there is no significant difference between results on complex and any other areas in respect to the classifiers. Another observation for this type of fragmented structure of plots concerns the images. The classification has better accuracy on the Sentinel-2, where the range is 83% to 96% (Austria) and on SPOT-5, which reaches 87% (Germany, Luxemburg). This range is similar to the accuracies for any other areas; for Sentinel-2 it ranges from 80% (Mali) to 98% (China), and for SPOT-5 from 74% (Pakistan) to 95% (China). For Landsat, these accuracies for complex areas are somewhat worse, from 79% (Poland) to 84% (Portugal). In comparison with the accuracies in any other area, OA is lower approximately about 10% (i.e., from 85% in Ukraine to 92% in Iran).

Figure 1 shows the overall accuracy for all study areas regarding the images and classifiers based on values presented in Table 2. Also, the considered classifiers are all used in any optical sensor: Landsat, Sentinel-2, SPOT5, or RapidEye.

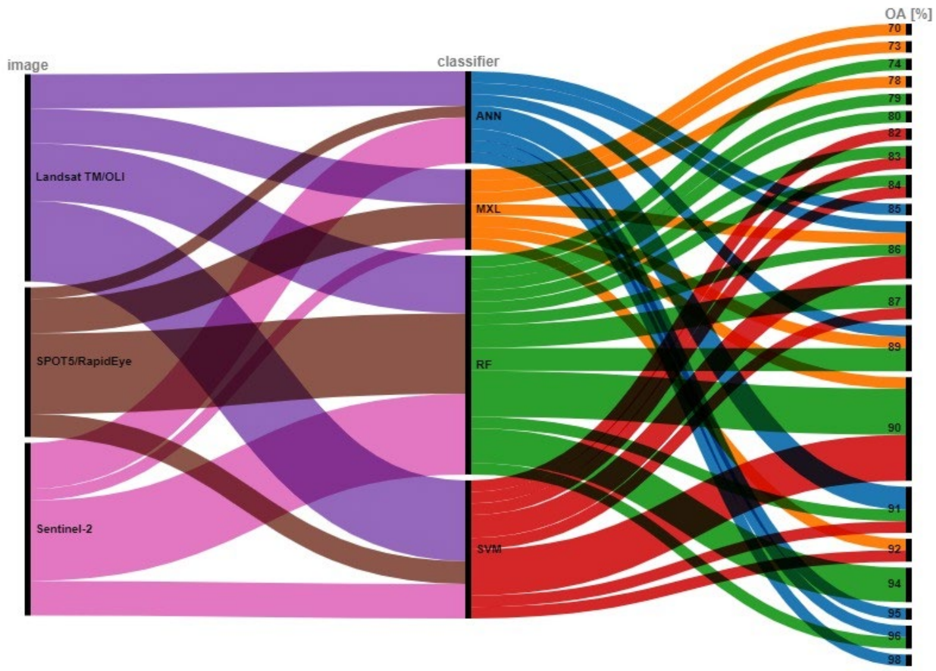

Figure 1. The overall accuracy (OA%) achieved regarding classifier and image (sensor), based on Table 2.

3.2. Dominant Species

The literature review provides an insight into which plant species are most frequently detected. These are usually dominant species cultivated in the temperate climate zone in the northern hemisphere such as spring and winter cereals, rapeseed, corn, sugar beet and grassland [5,31]. The number of species classified usually amounts to five to six classes or crop groups and does not exceed 12–15. The more species to be identified, the more difficult the task is, and the lower the accuracy of classification results. This results from the physical and phenological, and what follows is spectral similarity of the related species (for instance legumes), for which it is difficult to develop separate models. That is why these species "confuse" in the classification process and the end result of their classification is poor. Classes representing non-crops in agricultural areas, such as water, build-up areas or forests are also included in many studies [60], which in fact increases the overall accuracy and supports visualisation or further analyses concerning land cover. Earlier instances of SPOT-4, Landsat-8 and RapidEye images for diverse research areas all over the world yielded varying results, ranging from the best ones in the USA (OA equals 90–91%) to the poorest in Madagascar or Burkina Faso (OA equals 30–50%) [14,24,30,63]. Yet other commonly used approaches to agricultural areas classification, such as arable and non-arable areas (two general classes) results in an overall accuracy (OA) at the 85% level and enables differentiation between arable and non-arable lands, not indicating specific crops [5,18].

Table 3 shows commonly classified crops together with the accuracy of their classification. The dominant types of crops are maize, grassland, winter and spring cereals, rapeseed, sunflower, potatoes and sugar beets. Maximum values reported in scientific papers are presented together with the main method of their classification (ANN, RF, SVM, MXL) and the input data types. The results of classification are presented with the User's Accuracy (UA), as this measure was commonly used in the literature reviewed. For each crop classification, results were ordered from the poorest to the best results obtained. The RF method yielded the poorest results for spring cereals (16%) and potatoes (20%), while the SVM method yielded highly accurate results for the same crops: 90% for spring cereals and 94% for potatoes. Cited accuracy for other crops are usually within a range from 60% (maize, grasslands, sunflower) up to even 99% (rapeseed, maize). Juxtaposing the results for various crops it is possible to notice that the accuracy divergence is high and it is difficult to find a correlation between specific crops, classification method or data type.

Table 3. Dominant arable land classes in given areas and the User's Accuracy (UA) of their classification, together with the classification method: ANN, RF, SVM, MXL and the sensor types: L8—Landsat-8 (OLI), S2—Sentinel-2, TM and ETM—Landsat, S5—Spot-5.

Class Name	**Maize**												
UA (%)	**60%**	**77%**	**80%**	**88%**	**92%**	**93%**	**87%**	**89%**	**98%**	**99%**	**82%**	**90%**	**96%**
Classifier	RF	RF	RF	RF	RF	RF	ANN	ANN	ANN	ANN	SVM	SVM	SVM
Data [source]	L8 [30]	S2 [52]	S2 [56]	S2 [27]	S5 [55]	S2 [31]	L8 [34]	L8 [60]	S2 [61]	S2 [62]	S2 [66]	TM [33]	S2 [31]
Class name	Grassland												
UA (%)	76%	77%	91%	93%	63%	68%	89%	68%	80%	83%	94%	96%	
Classifier	RF	RF	RF	RF	ANN	ANN	ANN	SVM	SVM	SVM	SVM	SVM	
Data [source]	L8 [30]	S2 [31]	S2 [56]	S5 [55]	L8 [60]	S2 [61]	L8 [34]	TM [33]	L8 [32]	S2 [31]	S2 [56]	S2 [46]	
Class name	**Winter cereals**												
UA (%)	98%	68%	88%	92%	93%	72%	87%	90%					
Classifier	ANN	RF	RF	RF	RF	SVM	SVM	SVM					
Data [source]	S2 [58]	S5 [55]	S2 [31]	L8 [51]	S2 [52]	TM [33]	L8 [32]	S2 [31]					
Class name	**Spring cereals**												
UA (%)	39%	64%	16%	89%	90%	94%	53%	90%					
Classifier	ANN	ANN	RF	RF	RF	RF	SVM	SVM					
Data [source]	L8 [34]	L8 [60]	S5 [55]	L8 [51]	S2 [31]	S2 [58]	TM [33]	S2 [31]					
Class name	**Rapeseed**												
UA (%)	76%	86%	95%	96%	96%	99%	96%						
Classifier	RF	RF	RF	RF	ANN	ANN	SVM						
Data [source]	S5 [55]	L 8[51]	S2 [31]	L8 [30]	L8 [60]	L8 [34]	S2 [31]						
Class name	**Sunflower**												
UA (%)	67%	85%	63%	67%	92%	95%							
Classifier	ANN	ANN	RF	RF	RF	SVM							

Data [source]	L8 [60]	L8 [34]	L8 [30]	S2 [52]	S2 [31]	S2 [31]
Class name	**Black fallow land**					
UA (%)	80%	75%	78%	96%	49%	
Classi-fier	ANN	MXL	RF	RF	SVM	
Data [source]	TM [14]	TM [24]	L8 [30]	RE [54]	TM [33]	
Class name	**Potatoes**					
UA (%)	96%	20%	81%	85%	94%	
Classi-fier	ANN	RF	RF	SVM	SVM	
Data [source]	TM [14]	S5 [55]	S2 [56]	S2 [56]	L8 [32]	
Class name	**Sugar beets**					
UA (%)	70%	94%	79%	84%	96%	
Classi-fier	ANN	ANN	RF	RF	SVM	
Data [source]	L8 [60]	L8 [34]	L8 [51]	S5 [55]	S2 [56]	

Since Table 3 itself is rather extensive to facilitate its interpretation, Figures 2–4 illustrate the results and relations between crops, data (sensor), classifier, and accuracy. They show that classifiers achieve similar accuracy regardless of the type of crops (Figure 2). The majority of the crops reach the User Accuracy (UA) value from 60% to 99% with the median at the 87% level. Spring cereals group different kinds of cereals, hence this large variation of results from 50% to 90%. The best and the most consistent results were reported for rapeseed (from 90% to 96% of UA). Figure 2 summarizes a quantitative distribution with five standard statistics: the smallest value, lower quartile, median, upper quartile, and largest value.

Figure 3 shows the aggregation of User's Accuracy (boxes) as an average value in relation to images (vertical axis), and classifiers (horizontal axis). User Accuracy in percent (UA) was averaged for all crops and displayed from the lowest value (light colors) to the highest value (dark red). The count of UA value for crop types describing in the reviewed literature is shown as the size of square (from 1 to 14 as maximum). The best single result was achieved using the RF method on the RapidEye dataset for black fallow land. Since this value refers to single measure it cannot be used for comparison (similar to MXL method on TM for black fallow as well). The best mean values reached were for crops classified by SVM in Sentinel-2 time series images. The poorest results were indicated for crops classified by RF in SPOT-5 images similar to SVM in Thematic Mapper (TM) images on a 50% level.

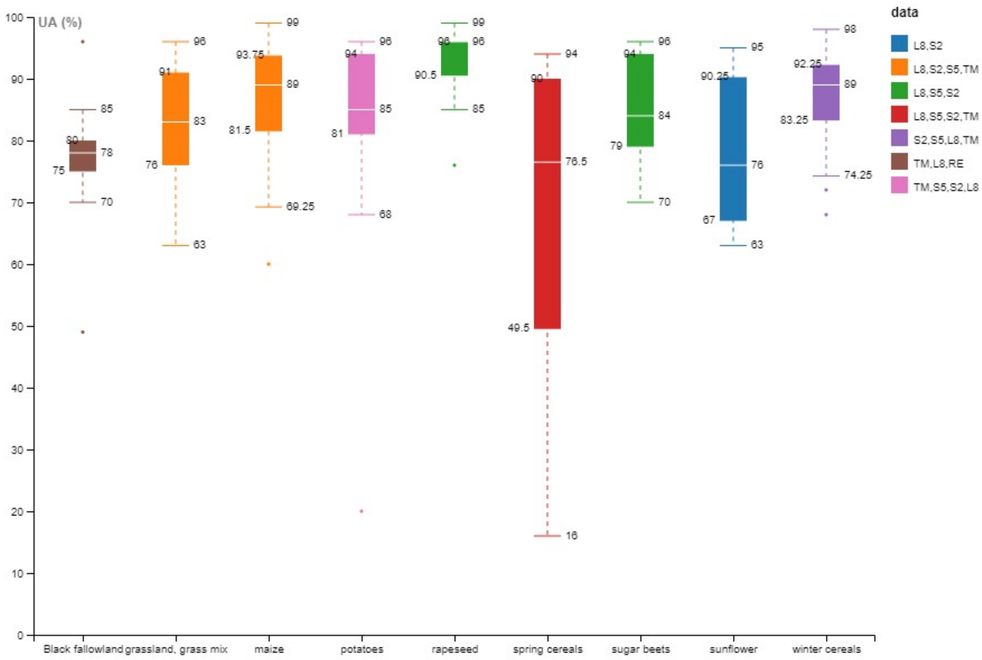

Figure 2. The distribution of crop type accuracy (UA%) based on Table 3. The colors indicate different sets of sensors used in the aforementioned studies.

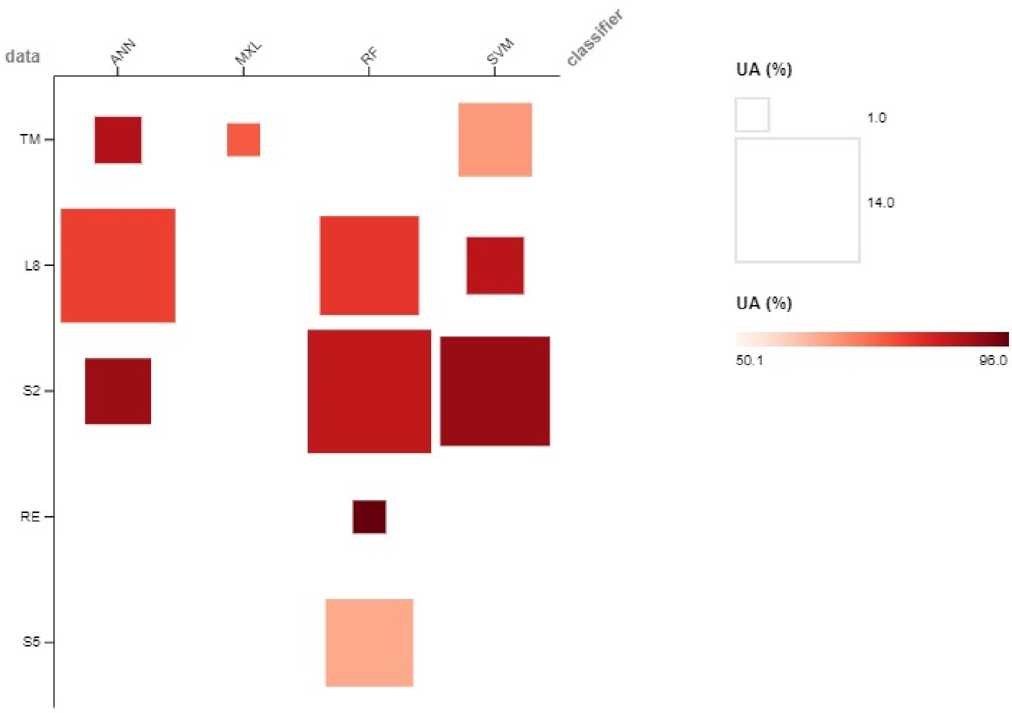

Figure 3. The relations between data (sensor), classifier and accuracy (UA%) calculated based on all crops from Table 3. The boxes show UA average values in color, and UA count in size.

The chart in Figure 4 represents the relations between crops, data (sensors) and achieved accuracy (UA). One should notice that crop types are recognizable at each dataset and there is no special inclination to choose the imagery for experiments. It is rather the plot size and agricultural structure and availability to determine of input data selection. Also it is worth mentioning that each sensor has a large dispersion of achieved accuracies (UA%). For Landsat 8 (OLI) it is from 39% to 99% and for Thematic Mapper is from

49% to 96%, while for Sentinel-2 is from 67% to 99%. For SPOT-5 this range is from 16% to 93%, therefore no direct relation between image resolution and value of accuracy is shown.

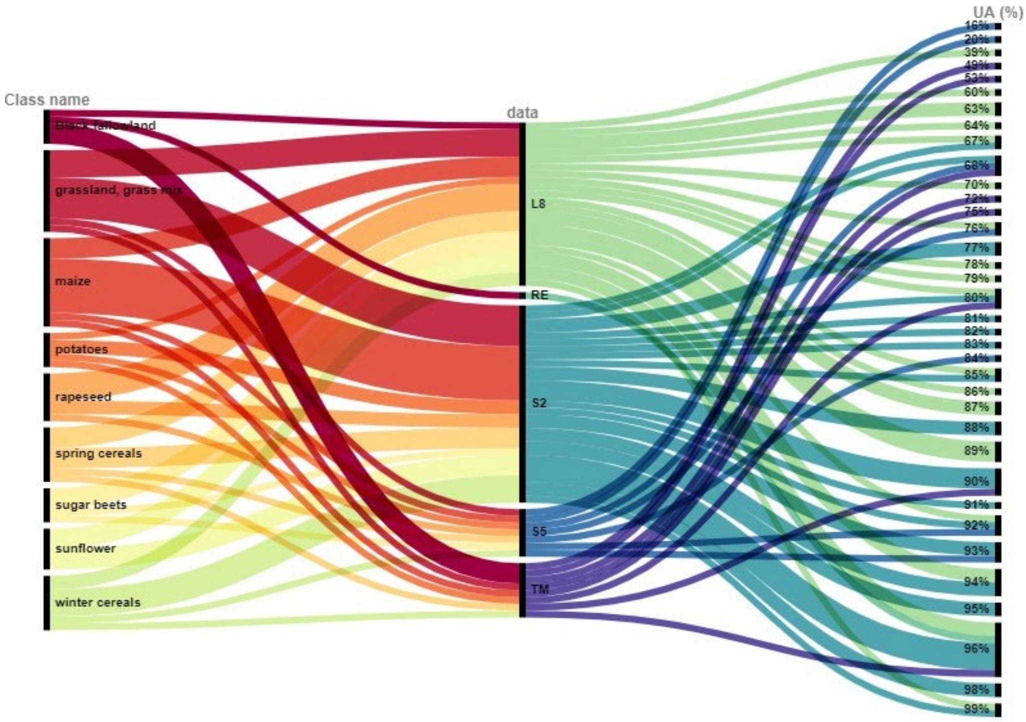

Figure 4. The relations between data (sensor), crops (class name) and accuracy (UA%) based on Table 3.

An additional juxtaposition of classification accuracy obtained in wheat recognition with use of diverse sensors and methods is shown in Table 4. Irrespective of the region and the method used, very good results were obtained, ranging from 76% (SVM, Landsat) to 98% (ANN, Landsat).

Table 4. Accuracy obtained in wheat recognition with use of diverse sensors and classifiers.

Method / Data	RF	SVM	ANN
Landsat	79% [30]	76% [33] 85% [32]	92% [34] 98% [60]
Sentinel2	83% [31] 95% [44]	91% [31] 96% [56]	98% [61] 90–99% [62]
SPOT5/RE	88% [55] 89% [52]		

It needs to be noted that the number of satellite images and the date they were acquired are of vital importance in a multitemporal analysis to maximize the differentiation of crop types. It would be ideal to acquire a maximum number of images throughout the growing season (image capture during every possible flight), but on the other hand, there are meteorological limitations for optical images, as well as equipment limitations concerning the processing and storing of such a large amount of data. The literature indicates the need to take into account at least 4 periods of the growing season: (1) plants at rest, after ploughing or sowing (bare soil dominates); (2) an increased rate of growth compared to natural vegetation; (3) the culmination moment of growth–maturity; and (4) a decrease in biomass–harvest and withering [5,6].

3.3. Structure and Size of Agricultural Plots

Classification of large plots, i.e., the size above 50 ha, based on the data from Landsat-8 yielded varying accuracy levels (OA range of 60–90%) depending on the method used and the character and structure of the area [28,35,37,66]. Classification for small plots, as conducted in Poland, indicates an overall accuracy of 77–89% [51], when SAR images were used the results reached as high as88% [29,35,67,68]. A similar to Polish fragmented agricultural structure and similar classification results were noted in Austria and Portugal, where the overall accuracy was of 76–83% in Austria [52] and 68–84% in Portugal [33]. Comparing these results (Table 2) one should notice that the agricultural structure is an important variable that makes an impact on the accuracy and feasibility of crop classification. Certain initiatives have been undertaken to resolve such problems all over the world independently of agricultural structure and size of plots. Their results can be seen in the open access software Sen2Agri and Sen4CAP used for crop classification developed in the ESA projects [69,70] and the OneSoil Map service [71]. The data published by OneSoil come from the satellite images supplied by the ESA on free-access service for Sentinel-2. 24 crops are identified with the accuracy of F1 = 0.91 with use of a neural networks algorithm in this service. The data included in the map include crop name, location, size, as well as the crop size estimate for the whole country. Machine learning algorithms identify crop boundaries with an accuracy of up to five metres [71]. Yet, these systems have limitations and can be used to give an overview of the distribution of crops for smallholders where the width of a parcel is sometimes 10 m or less [51,72].

4. Discussion

As was previously mentioned, it is difficult to compare the classification results due to differences in cultivation methods or agricultural features of the studied areas. Moreover, examples of multi-site assessments, which compare the performances of the same classification method in different agro-systems, are very scarce [5]. Examination of the accuracy of automated crop identification is closely related to the specific features of the regions and the specific kinds of crops, so that is why the results tend to be unique. Hence, the analysis of the results achieved on arable land classification with the use of optical data has limitations. To make feasible the comparison of the outcomes, the review included only the main optical image sensors the Landsat (18 out of 46 studies), Sentinel-2 (15), SPOT-5 and RapidEye (together 13 out of 46). Although Landsat images are still the most popular in crop recognition, areas with small-holdings and fragmented structures are preferably analysed in Sentinel-2, SPOT5, or RapidEye images because of the spatial resolution and better accuracy, e.g., in Spain OA reached the level of 89–91% [31], in Luxemburg 87% [55] (Table 2). Still, it is a little lower than on large plots. For example in Ukraine where the dominant field area is approx. 50 ha, 94% of OA was achieved using SPOT-5 [45], and 90% of OA in the USA [16] and Canada [36]. There are also interesting studies in Germany using Landsat TM/ETM showing 73% of OA [6] while using SPOT5 and RapidEye 87% [55].

The most popular classifiers were Random Forests (20 studies), Support Vector Machine (12), Artificial Neural Network (8), and Maximum Likelihood (8), taking into account an agricultural structure as well. It should notice a slight dominance of RF methods more often chosen for such regions (Table 2). Results from this classifier achieve OA from 79% [51] to 90% [30] using Landsat, from 80% [27] to 89% [31,56] using Sentinel-2, and from 74% [18] to 94% [45] on SPOT5. Using the SVM classifier, the OA was from 84% [33] to 92% [32] on Landsat, from 83% [46] to 91% [56] on Sentinel-2, and from 87% [57] to 90% [16] on SPOT5. For ANN, outcomes were 85% [34] to 89% [36] on Landsat and 91% [58] to 98% [62] on Sentinel-2. Maximum Likelihood classifier was normally used to compare the results from other classifiers and has lower OA values (about 4–5 percent) [6,16,64].

It was not considered in the time range of acquired images, since each study area had a specific, adjusted and feasible timeline. However, the earlier the estimation (ideally before the harvest), the more efficient the management [5]. The results discussed in Valero [18] showed that the cropland extent accuracy increased when the number of images increased through the agricultural season. The real-time classification results yielded accuracies around 80% in the middle of the season and approximately 90% at the end of the season. The impact of missing observations in some periods of the year was also found to be a serious limiting factor [18]. The number and timing of image acquisition is crucial to distinguishing crop types [6].

There are also no evident findings if the number of crops have an influence on classification accuracy. It is rather a case of the particular agricultural structure than the number of crop types. However, it should be noticed that the overall accuracy is higher if the list of crops is shorter. For instance, Valero et al. reported 90% of accuracy for crop/non-crop mapping on 12 different test sites spread across the globe [18]. While in Poland, classification of 19 classes resulted with 89% of overall accuracy [51], and in Spain for 9 classes the percentage was the same [31]. In Germany, classification of 12 types of crops reached 73% of OA [6]. The list of crops is different for different regions, but the most common crop type is wheat. For this cereal, the best results above 90% of accuracy were achieved using the ANN algorithm on Landsat [35,60], on Sentinel-2 [61,62], and using SVM [31,56] or RF [56] on Sentinel-2 (Table 4). The other popular investigated crop types are maize, rapeseed, potatoes, sugar beets, and grassland, with an average UA value between 83% and 90%. Spring and winter cereals are very similar in results, reaching the average UA value of 76% and maximum UA value at the 94–95% level.

It was observed that the investigated areas for crop mapping are focused on a specific region of the world without comparing the effectiveness of their methodology in different conditions. Only a few papers [5,17,18] that covered this topic tested their methods on different areas. Differences in agronomic practices, field sizes, climatic differences, etc. are major challenges for large-scale mapping tasks. Another reason may be that the availability of training data for large areas and the spatial transferability of classification models remain a problem. Nevertheless, machine learning methods prove useful in satellite image classification for a few reasons. Most of all, these are universal algorithm systems mapping multidimensional data sets (multispectral and multitemporal data). These algorithms are capable of learning and adapting to the changing environment and choosing an ideal set of parameters and their organisational structure to solve the task. Moreover, they are capable of generalising the acquired knowledge and thereby enable the repeatability of results [17,35]. Table 5 juxtaposes the most frequently cited advantages and disadvantages of the three chosen machine learning algorithms: Random Forests (RF), Support Vector Machine (SVM) and Artificial Neural Networks (ANN).

Table 5. Most frequently cited advantages and disadvantages of chosen machine learning algorithms used in crop classification in satellite images. Based on [27,39,51,55].

Algorithm	Disadvantages	Advantages
RF	Increase in the amount of training data does not increase accuracy; Difficulty interpreting the results; Variability of the results	Effective for big data sets and small amount of training samples; Low sensitivity to the amount of data input, resistance to "noise"; Lack of overfitting (resistance to overtraining); Low number of parameters defined by the user;

		Analysis of feature (variable) importance; Low computational requirements
SVM	Multitude of parameters to be optimised; Difficulty building a universal model; Sensitivity to feature (variable) choice; High computational requirements	Accuracy even for a low number of training grounds, including mixels; Possibility of adjusting parameters to specific cases (optimisation)
ANN	Long period of building and optimising the network; Large training set required; Relatively long computation process; Possibility of "overtraining"	High tolerance to lack of data, weak representation or noise interference in the training data; Adaptive learning from the training data streams–minimising errors; Varied types of variables used in the model

The results obtained do not depend on classifiers as much as they do on local environmental conditions. Generally speaking, the more data, i.e., Landsat 8 plus Sentinel-2, the higher accuracy and better chances of success [51,53]. However, larger data sets result in higher data divergence and a higher potential for predictive error. On the other hand, simpler models with a bigger amount of data seem better than more complex models with a smaller amount of data. These constitute the basis for team modelling techniques using the "collective power" to predict results [12,39]. Growing amounts of EO data, especially time series collections, are accelerating advanced computing needs and capacities. Furthermore, the increasing availability of computing platforms and geospatial analysis as a service are major drivers of the advancement of crop mapping research. The continuous increase in the number of scientific publications on the use of optical data to distinguish between types of crops reflects the great advantage of multi-temporal analysis of data in terms of their informative content for crop recognition [68].

5. Conclusions

The current study has reviewed the literature on the progress of remote sensing methods in recognition of crop types. Empirical evidence has shown that satellite images offer invaluable data sources in crop identification at regional and local scales. However, although the crop identification using ML methods results with very high accuracy (above 90%), the modelling of crops from remote sensing data remains a challenge in terms of developing models that can be used efficiently in all environments. The general outcomes from this study can be summarized as follows:

- There is no significant difference between the accuracy achieved from different ML algorithms, yet on average the ANN classifier is better than the others by a few percentage points.
- For complex, fragmented regions, better results were achieved using Sentinel-2 or SPOT-5 rather than Landsat images, but the level of accuracy can still be improved.
- For areas with large plots there is no difference in the level of accuracy achieved from any HR images.

Many studies prefer the simple and straightforward approach of layer-stacking and multitemporal data analysis. There are still some problems to be considered, like advisable temporal sequence of images versus data availability or expected number of crops versus a number of possible identified classes. The spatial and temporal transferability of the models still remains as one of the main issues. Future trends and possible development directions in automated crop recognition might include the following:

- A multi-seasons approach dealing with an increasing number of images captured over years;
- multi-sensor image fusion, optical and radar [29,67,68], or even satellite and aerial or UAV data for large-scale mapping;
- the creation of training samples and processing automation archives into the universal and repeatable models.

Even with considerable experience, developing machine learning applications is still an experimental and iterative process, regardless of whether an already well-known algorithm is used. In each case, the algorithm needs to be trained and tuned to the agricultural context and image dataset. Machine learning is a powerful tool and is extremely efficient when the user possesses the thorough knowledge of the agricultural structure.

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