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Crop type classification using a combination of optical and radar remote sensing data: a review

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ABSTRACT

Reliable and accurate crop classification maps are an important data source for agricultural monitoring and food security assessment studies. For many years, crop type classification and monitoring were focused on single-source optical satellite data classification. With advancements in sensor technologies and processing capabilities, the potential of multi-source satellite imagery has gained increasing attention. The combination of optical and radar data is particularly promising in the context of crop type classification as it allows explaining the advantages of both sensor types with respect to e.g. vegetation structure and biochemical properties. This review article gives a comprehensive overview of studies on crop type classification using optical and radar data fusion approaches. A structured review of fusion approaches, classification strategies and potential for mapping specific crop types is provided. Finally, the partially untapped potential of radar-optical fusion approaches, research gaps and challenges for upcoming future studies are highlighted and discussed.

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1. Introduction

According to the United Nations, the world population in 2030 and 2050 is expected to reach 8.6 billion and 9.8 billion people, respectively (UN 2017). In other words, every year, around 83 million people are added to the world's total population. The continuous increase in the human population and the concurrently increasing global demand for food will become major challenges for mankind that will influence the future actions towards food security and nature conservation (FAO 2009). Several studies including Godfray et al. (2010) and Foley et al. (2011) discussed the need for a global strategy to ensure future food security, where agriculture plays one of the active roles.

Crops such as rice, wheat, corn and barley are major food resources in many parts of the world, thus information on their spatial distribution and condition are significantly important at regional, national and even global level. To acquire such information on

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Supplemental data for this article can be accessed here croplands over large agricultural regions, satellite Earth Observation (EO) data is an essential data source. Traditionally, remote sensing for agricultural applications has been focused mainly on optical data, acquired at the visible and near-infrared part of the electromagnetic spectrum. Nowadays, with the advancement in sensor technology and processing capability, it becomes possible to expand methodological approaches and use new complementary data sources for simultaneous analysis of multi-source data. As a result, in the last two decades, multi-source image analysis is gaining increasing attention from the remote sensing community.

Remote sensing image fusion is a valuable tool for processing and analyzing multi-source satellite images. It allows detecting in more detail the qualities and properties of sensed objects on the ground which cannot be identified in the respective individual image sources (Pohl and van Genderen 1998). A number of studies have shown that the synergetic use of various spatial data sources can increase the classification accuracy (e.g. Solberg 2006; McNairn, Champagne, and Shang 2007; McNairn et al. 2009; Qiao et al. 2014). Particularly, for land use and crop type classification the necessity of multi-sensor data analysis is becoming more and more obvious, e.g. for the separation of crop types that resemble each other in one data source, or in regions with frequent cloud cover. The opportunity to simultaneously utilize information from a broader range of the electromagnetic spectrum than it is typically offered by individual sensor systems has opened new perspectives for remote sensing.

Multi-sensor image fusion provides broader information content about target objects from different perspectives of spatial, spectral and temporal characteristics. The review of Pohl and van Genderen (1998) was one of the first studies discussing the advantages and techniques of remote sensing data fusion, which was then followed by a second review (Pohl and van Genderen. 2015) where the authors categorize and explain various fusion approaches. In literature, different aspects of data fusion such as its influence on classification accuracy (Colditz et al. 2006), advances in applications (Dong et al. 2009), current challenges and opportunities (Mura et al. 2015) can be found. A recent paper by Joshi et al. (2016) gave an extensive overview of studies which used optical and radar data fusion approaches for land use mapping purposes. Among current studies on data fusion, approaches combining optical and radar data for the agricultural land monitoring are considerably increasing.

There are only a few review studies focusing on the application side of satellite data fusion methods. The review of Joshi et al. (2016) is the first overview of the application of satellite data fusion for land monitoring and classification. However, a review of optical and radar data fusion focusing on the potential for crop type classification and monitoring is still missing.

The overall goal of this review paper is to give a comprehensive overview of the current state-of-the-art of synergetic use of optical and radar remote sensing data for crop type classification. The paper thus aims to give (1) an overview of research studies focusing on crop type classification using multi-sensor (optical and radar) data; (2) identify common patterns and trends in the choice of fusion level, methods and classification approaches; (3) summarize common findings and conclusions of the reviewed studies; and to (4) identify research gaps and possible future development directions.

2. Reviewed studies: overview and general characterization

The Scopus abstract and citation database was chosen to search for the relevant literature. This choice was motivated by the extensive breadth of peer-review journal and conference proceeding coverage as well as advanced literature analysis tools. Query statements covering all possible combinations of terms (Table 1) related to optical and radar remote sensing, agriculture and crop classification were used. For each of the main search terms several synonyms were chosen and used in the query. This was necessary since authors may refer to 'data fusion' using various analog words such as 'combination', 'mixture', 'union', 'synergy', 'merge' etc. The same is true for all four search terms. The search query consisted of four parts each representing one search term (see Table 1). Within each query part the logical operator 'OR' was used to make sure that at least one of the synonym words is present in title, abstract or key words of a paper. These four query parts were combined in one search query using the 'AND' logical operator, which ensures the appearance of representatives of each of the four parts in the paper. No time limits were applied in the search process (the query was done on 4 July 2018). From the resulting list only those publications that match the topic of data fusion (optical-radar) for crop type classification were individually selected. The list of selected studies can be found in the supplementary materials S1.

Optical and radar synergistic studies on land use and land cover classification without discriminating crop types were not considered since this topic was recently reviewed by Joshi et al. (2016). On the whole, 73.3% of the publications were from peer-reviewed international journals and 26.7% from conference proceedings. Only peer-reviewed conference proceedings were considered in this review such as International Geoscience and Remote Sensing Symposium (IGARSS) and The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.

As a result, this review considers 75 publications. Main sources of peer-reviewed publications included in this review are the journals: International Journal of Remote Sensing (14 papers), Remote Sensing (8 papers) and Canadian Journal of Remote Sensing (6 papers). The full list of the literature sources could be found in the supplementary materials S2.

Most of the reviewed articles are case studies on the topic of crop type classification using optical and radar data. Additionally to the reviewed case studies, literature on data

Table 1. Main search words and their analogs used in the Scopus search query.

Main search words	Scopus search query	Logical operator between query parts
Fusion	(TITLE-ABS-KEY (**synerg***) OR TITLE-ABS-KEY (**fusi***) OR TITLE-ABS-KEY (***comb***) OR TITLE-ABS-KEY (***mix***) OR TITLE-ABS-KEY (***uni***) OR TITLE-ABS-KEY (**merg***))	
		AND
Optical data	(TITLE-ABS-KEY (**'optical'**) OR TITLE-ABS-KEY (**'vegetation ind*'**))	
		AND
Radar data	(TITLE-ABS-KEY (**'SAR'**) OR TITLE-ABS-KEY (**radar**) OR TITLE-ABS-KEY (**microwave**))	
		AND
Crop type	(TITLE-ABS-KEY (**agricultur***) OR TITLE-ABS-KEY (**crop***) OR TITLE-ABS-KEY (**agro***) OR TITLE-ABS-KEY (**phenolog***))	

fusion theory and recent advancements (Ehlers 1991; Pohl and van Genderen. 2016), pixel level image fusion techniques (e.g. Harris, Murray, and Hirose 1990; Hong, Zhang, and Mercer 2009) and application of radar remote sensing in agriculture (McNairn and Brisco 2004; Steele-Dunne et al. 2017) were analyzed. 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.

The reviewed papers on crop type discrimination were published between 1978 and 2018. Five out of these studies are dated before 1990 (e.g. Ahern et al. 1978; Li, Ulaby, and Eyton 1980; Ulaby, Li, and Shanmugan 1982; Brisco, Brown, and Manore 1989; Fiumara and Pierdicca 1989). As it is shown in the upper part of Figure 1, an overall increase in the number of research publications on this topic can be observed over time, particularly since 2014. The lower part of Figure 1 relates the lifetime of optical and radar earth observation satellites to the publication of respective synergistic studies. The citations number taken from Scopus increased simultaneously as highlighted in Figure 2.

With regard to crop type discrimination, the reviewed studies have mainly concentrated on cereals, oilseed and sugar crops. Cereals (corn – 35 studies, wheat – 31 studies, barley – 16 studies, oats – 9 studies, rye – 5 studies), which are important food crops and a significant source of protein, are the most commonly examined crop types (Figure 3). Nine studies were exclusively devoted to the identification of rice, a crop type which is of high relevance for global food and nutrition security. Root, tuber crops (potatoes – 6 studies, yams – 1 study) and leguminosas (peas – 9 studies, beans – 5 studies, lentils – 4 studies, lupins – 1 study) are less frequently studied. Chapter 5 will provide more detailed information on the studied crop types and suitable discrimination approaches.

2.1. *Study sites and their extent*

Study sites are distributed among 30 countries, as illustrated in Figure 4. When considering the United Nations geoscheme for defining sub-continental regions, more than half of the studies focus on Asia (Eastern Asia – 11 studies, South-East Asia – 7 studies, Western-Asia – 5 studies, South-Asia – 4 studies) and Europe (Western Europe – 9 studies, Southern Europe – 8 studies, Eastern Europe – 4 studies and Northern Europe – 3 studies) followed by North America (22 studies), Africa (West Africa – 3 studies), South America (2 studies) and Australia (1 study). Four of the reviewed studies conducted their research in two different countries (Ghana and Burkina Faso (Forkuor et al. 2015), South Korea and USA (Park and Im 2016; Park et al. 2018), Japan and USA (Qi et al. 2003)). The studies conducted in Canada, the USA, China and Italy cover approximately 40% of all publications. To some extent, the global spatial arrangement and distribution of study sites show spatial similarity with croplands distribution across the world. But despite the fact that Central Asia, Southern America and Africa have extensive amounts of croplands, these regions were subject to only five of the reviewed studies. Please note again, that qualitative and quantitative analysis of the literature is purely based on the 75 studies which were selected using the search queries shown in the Table 1.

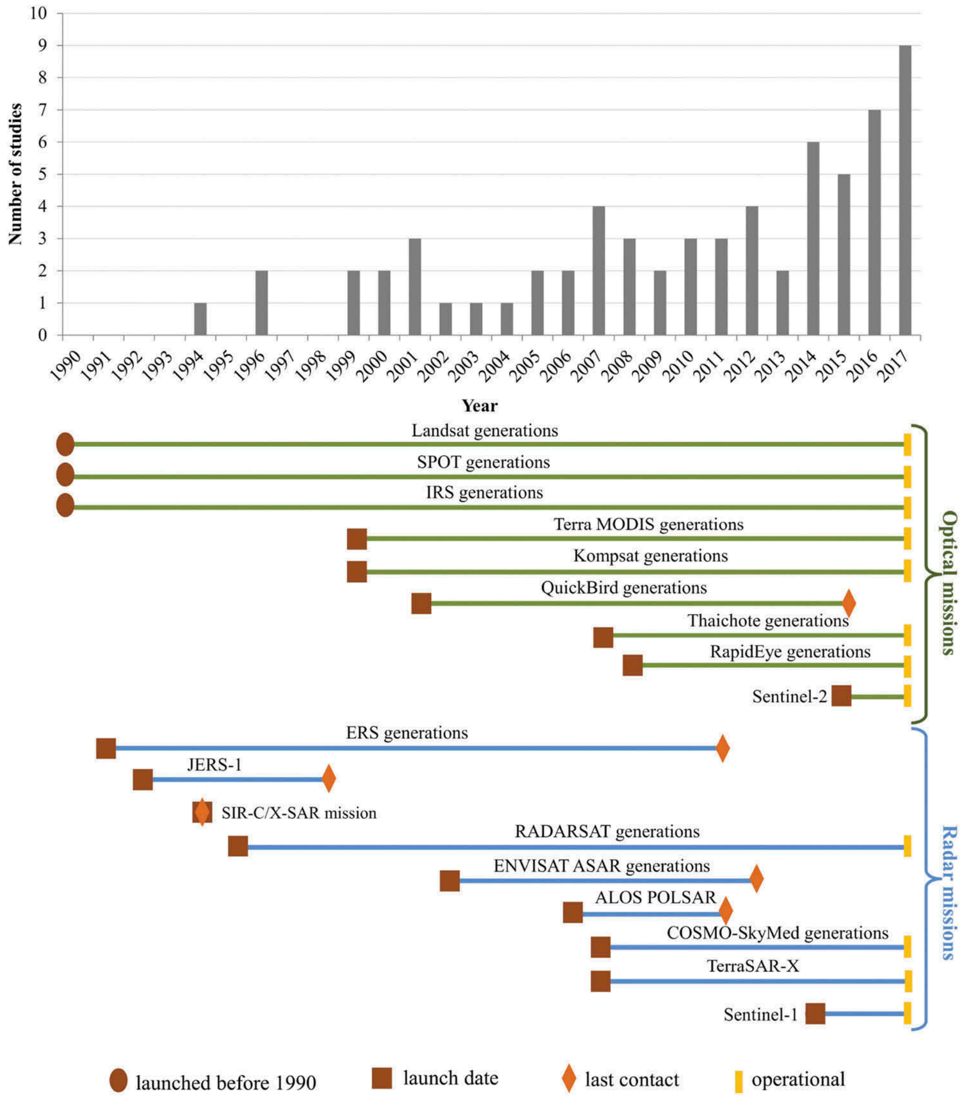

Figure 1. Temporal distribution of reviewed studies (top) and availability of relevant Earth Observation satellites (bottom). Five papers, published between 1978 and 1990 are not displayed for improving visualization. Since the final number of publications from the current year 2018 cannot be presented yet, this year was excluded from the diagram. All studies conducted before 1990 utilized combination of Landsat-5 and Airborne radar systems.

Almost half of the studies conducted their research on areas of less than 1,000 km^2. As it can be noted from Figure 5, with the increasing size of study areas, the number of publications is decreasing. Only one study, conducted by Torbick et al. (2017), was performed at the national level, covering all territory of Myanmar (676,578 km^2). Relatively large study sites (20,000 km^2 –50,000 km^2) are associated with countries with extensive cropland areas such as Canada, China, Australia and Ukraine.

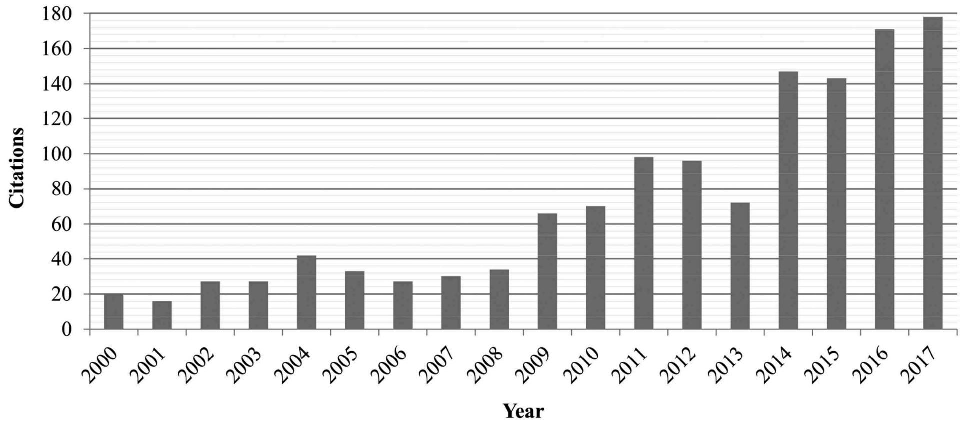

Figure 2. Number of citation per year of reviewed literature.

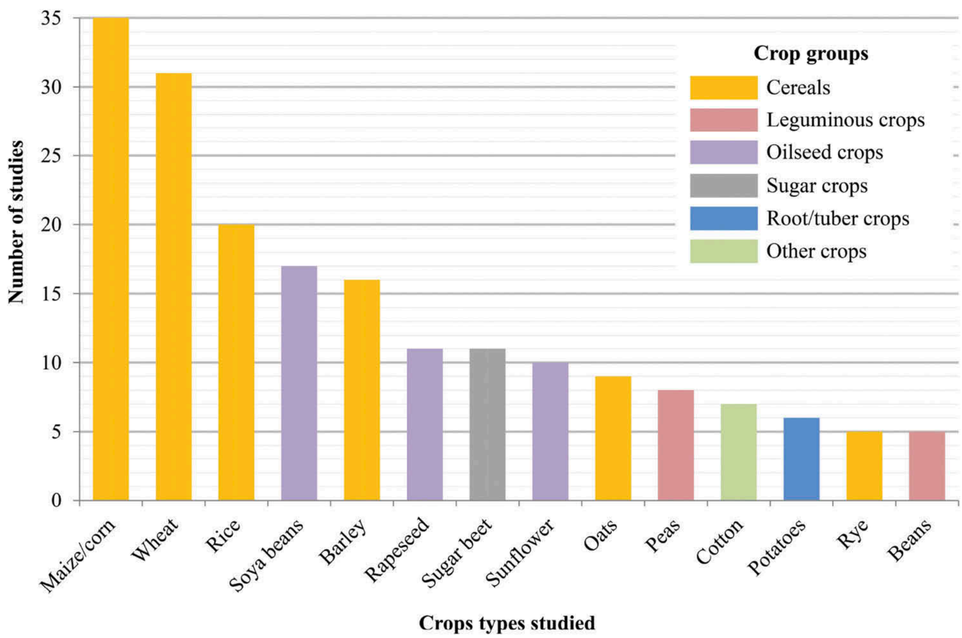

Figure 3. Number of studies focusing on particular crop types.

2.2. *Combination of sensors and aspects of multi-temporal information*

In total, data from ten optical and ten radar sensors were synergistically used in the reviewed studies. Tables 2 and 3 list these sensors and their technical characteristics. The majority of the studies (57 publications) examined data from one radar and one optical sensor, whereas the rest of the reviewed publications used image data from one optical and two radar (9 studies), two optical and one radar (5) or two optical and two radar satellites (3). Only one study utilized data of one optical and three radar satellites (Shang et al. 2008). Figure 6 shows all sensor combinations and their frequency of use in the reviewed publications.

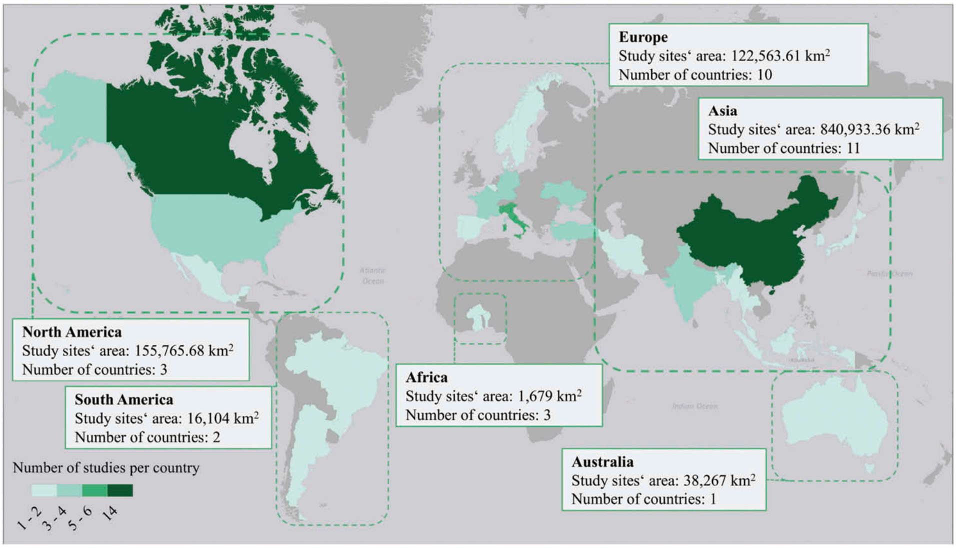

Figure 4. Number of studies conducted per country and region on synergistic use of optical and radar remote sensing data for crop type classification.

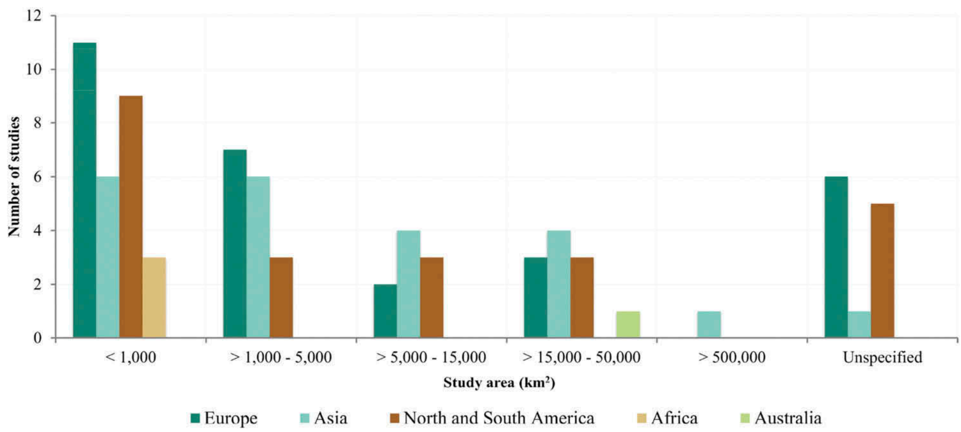

Figure 5. Spatial extent of study sites of the reviewed articles focusing on synergetic use of optical and radar remote sensing data for crop type classification. Twelve reviewed articles, which did not provide study extent information, are not included in this diagram.

The dominant combinations of sensors, representing half of the studies, are Landsat + RADARSAT (12 studies), Landsat + Sentinel-1 (8), Landsat + ASAR (7) and Landsat + ERS (7). Optical images of the Landsat series were used in the majority of studies (47 out of 75) followed by sensors of the SPOT (11) and RapidEye (9) missions. The most frequently involved radar sensor is RADARSAT, which contributed to 27 studies. The use of other radar sensors such as ERS (12 studies), Sentinel-1 (11), ALOS PALSAR (10) and ASAR (10) was distributed relatively equally. Additionally to a combination of optical and radar images, auxiliary information such as field boundaries e.g Larrañaga, Álvarez-Mozos, and Albizua (2011) and topographic or land cover maps e.g. Pinheiro, Carrao, and Caetano (2007) were used in some cases.

Table 2. Main characteristics of radar remote sensing satellites used in the reviewed studies (excluding airborne sensors).

Mission	Live time	Operator	Frequency (band)	Centre frequency (GHz)	Swath width (km)	Image resolution (m)	Polarization	Incidence angle (°)	Repeat rate (days)
ENVISAT ASAR	2002–2012	European Space Agency	C	5,331	56–40	30,000–1,000	Quad.	14 to 45	35
ERS-1	1991–2000	European Space Agency	C	5,3	5–500	10,000–50,000	VV	18 to 47	35
ERS-2	1995–2011								
RADARSAT-1	1995–2013	Canadian Space Agency	C	5,3	50–500	8–100	HH	10 to 59	24
RADARSAT-2	2007-act.	Canadian Space Agency	C	5,405	18–500	3–100	Quad.	10 to 60	24
Sentinel-1	2014-act.	European Space Agency	C	5.405	20–400	5–40	Dual.	18.3 to 47	12
SIR-C/X-SAR	1994–1994	NASA	L/C/X	1.25/5.3/9.6	15–90	10–30	L/C: Quad, X:VV	15 to 55	–
ALOS PALSAR	2006–2011	Japanese Space Exploration Agency	L	1.27	70–350	10–100	Quad.	8 to 60	46
JERS-1	1992–1998	Japan Aerospace Exploration Agency	L	1.275	75	18	HH	35.21	44
COSMO-SkyMed	2007-act.	Italian Space Agency	X	9.65	10–200	1–100	Quad.	18 to 59.9	16
TerraSAR-X	2007-act	German Aerospace Agency	X	9.65	5–150	1–16	Quad.	20 to 55	11

Table 3. Main characteristics of optical remote sensing satellites used in the reviewed studies (excluding airborne sensors).

Mission	Live time	Operator	Bands	Wavelength range (μm)	Spatial resolution (m)	Scene size (km)	Altitude (km)	Repeat rate (days)
Landsat[*7]	1972-act.	USGS[1] & NASA[2]	8MS[3] + 1Pan.[4] + 2Ter.[5]	0.43–12.51	MS: 30; Pan:15; Ter:100.	170 x 185	705	16
SPOT[*5]	1986-act.	Space Agency of France	3MS[3] + 1Pan[4] + 1SWIR[5]	0.49–1.75	MS:10; Pan:5; SWIR:20.	60 x 60	832	26
RapidEye	2008-act.	BlackBridge AG	5MS[3]	0.44–0.85	MS:5	77 x 77	630	5.5
IRS[*1C]	1988-act.	Indian Space Research Organization	4MS[3] + 1Pan[4] + 2SWIR[5]	0.52–1.70	MS: 23.5; Pan:5.8; SWIR:70.	141 x 141	817	24
Terra MODIS	1999-act.	NASA[2]	4MS[3] + 3SWIR[5]	Band 1–7: 0.45–2.15	Band 1–2:250; Band 3–7:500.	10 x 10	705	16
QuickBird	2001–2015	DigitalGlobe	4MS[3] + 1Pan[4]	0.45–0.9	MS:2.90; Pan:0.65.	16.8 x 16.8	450	3,5
Thaichote	2007-act.	Thai Ministry of Science and Technology's Space Agency	4MS[3] + 1Pan[4]	0.45–0.9	MS:15; Pan:2.	22 x 22	822	over Thailand – 3
Kompsat[*2]	1999-act.	Korea Aerospace Research Institute	4MS[3] + 1Pan[4]	0.45–0.9 [*2]	MS: 1; Pan: 4.	15 x 15	685	3
Sentienl-2	2015-act.	European Space Agency	10MS[3] + 3SWIR[5]	0.443–2.19	4 bands – 10; 6 bands – 20; 3 bands – 60.	Tile: 100x100	786	5

*[n] – numbers are given for the n-th satellite series of the mission;
[1]USGS = United States Geological Survey;
[2]NASA = National Aeronautics and Space Administration;
[3]MS = Multi-spectral;
[4]Pan = Panchromatic;
[5]SWIR = Short-wave infrared.

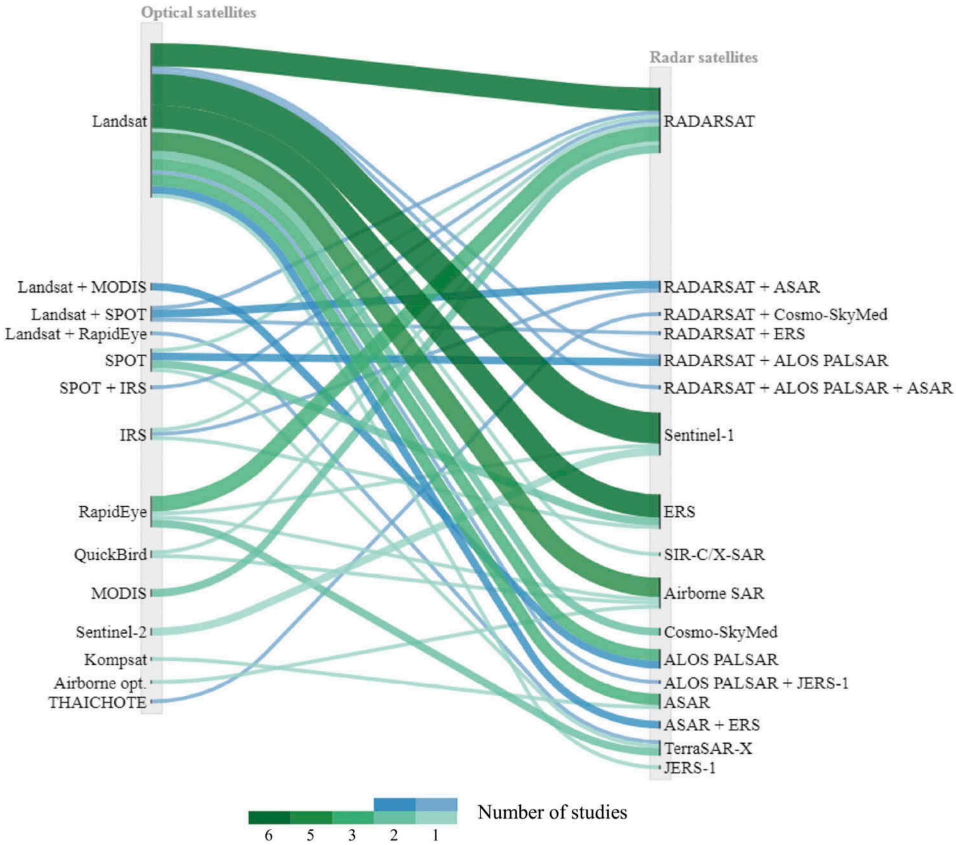

Figure 6. Combination of optical and radar sensors used in studies for crop type classification covered by this review. Studies which used two sensors (1 optical + 1 radar) are shown in green, whereas studies which used three or more sensors are shown in blue colour.

The majority of the radar and optical synergistic studies report an advantage of using satellite image time series (SITS). A combination of optical and radar SITS allows to reduce temporal gaps (mostly occurring due to clouds) and gives the possibility to monitor the growing cycle of crops (McNairn et al. 2009). (Inglada et al. 2016) examined the impact of SAR SITS on the classification results by fusing time series of eleven Landsat scenes with nine Sentinel-1 scenes. In this study, significant improvements in accuracy were reported showing that land cover maps in agricultural areas can be generated early in the growing season with satisfactory accuracy. Shang et al. (2008) demonstrated that acceptable accuracy might be achieved already in the early growing season even if only one Landsat image was complemented by two ASAR (VV/VH polarization) images. Zhou et al. (2017) concluded that in case of winter wheat classification, when an optical image cannot be utilized due to considerable cloud cover, it can be replaced by a SAR image without any adverse influence to the quality of the classification. Nonetheless, the combination of optical and SAR time series showed superior performance (F1 measure = 98.06%) for winter wheat detection compared to single source image classifications.

Nowadays, the increasing availability of Earth Observation (EO) data triggers the elaboration of scientific approaches for multi-source data analysis. Specifically, the Sentinel satellite missions of the Copernicus program and the Landsat mission provide a unique set of free and open access EO data of unprecedented spatial-temporal resolution that are highly suited for agricultural applications. Thus, Sentinel data has been increasingly used in the recent multi-sensor data analyses for agricultural applications (e.g. Kussul et al. 2018; Mansaray et al. 2017; Lussem, Hütt, and Waldhoff 2016; Kussul et al. 2016b; Sonobe et al. 2017).

3. Data fusion concepts and categories in remote sensing

Methods that integrate data from different sources for combined analysis are called data fusion, but also multi-temporal change detection and pan-sharpening can be assumed as remote sensing data fusion methods. Data fusion is being used not only in remote sensing but also in a wide range of other research fields such as ocean surveillance, medical diagnosis, strategic warning defence and robotics (Hall and McMullen 2004). Depending on the scientific field, the definition of data fusion may vary considerably but even the definitions used in the field of remote sensing are not consistent. In remote sensing, the term data fusion has different variations such as information fusion (Sun et al. 2003), remote sensing image fusion (Pohl 2016), image fusion (van der Meer 1997) and multi-sensor image fusion (Franklin and Blodgett 1993). All these variants are focused on EO image fusion, image interpretation or used in the context of pan-sharpening (Schmitt and Zhu 2016). Table 4 provides examples of most cited data fusion definitions in remote sensing literature including the most frequently used definition by van Genderen and Pohl (1994).

Multi-sensor data fusion approaches belong to the remote sensing 'multi' concept which conceptually describes the combined use of diverse datasets. This concept covers multi-sensor, multi-temporal, multi-spectral or multi-frequency, multi-polarization and multi-scale image analysis aspects (Solberg 2006). Pohl and van Genderen (1998) listed

Table 4. Examples of the most cited definitions of the data fusion terms in remote sensing domain (adapted from Schmitt and Zhu (2016)).

Data fusion definition	Reference
'Image fusion is the combination of two or more different images to form a new image by using a certain algorithm'	van Genderen and Pohl (1994)
'Data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of "greater quality" will depend upon the application'	Wald (1999)
'Multi-sensor data fusion is a process of combining images, obtained by sensors of different wavelengths to form a composite image'	Dong et al. (2009)
'Remote sensing data fusion aims to integrate the information acquired with different spatial and spectral resolutions from sensors mounted on satellites, aircraft and ground platforms to produce fused data that contains more detailed information than each of the sources definition'	Zhang (2010)

categories of remote sensing data synergy which are utilized for various research purposes. The main focus of this review paper is on multi-sensor (radar-optical) image analyses. Nevertheless, multi-temporal and multi-resolution aspects of satellite image fusion are also relevant for most of the reviewed studies.

The actual methods that are used for image fusion are drawn from a wide range of research areas such as artificial intelligence, pattern recognition, statistical approaches, formation theory, etc. (Zeng, Zhang, and van Genderen 2006). Table 5 presents the image fusion methods that are most commonly employed in the reviewed studies. This table also structures the data fusion methods into three categories according to the processing level at which fusion is performed: pixel level fusion, feature level fusion and decision or symbol level fusion. A fourth fusion level refers to the combination of signals coming from dissimilar sensors into a new signal with an enhanced signal-to-noise ratio than previous signals (Solberg, Taxt, and Jain 1996). Data fusion at signal level was however not used in any of the reviewed studies and is thus not further discussed in this review paper.

The fusion at pixel level implies merging the individual pixel values of each input dataset to new fused pixel values using various fusion techniques. Feature level fusion merges features (also named 'variables') extracted from raw data at intermediate processing levels (Solberg, Jain, and Taxt 1994). For instance, a simple layer combination of optical features such as spectral reflectance, vegetation indices etc. and radar features such as texture information, backscattering coefficient, polarization ratio etc. is an example of feature level fusion. Decision or symbol level fusion combines the outcomes of individual classifications to produce a final map (Zhang 2010). The initial pre-classification of each input dataset is followed by a knowledge-based weighting of the individual classification results leading to a final classification. Figure 7 graphically illustrates the pixel, feature and decision fusion levels. Image fusion at feature level was performed by the majority of reviewed studies (54 studies), followed

Table 5. Commonly used data fusion methods in the reviewed literature.

Fusion level	Fusion methods	Reference (example)
Pixel-level fusion	Simple band combinations	Blaes, Vanhalle, and Defourny (2005)
	Principal component analysis (PCA)	Vescovi and Gomarasca (1999)
	Intensity, Hue and Saturation (IHS)	Feingersh, Gorte, and van Leeuwen (2001)
	Discrete Wavelet Transform (DWT)	Gibril et al. (2017)
	Brovey Transform (BT)	Firouzabadi and Sadidy (2006)
	Ehlers fusion (EF)	Abdikan et al. (2015)
	High Pass Filter (HPF)	Abdikan and Sanli (2012)
Feature-level fusion	Separability measures	Dusseux et al. (2014), McNairn et al. (2002), Michelson, Liljeberg, and Pilesjö (2000)
	Feature layer combinations	Zhou et al. (2017)
	Maximum separability and minimum dependency (MSMD)	Khosravi, Safari, and Homayouni (2018)
Decision-level fusion	Bayesian formulation	Solberg, Jain, and Taxt (1994)
	Voting strategy	Waske and van der Linden (2008)
	Heuristic class allocation	Hill et al. (2005)
	Contextual fusion	Ban, Hu, and Rangel (2010)
	Dempster Shafer theory	Betbeder et al. (2014)

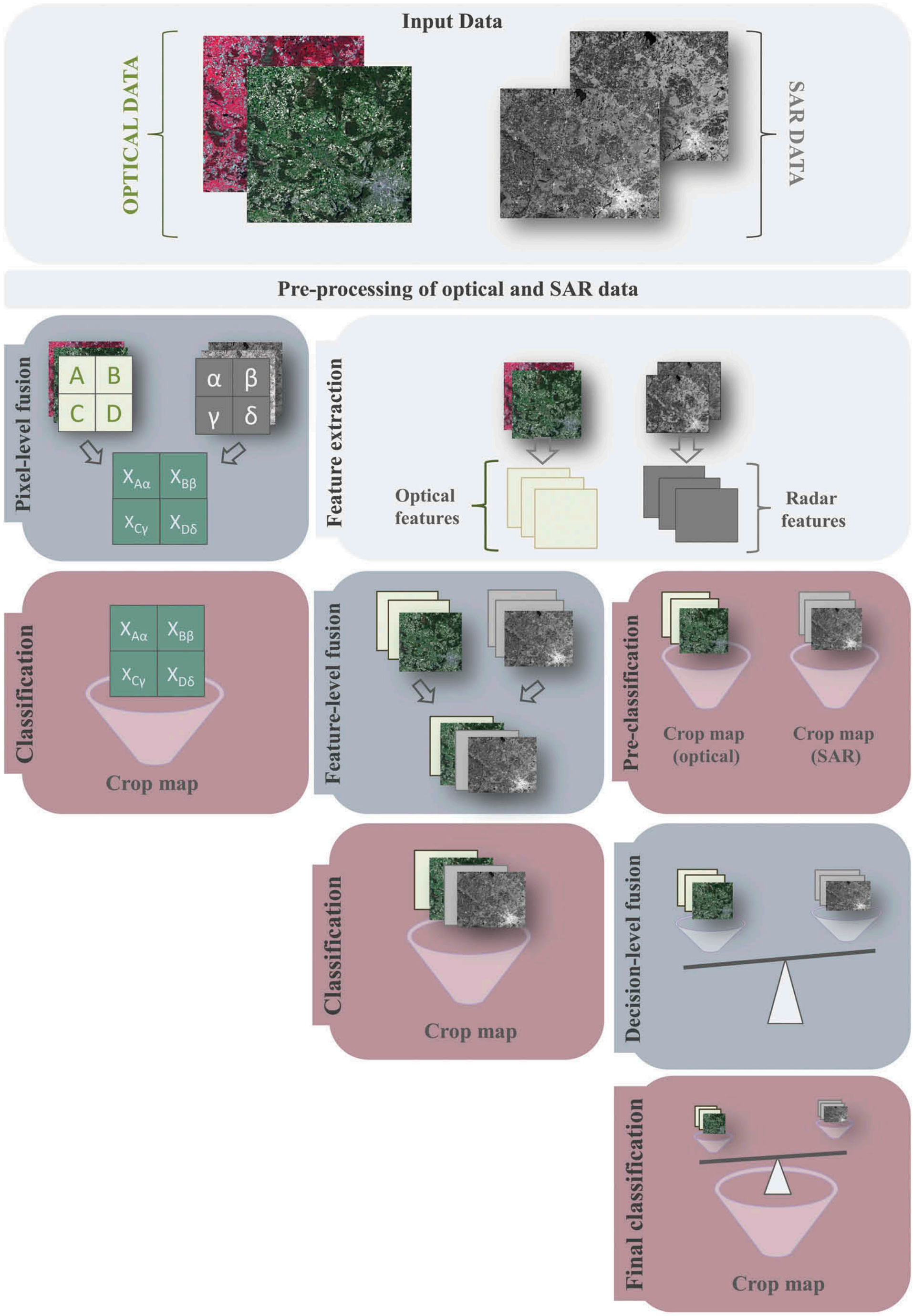

Figure 7. Fusion of optical and radar data for crop type classification at pixel-, feature- and decision levels.

by pixel level fusion (13 studies) and decision level fusion (8 studies). More information about fusion levels and applied techniques are given in the following sub-chapters.

3.1. *Pixel level fusion*

Pixel level image fusion is conducted at a low processing level, where the input is usually pre-processed optical and radar channels. The purpose of pixel fusion varies from case to case, but it is mainly focused on the improvement of spatial resolution, structural and textural details and preservation of a spectral fidelity of the original multispectral imagery (Zhang 2010). Like with other fusion methods, input raster are geocoded and/or co-registered before the fusion. Pixel level fusion methods vary from simple colour composition techniques to more complex hybrid methods which utilize the combination of two or more algorithms at once. A number of studies perform comparative research where the performance of different pixel level fusion techniques is evaluated. Among the reviewed studies, the most frequently applied optical-radar fusion methods are principal component analysis (8 studies), intensity-hue-saturation (7), discrete wavelet transform (5), Brovey transform (4), Ehlers fusion (4 studies) and high pass filter (4 studies). Figure 8 shows the frequency of different pixel level fusion methods as used in the reviewed studies. Methods such as the adjustable SAR-MS and Bayesian data fusion (Abdikan et al. 2015) were examined by single studies only. The Dempster Shafer theory of evidence was utilized in two studies (Le Hegarat-Mascle et al. 2000; Betbeder et al. 2014).

Taxt and Schistad Solberg (1997) grouped pixel level fusion approaches into three categories which are statistical methods, Dempster-Shafer theory and neural networks. Pohl and van Genderen (2015) revised this categorization with the aim to adapt it to the availability of novel fusion approaches and suggested five broad groups of image fusion techniques:

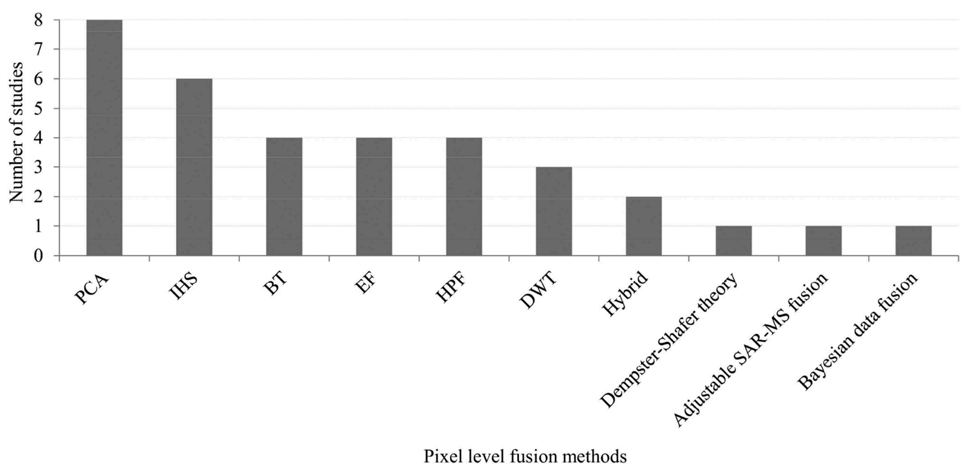

Figure 8. Pixel level fusion methods used in the reviewed literature on combination of optical and radar remote sensing data for crop type classification.

(1) Component substitution methods;
(2) Numerical and statistical image fusion;
(3) Modulation-based techniques;
(4) Multi-resolution approaches,
(5) Hybrid techniques.

These groups of fusion techniques are described in detail in the following sub-chapters except for numerical and statistical image fusion, as it was not used in the reviewed literature.

3.1.1. *Component substitution techniques*

Component substitution techniques transform selected input bands of the original images to new data space with new substituted images (Pohl and van Genderen 2015). In the reviewed studies, the most utilized component substitution techniques are principal component analysis (PCA) and intensity, hue and saturation (IHS) transform.

PCA is one of the widely used methods of pixel level data fusion, which allows reducing redundancy within data, but at the same time, keeping the most relevant information (Chavez Jr and Kwarteng 1989). In case of optical-radar data fusion, this method converts a set of inter-correlated optical and radar variables into a set of uncorrelated variables by merging the original information (Sukawattanavijit and Chen 2015). PCA is a tool to reduce large data amounts with redundant information and may thus reduce the required processing power (Vescovi and Gomarasca 1999). Sukawattanavijit and Chen (2015) deduced that results of PCA demonstrated better performance compared to other pixel level fusion methods because of the ability to compress large amounts of spectral and backscattering information without major loss of vital information. Moreover, Abdikan and Sanli (2012) concluded that spatial characteristics acquired from SAR images as well as spectral information of optical images were better conserved in PCA than in IHS.

Feingersh, Gorte, and van Leeuwen (2001) reported that fused optical-radar features produced with PCA result in better classification accuracy for crop type classification compared to features produced by IHS. Adverse to this, the study of Sanli et al. (2017) highlighted that even though PCA improved the accuracy of the detection of particular crops the overall accuracy of the classification did not improve considerably compared to classification results from other pixel-level fusion methods. Also, Sukawattanavijit and Chen's (2015) results showed remarkable improvement of classification for herbaceous crops when using PCA method, but the quality of delineation of other land cover classes such as forest, river and urban areas did not change significantly. The study of Haldar et al. (2012) which was specifically focused on jute and tea delineation showed that an overall accuracy of 94% for jute and 92% for tea could be achieved by using PCA fusion of four optical and two SAR images (HH and HV).

Compared to PCA, IHS allows the fusion of a limited amount of input bands. The IHS transform technique was initially conceived for combining high resolution radar data with other remote sensing images to provide a unique set of high spatial and spectral resolution colour imagery (Harris, Murray, and Hirose 1990). Hong et al.

(2011) for instance used IHS and wavelet integration to fuse low-resolution multi-spectral information from MODIS with high-resolution RADARSAT-2 imagery. While Raghavswamy et al. (1996) found that IHS transformation works better than combination of co-registered data sets of SAR and optical data for the delineation of plantations like casuarina, coconut etc. Abdikan and Sanli (2012) concluded that IHS shows worst statistical results in agricultural areas compared to other fusion methods such as HPF, DWT and PCA. Sanli et al. (2017) concluded that multi-sensor data combination considerably improves the final accuracy of wheat and vineyard classes, but among all tested pixel level fusion methods IHS showed the worst results in qualitative and quantitative respects.

3.1.2. *Modulation-based techniques*

The modulation-based fusion techniques are centred on the idea of integrating high-resolution spatial information into multispectral images (Zhang 2010). An example could be the fusion of normalized multispectral bands and higher-resolution SAR imagery. Among reviewed articles, Brovey transform (BT) and high pass filter (HPF) are the mostly used modulation-based methods.

BT, also known as colour normalization transform, merges data from different sensors and tries to keep spectral fidelity of inputs but replace the brightness information with the high-resolution band (Vrabel 1996; Pohl and van Genderen 1998). Firouzabadi and Sadidy (2006) mentioned that fused images from Landsat and RADARSAT show more details of the sensed scene than each dataset separately and particularly BT technique is able to provide an image with better visual separation between forest and cultivated rice areas. Haldar et al. (2012) study showed that BT presented highest classification accuracy for the identification of jute and tea fields using single date images of IRS-1C, RADARSAT and Envisat ASAR.

HPF inject textural and spatial details of the high resolution dataset into the lower resolution dataset (Schowengerdt 1980; Gangkofner, Pradhan, and Holcomb 2007). Sukawattanavijit and Chen (2015) concluded that for maize PCA and HPF fusion methods outperform IHS and BT with regard to the overall classification accuracy. In addition to above-said, Abdikan and Sanli (2012) stated that the HPF fusion performs best compared to all other pixel-level fusion methods for agricultural area. Sanli et al. (2017) pointed out that the use of the HPF method positively effects to the classification accuracy of wheat but not vineyards.

3.1.3. *Multi-resolution analysis*

The multi-resolution based image fusion method decomposes input images into several channels and forms a multi-scale image pyramid (Nunez et al. 1999). Each pyramid level corresponds to a coarser resolution channel with corresponding spatial details (Zhang 2010). The most used multi-resolution analysis techniques include wavelets and curvelets. In the wavelet-based fusion approach, spatial information extracted from SAR imagery is injected into optical images, which allows minimizing the deformation of spectral information.

The wavelet-based fusion approach was used in three reviewed studies. The study of Gibril et al. (2017) showed that the performance of the discrete wavelet transform (DWT) method was slightly lower compared to other investigated methods when classifying oil palm, coconut and rice. Abdikan and Sanli (2012) pointed out that it can be a very promising approach for urban areas if PALSAR data is investigated, but not for agricultural areas. Although DWT improves the accuracy of wheat field identification from other land cover classes such as residential or pasture, it does not significantly affect the overall accuracy compared to other pixel-level fusion methods (Sanli et al. 2017; Gibril et al. 2017).

3.1.4. *Hybrid pixel level fusion techniques*

As the name implies, hybrid methods involve the incorporation of two or more data fusion techniques and thus allow utilizing the advantages of each input method (Pohl and van Genderen. 2015). One of the well-known hybrid fusion techniques is the Ehlers fusion method (Klonus and Ehlers 2007). This method uses IHS and inverses IHS methods that conserve the spectral information of input optical data, which can be useful to conduct visual classification. Comparative studies of Abdikan and Sanli (2012) on the discrimination of agricultural area and Abdikan et al. (2015) on the classification of cotton and corn showed that the Ehlers method outperformed all other pixel-level fusion methods and demonstrated better visual and statistical outcomes. Hong et al. (2014) compared the layer stacking method to the hybrid method developed by Hong, Zhang, and Mercer (2009) to classify alfalfa fields and grassland. This hybrid fusion approach uses IHS and wavelet integration to combine high spatial resolution SAR data with low-resolution optical images. Results showed that the hybrid method allows fusing optical and SAR data in an optimal way and improve the classification accuracy of alfalfa significantly compared to stacked channels.

3.2. *Feature level fusion*

Feature level fusion is performed by merging original or delineated image layers (so-called features or variables) features such as spectral bands and indices, textural information, backscattering data etc. of optical and radar satellite datasets. This approach allows utilizing the most relevant features of each data source and thus advances the classification accuracy. In this high-level fusion method (Zhang 2010), feature layers extracted from original images are combined to form a new multi-layer dataset containing the most significant information for classification.

Fourteen of the reviewed studies gave a preference to a simple and straightforward approach of band combination without conducting any prior feature extraction and feature selection steps (e.g. Torbick et al. 2017; Parks 2012; Fiumara and Pierdicca 1989). Other studies performed band selection e.g. based on Jeffries-Matusita (J-M) distance (e.g. Michelson, Liljeberg, and Pilesjö 2000; Erasmi and Twele 2009), in order to select the most promising combination of channels for increasing classification accuracy. Feature level fusion does not always imply the combination of spectral bands and radar backscattering data. The majority of the reviewed studies (30 studies out of 54) combined not only original optical or radar channels but also features extracted from these datasets (Sheoran and Haack 2013; de Alban et al. 2018). For instance, Park et al. (2018) merged 10 input datasets which consisted of original Landsat bands, vegetation indices (NDVI, NDWI) and SAR backscattering information. Mansaray et al. (2017) stacked five Sentinel-1A images with NDVI, MNDWI images using the bilinear interpolation techniques. The study of Gibril et al. (2017) compared the performance of pixel level fusion methods such as BT, DWT and Ehlers fusion with a simple combination of optical and SAR layers for palm oil, coconut and rice fields classification. Results showed that the stacked dataset of Landsat-8 and RADARSAT-2 improves the classification of crops compared to single source images as well as other pixel level fusion techniques, and gives the highest accuracy when using the SVM classification in contrast to other fusion methods. The feature level combination of SAVI extracted from two dates of Landsat images and RADARSAT SAR data resulted in an overall classification accuracy of 90% when classifying corn, soybeans, peanut, and cotton fields (Xu et al. 2004). . But also other studies showed that the integration of optical or radar features as separate layers in a stacked dataset boosts the performance of classification by providing additional information (e.g. Mansaray et al. 2017, who investigated rice; Forkuor et al. 2014 – cotton, maize, millet, sorghum, rice, yam; Torbick et al. 2017 – rice). The following sub-chapters give an overview on optical and SAR features and feature selection approaches commonly used in feature level fusion approaches for crop type mapping.

3.2.1. *Optical features*

Spectral features extracted from optical data can serve as indicators of vegetation condition, chlorophyll content, plant water content and phenology by providing information about the reflective and emissive characteristics of crops at the visible and near-infrared wavelengths. Spectral reflectance values of remotely sensed targets contain valuable information for the class discrimination; nevertheless, the distinction of two crop types with similar spectral characteristics, phenologies and crop calendars is challenging based on surface reflectance only. Lu and Weng (2007) stated that addition of various features improves the performance of the classifiers. In the following paragraphs, we discuss the inclusion of vegetation indices (VI), biophysical variables and texture variables, which were hypothesized to provide broader and more suitable information for classification of crop types.

Among the commonly used optical features, vegetation indices (VI) play a major role. As a qualitative measure of vegetation cover, VIs are simple and effective. VIs were involved in the classification process in almost all reviewed studies. Indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Simple Ratio (SR) and Enhanced Vegetation Index (EVI) are most frequently used compared to other indices. Zhou et al. (2017) indicated that the highest separability between winter wheat and rapeseed in Jiangsu province (China) could be observed from the time series of SR and NDVI values. The results of the Maximum Separability and Minimum Dependency (MSMD) feature selection method proposed by Khosravi, Safari, and Homayouni (2018) showed that the Soil-Adjusted Vegetation Index (SAVI) was the optimal VI used to classify wheat, canola, soybeans, oats, corn and peas in the south-west district of Winnipeg (Manitoba, Canada). Park and Im (2016) highlighted that NDWI and NDVI appeared more contributing than the other variables for the success of paddy rice classification. For example, Inglada et al. (2015) concluded that NDVI and NDWI together with surface reflectance and brightness values are the most suitable optical features which grasp almost all vital information for crop type classification, which on this study were maize, sorghum, cow peas and cotton.

Additionally to vegetation indices, Dusseux et al. (2014) extracted biophysical variables, namely Leaf Area Index (LAI) and the fraction of vegetation cover (fCOVER) from optical satellite images. The transformed divergence (TD) measure indicated that temporal profiles of LAI have higher importance for winter wheat, maize and grassland classification than temporal profiles of fCOVER and NDVI. The changes in temporal profiles provide important information for successful crop type classification. Salehi, Daneshfar, and Davidson (2017) highlighted the importance of multi-temporal imagery for crop type (e.g. cereals, oilseed crops) classification compered to mono-temporal data.

Texture information extracted from optical images can also contribute to improve crop type discrimination. Khosravi, Safari, and Homayouni (2018) reported that, in a classification of wheat, soybeans, corn, canola, oats and peas, indicators of textural homogeneity, variance and contrast had the most important positive influence on the classification accuracy. These variables, in addition to pixel-based spectral reflectance values, provide advanced information about the target objects under investigation. The top part of Table 6 lists optical features commonly used in the reviewed studies.

3.2.2. *Radar features*

In the reviewed feature level fusion studies, variables extracted from SAR data were mainly used in a role of complementary information to optical data. SAR data generally contains valuable information about physical and structural properties of the land surface. The majority of the conducted feature selection studies showed that SAR variables such as backscattering coefficient, interferometric coherence, texture and polarization are able to grasp the most important information of a SAR time series for crop type mapping. The SAR features which were commonly extracted for crop type classification purposes are listed in Table 6 (bottom).

The backscattering coefficient, as the main indicator of crop structure at different phenological stages, is one of the primary SAR variables which was frequently used in

Table 6. Optical and radar features employed in feature level fusion.

Family	*Feature name*	*References*
OPTICAL FEATURES		
Vegetation indices	Normalized Difference Vegetation Index (NDVI)	Mansaray et al. (2017), Qi et al. (2003)
	Normalized Difference Water Index (NDWI)	Wang et al. (2015b)
	Spatial Ratio (SR)	Zhou et al. (2017)
	Enhanced Vegetation Index (EVI)	Torbick et al. (2011)
	Normalized Difference Flood Index (NDFI)	Villa et al. (2015)
	Red Green Ratio Index (RGRI)	Fontanelli et al. (2014)
	Simple Vegetation Index (SVI)	Haldar and Patnaik (2010)
Spectral reflectance	Red, NIR and MIR	Haldar and Patnaik (2010)
Biophysical variables	Leaf Area Index (LAI), fCOVER	Dusseux et al. (2014)
Texture variables	Homogeneity, variance, contrast	Khosravi, Safari, and Homayouni (2018)
RADAR FEATURES		
Haralik textures	Energy, Entropy, Inverse Difference Moment	Inglada et al. (2016)
Polarization	Polarization ratio	
	Polarization intensity	Li, Ulaby, and Eyton (1980)
	Circular polarization ratio	
Polarimetric decomposition	Freeman–Durden and Cloude–Pottier	Dusseux et al. (2014)
Backscattering	Backscattering coefficient	Ahern et al. (1978)
Coherence	Repeat-pass interferometric coherence (γ)	Villa et al. (2015)

the reviewed studies. The intensity of the backscatter coefficient significantly varies depending on crop canopy structure. But also the incidence angle of the radar system and the moisture content of the land surface considerably influence the strength of the backscattering value. Thus, backscattering coefficients of crop types with resembling canopy structure are similar, which leads to difficulties in the distinction between crop types of similar physiognomic properties. For instance, McNairn et al. (2002) reported difficulties in the separation of broadleaf crops due to similar backscattering coefficients.

Moreover, the changes in backscattering intensity over time give additional information for distinguishing crop types, because of the individual development properties (phenological stages) each crop type has. The number of SAR images required for building informative temporal backscattering profiles highly depends on the complexity of a cropping system (Steele-Dunne et al. 2017). Skakun et al. (2016) explored the effect of backscattering coefficients on winter and summer crop classification. The results of these experiments showed that addition of backscattering intensity data leads to better separation of sunflower, soybeans and maize compered to single-source classification, and increases the classification accuracy from 86.01% to 90.10%. In addition, the inclusion of backscatter features of TerraSAR-X data turned out to be an important feature for the separation of rice and yam as well as for cotton and maize in West Africa (Forkuor et al. 2014). The results of Zhou et al. (2017) feature selection approach suggest that the backscattering intensity was more important for classification of winter wheat than texture and coherence information.

Along with the backscattering coefficient, polarization information was engaged in the classification process in almost all reviewed studies. Multi- or cross-polarized images provide information which tends to improve the crop type separability and crop diversity compared to single polarization data (Wang et al. 2015a). Polarimetric data can provide information about vegetation height, shape, distribution and geometric structure which positively affects the classification accuracy. However, Gebhardt et al. (2012) concluded that full polarized data (in this case TerraSAR-X Quadpol mode) does not substantially facilitate rice fields discrimination, while dual-polarized mode VV/VH is able to grasp the most significant information. Forkuor et al. (2014) and Inglada et al. (2016) agreed that VV polarization appears more important than VH polarization which contains volume scattering (see supplementary material S1 for crop types). This was explained by the fact that NDVI and VH polarization can be correlated which leads to data redundancy. Erasmi and Twele (2009) expressed the idea that only polarization ratios (e.g. Normalized Difference Polarization Ratio, Spatial Homogeneity) can lead to notable improvements of rice and cocoa separability compared to local statistics of co-cross-polarized data.

In conjunction with polarization information, different textural SAR measures were considered in the reviewed studies. Texture is an important attribute of SAR images with strong ability to distinctly characterize target objects in the image. Several factors such as orientation, scale and the spatial relation between texture elements affect the surface texture of target objects (Kandaswamy, Adjeroh, and Lee 2005). Image texture analysis methods like grey level co-occurrence (Ban, Hu, and Rangel 2010) and Markov random fields (Sandholt 2001) are widely used approaches to delineate texture metrics from SAR data. Ulaby et al. (1986) pointed out that textural variables retrieved by the grey level co-occurrence method are the most useful way of examining the content of remotely sensed images. Most of the studies reported that the SAR texture information in combination with optical data can provide superior classification results compared to the case when optical or radar data are used alone (Presutti et al. 2001; Zhou et al. 2017). Inglada et al. (2016) calculated three families of texture measures, namely local moments, Haralik textures (Haralik 1979) and the Structural Feature Set (Huang, Zhang, and Li 2007). The results of a feature selection algorithm showed that Haralik textures (energy, entropy and inverse difference moment) together with other SAR features such as polarization ratio, local mean and VV imagery could provide most of the information for a successful classification of crops such as corn, sunflower, rapeseed, alfalfa, soybean, and wheat/barley. An experiment of Kurosu et al. (1999) showed that integration of textural statistics to the original SAR images significantly improves rice classification accuracy. In contrast, Sheoran and Haack (2013) indicated that texture data did not prove beneficial for classification of almonds, cotton, alfalfa and fallow crops.

Coherence is another SAR feature where cross-channel correlation can be used as a helpful source of information for target object classification (Touzi et al. 1999). The test of Zhou et al. (2017) showed that adding coherence and texture information to the classification of winter wheat improves the accuracy.

3.2.3. *Feature selection methods*

At feature level fusion, special attention has to be given to the feature selection process. The selection of best-performing features helps to reduce the number of attributes and thus the requirements with regard to data storage and processing power. These aspects are particularly relevant as some features of optical and radar data can have high inter-correlation, which leads to data redundancy. Nonetheless, many machine learning methods are less affected by data redundancy compared to parametric methods (Maxwell, Warner, and Fang 2018). Another aspect is that some features have low or even misleading information content for the envisaged classification purpose.

Half of the reviewed studies, which used feature level fusion, pre-selected input features based on expert knowledge or through trial and error. Several studies selected commonly used optical and SAR variables such as vegetation indices, texture information and backscattering coefficients based on previous knowledge from literature (e.g. Presutti et al. 2001; Fontanelli et al. 2014; Wang et al. 2015; Park and Im 2016;).

Statistical or automated feature selection approaches were carried out by half of the feature level fusion studies. Inglada et al. (2016) for example selected the most relevant SAR features based on the variable importance estimated within the Random Forest classifier. The optical features were selected based on previous research conducted by Inglada et al. (2015). The classification accuracy using random permutations of each SAR feature was compared to the case without permutations. The decrease and/or increase in classification error is so-called variable importance value for each feature. A straightforward approach to identify best performing combination of variables was presented in Zhou et al. (2017). Ten possible combinations of SAR and optical features were classified separately in order to identify the feature set combination which shows highest classification accuracy for winter wheat. The performance of selected individual optical and radar features for crop type classification was mentioned in previous sub-chapters 3.2.1. and 3.2.2. .

Several studies employed tests which allow measuring the spectral separability between two classes in order to assess best performing feature sets. In the reviewed literature, the most frequently used separability measures were TD and J-M distance measures. The indices of separability, their properties and limitations in the context of crop type classification were closely discussed in Thomas et al. (1987). Dusseux et al. (2014) and McNairn et al. (2002) exploited the TD measure in order to assess and compare the ability of temporal profiles of optical and radar features to distinguish grassland from winter wheat and maize. The most discriminative features extracted from optical and SAR data were selected based on the TD analysis results. J-M distance measure was also widely used in order to determine which combination of channels contained the most valuable information for classification (e.g. Michelson, Liljeberg, and Petter 2000; Hill et al. 2005; Sonobe et al. 2017; Lobo, Chic, and Casterad 1996). The J-M distance provides a measure of the average distance between class density functions (Richards and Richards 1999). Based on the results of J-M distance, Michelson, Liljeberg, and Petter (2000) concluded that SAR time series data contained more information to separate, general land cover classes than optical data, but the highest separability between agricultural sub-classes (e.g. sugar beet, potato, rapeseed, wheat, rye, barley, oats) was achieved when optical and SAR data were combined.

A recent study of Khosravi, Safari, and Homayouni (2018) introduced a feature selection method called maximum separability and minimum dependency (MSMD) approach. The proposed technique is designed to select the most relevant features and remove redundant features. The MSMD method consists of two main parts, namely a distance-based measure (highest separability value of radar features) and a correlation-based measure (lowest correlation among optical features). The most commonly selected and used optical and radar features of this review are illustrated in Figure 9.

3.3. *Decision level fusion*

At decision level fusion, first individual classifications are performed using each input data source separately and the results are then combined based on decision rules which result in a deliberate decision (Solberg 2006). Decision level fusion approaches can take advantage of the best classification results from both optical and radar images, thereby increasing the quality of the final classification (Ban, Hu, and Rangel 2010).

Decision level fusion was performed in eight of the reviewed studies. The majority of these studies introduced their own frameworks for fusion of the individual single source classification results. The standard framework of decision level fusion methods is a rule-based combination of the classification results acquired from optical and SAR images (Soria-Ruiz, Fernandez-Ordoñez, and Woodhouse 2010). The knowledge-based decision fusion of optical and SAR classification results presented in Ban, Hu, and Rangel (2010) showed significant improvement over the results achieved only by optical data. The additional use of SAR backscatter information increased the accuracy of several classes such as rapeseed and soybean from ~70% to ~90%. The study of Okamoto (1999) is an example of a sequential decision level fusion, wherein iterative classification results of each prior classification are sequentially used for the decision process. First, classification results, achieved from the optical data, were used to identify arable lands, when

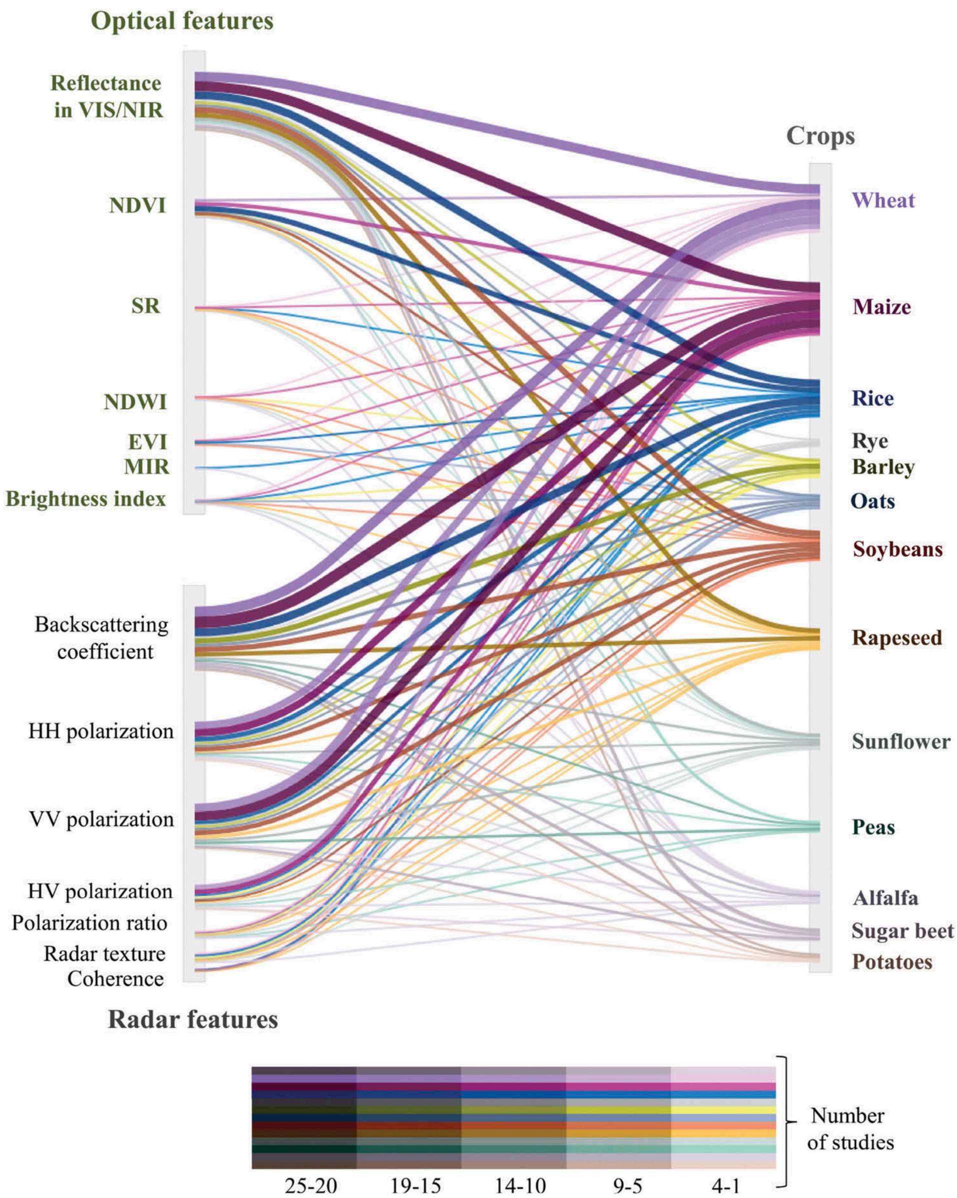

Figure 9. Frequency (size of connection lines) of the usage of optical and radar features for crop type (colour of connection lines) classification.

afterwards result of SAR backscatter thresholding was used to spot rice-plated areas within the previously identified arable lands in Indramayu Province, Indonesia. Hill et al. (2005) used optical and radar data individually to classify grass crops and pasture (for more specific crop information see supplementary material S1) properties in a simple and straightforward approach where SAR data was used to classify canopy height and optical data was used to quantify greenness. The fusion of these classification results produced better accuracy than classifications by each sensor alone.

Waske, Menz, and Benediktsson (2007) applied SVMs to classify optical and SAR data individually. The SVM approach was used once more and trained on the rule images of previous classification results. The authors pointed out that the major reason for success was the use of optical and radar data in a combination since the individual sensor data was not equally reliable.

The work of Waske and van der Linden (2008) addressed the problem of multi-sensor image classification using a multi-level segmentation approach by considering not only spectral or backscattering information but also the spatial context on different scales. Dataset from Landsat-5, Envisat ASAR and ERS-2 were classified separately using SVM. Then, the results were used in a decision fusion to perform final classification of cereals, rapeseed and root crops. The combination of the two classifiers, namely SVM and RF was another advantage of the fusion framework which allowed utilizing the strengths of both algorithms.

4. Image classification approaches

Along with the appropriate selection and pre-processing of satellite input data, the selection of a suitable classification approach is an important step towards a successful synergetic classification of crop types. Figure 10 displays the classification methods which were used more than once in the reviewed literature between 1990 and 2017. Classification approaches such as the ISODATA algorithm (Hong et al. 2014), Mahalanobis Distance (MD)-based classification (Cheng et al. 2016), Kernel-based extreme learning machine (KELM) (Sonobe et al. 2017) and Gaussian Mixture class (Sandholt 2001) classification were tested by single studies only.

4.1. *Parametric vs non-parametric classification methods*

The choice between parametric and non-parametric classification methods was also one of the major topics which were investigated in the reviewed literature. Different to non-parametric

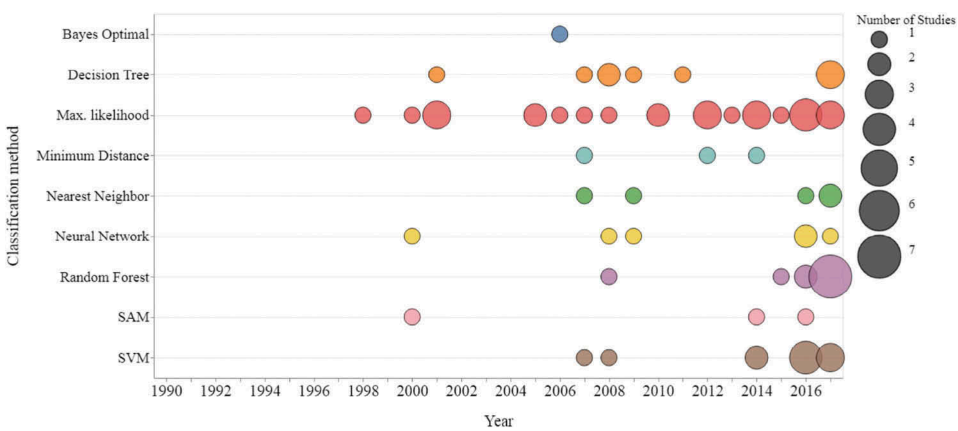

Figure 10. Temporal distribution of classification approaches which were used in the reviewed literature on combination of optical and radar remote sensing data for crop type classification.

approaches, parametric classification approaches draw statistical assumptions on the data e.g. on normal distribution. Many research papers motivate their choice of a classifier based on popularity and frequency of appearance in previous publications e.g. Abdikan et al. (2015), which however does not imply the superiority of a technique. The parametric classifier which is most frequently utilized approach in the reviewed studies is Maximum Likelihood Classifier (MLC). However, Pinheiro, Carrao, and Caetano (2007) reported that the parametric Maximum Likelihood classifier are not flexible enough to work with complex muliti-modal distinctions, which leads to poor classification results. Particularly, for multi-source data with heterogeneous information, the parametric classifiers may not be the best choice. Thus non-parametric classifiers such as support vector machines, random forest and decision trees which do not make any statistical assumption on data distribution are gaining more attention in the recent years (Figure 10). A comparison between a parametric (MLC) and a non-parametric (RF) classifier was for example conducted by Salehi, Daneshfar, and Davidson (2017). Results showed very close accuracy outcomes for cereals, soybeans, canola and corn crops; however, a slight outperformance of the non-parametric RF classifier was reported.

4.2. *Supervised vs unsupervised classification methods*

The majority of the reviewed studies gave preference to supervised (69 studies) rather than unsupervised (6 studies) classification methods. A number of studies chose supervised classification approaches based on the results of earlier studies which came up with the conclusion that supervised methods outperform the results of unsupervised methods e.g. Larrañaga, Álvarez-Mozos, and Albizua (2011) . Nevertheless, several studies have reported the advantages of applying unsupervised classification methods on multi-source data (Okamoto 1999; Le Hegarat-Mascle et al. 2000; Hong et al. 2011; Hill et al. 2005; Kussul et al. 2016a; Hong et al. 2014). Hong et al. (2014) claimed that the unsupervised classification had more advantages compared to supervised methods for differentiating grassland and alfalfa, as prior information is not necessary and as supervised methods allow to discover unknown classes. It was also pointed out that classification of the scene into several homogenous clusters is very useful for radar related classification. The study of Hill et al. (2005) which is focused on grass crops and pasture classification in Western Australia, gave preference to an unsupervised classification approach. The reasoning behind was that continious changes in the structure and composition of grasslands make a selection of trusthworthy training data impracticable, thus unsupervised method seemed to be better suited of this case studies. Le Hegarat-Mascle et al. (2000) focus on unsupervised classifications of mono-source and multi-source data. The classifications were performed using a Bayesian model (mono-source) and the Dempster-Shafer evidence theory framework (multi-source) where unsupervised classification results showed that fusion of Landsat and ERS provided the most robust classification of wheat, maize, barley etc. (for full list of the crops please check supplementary material S1). It is worth mentioning the existance of hybrid approaches, where initial unsupervised classification is followed by data analysis and interpretation or by supervised classification (e.g Thenkabail, Schull, and Turral 2005).

As it was mentioned above, the majority of the reviewed studies utilized supervised classification methods. One of the conventional classification approaches that is also available in most of the commonly used commercial software packages is the

Maximum Likelihood Classifier (MLC). This method was used in 29 of the reviewed studies and did not lose popularity from 1990ies until today (Figure 9). Since MLC is a parametric method, it is highly depending on the suitability of the probability model and in the quality of training data (Iannini, Molijn, and Hanssen 2013). Despite the fact that parametric MLC was used in almost half of the reviewed studies, Waske, Menz, and Benediktsson (2007) claim that this classification approach is not adequate for classifying fused images and suggest that non-parametric supervised methods are more suitable. The study of Pinheiro, Carrao, and Caetano (2007) confirmed and supported this statement.

Supervised machine learning classification approaches such as Random Forest (RF), Support Vector Machines (SVMs), *k*-Nearest Neighbour (*k*NN), Neural Networks (NN) and Decision Tree (DT) were utilized by 47 of the reviewed studies. For example, Abdikan et al. (2015) compared the performance of SVM, RF and kNN on the fused (TerraSAR-X and RapidEye) and single source (RapidEye imagery) EO data to classify corn and cotton fields. In both cases, classification accuracy exceeded the 90% threshold.

The quality of training samples is an important aspect that influences the results and accuracy of supervised classification procedures. In the reviewed studies, ground truth data were mainly gathered during field trips e.g. Presutti et al. (2001), McNairn et al. (2002), Inglada et al. (2016), Torbick et al. (2017), accessed from farmer's declarations e.g. Abdikan et al. (2015), derived through visual interpretation of very high resolution optical imagery e.g. Park and Im (2016) or provided by governmental agricultural organizations or ministries e.g. Lussem, Hütt, and Waldhoff (2016). Ground truth data contained information about crop types and condition, growth stage, height, soil temperature and water content e.g. Raghavswamy et al. (1996), Hill et al. (2005).

4.3. *Pixel-based vs object-based classification*

Pixel-based approaches are classical image analysis methods for remote sensing based classifications. Object-based approaches have rapidly gained popularity over last two

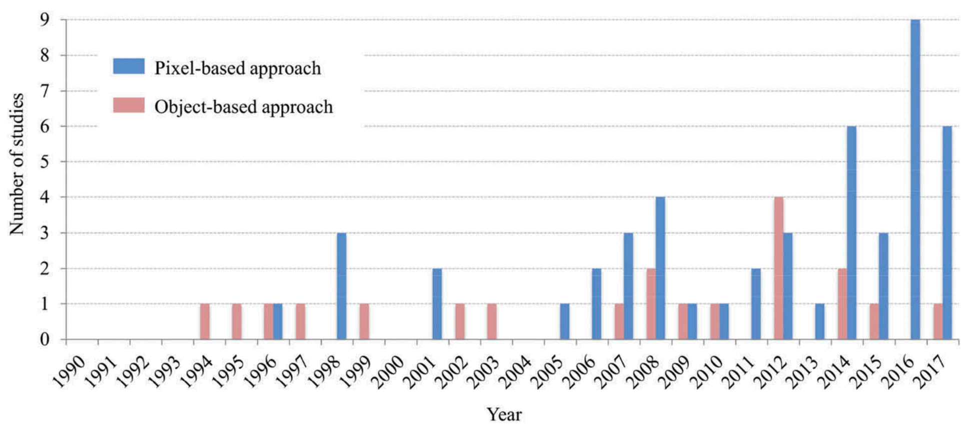

Figure 11. A number of studies using pixel-based and object-based image analysis approaches focusing on synergetic use of optical and radar remote sensing data for crop type classification (since 1990).

decades but interestingly, in the reviewed literature, they are less frequently used during the last three years (Figure 11). Compared to pixel-based methods, object-based classifications have the advantage of including of landscape objects such as shape, area, boundary length or relation to neighbouring objects into the classification process. For instance, major roads can be easily differentiated from an agricultural field with bare soil by considering shape characteristics of the respective object (Ban, Hu, and Rangel 2010). One of the critical tasks in object-based classification approaches is the segmentation. Segments or objects are the smallest units of a segmented image and are composed of spectrally or texturally homogenous pixels. The importance of spectral and spatial homogeneity components in identifying cereal fields was highlighted by Qiao, Daneshfar, and Davidson (2017). Salehi, Daneshfar, and Davidson (2017) discussed the issue of over-segmentation and under-segmentation. They also supported the idea of using average spectral or backscattering values of objects (crop fields) rather than single pixel values, since fields with single crop types usually have relatively homogenous radiometric characteristics. Many studies came up with the conclusion that object-based classification approaches are superior to pixel-based approaches (e.g. Gibril et al. 2017; McNairn et al. 2002; Larrañaga, Álvarez-Mozos, and Albizua 2011; Erasmi and Twele 2009). Ban, Hu, and Rangel (2010) reported on the effectiveness of object-based classification approaches for decision level fusion. The performance of decision level fusion using object-based classification results could grasp advantages of both optical (QuickBird) and SAR (RADARSAT) classifications and showed good classification accuracy for crop types such as soybeans and rapeseed. Nonetheless, the results of the object-based classification are highly dependent on the quality of the segmentation approach (Shackelford and Davis 2003). The small-scaled complexity of agricultural landscapes and the spatial and spectral inhomogeneity of agricultural fields in some study regions can hinder satisfactory segmentation results (Forkuor 2015). On the other hand Hong et al. (2011) deduced that the fused images contain more spatial detail rather than optical or radar images alone, which gives an opportunity to successfully identify field boundaries using object-based segmentation methods. An observation of Lobo, Chic, and Casterad (1996) was that adding radar variables increases the accuracy of both pixel-based and field-based classification results of rice, alfalfa, sunflower and maize, but the positive effect was larger to field-based classification rather than pixel-based classification.

A combination of pixel-based and object-based classification (see supplementary materials S1 for crop types) was used by Forkuor et al. (2014) in their study in the north-western part of the Republic of Benin. Initial pixel-based classification using RF classifier was combined with field boundaries derived from segmentation which allowed overcoming an issue of high spectral within-field heterogeneity. As it was mentioned in earlier studies, the main drawback of the pixel-based classification is the ‘salt and pepper’ effect caused by a number of misclassified pixels within a single agricultural field. However, a case study by Hong et al. (2011) showed that even if object-based classification is utilized, some fields may appear heterogeneous, e.g. due to intercropping of different crop types within one field.

5. Separability of crop types based on optical and radar data

Optical and radar data reflect various properties of crops with respect to their spectral, structural, biophysical or agronomic characteristics. Several studies reported that SAR data show better performance in distinguishing certain crops but are not as well suited for distinguishing others (e.g. McNairn et al. 2002; Ban, Hu, and Rangel 2010; Inglada et al. 2016). The same is true for optical images. For instance, it was reported that optical images from Landsat are not able to provide good separability between flax – sunflower and canola – cereals, but adding one radar RADARSAT or ASAR image to the classification procedure considerably improves the classification accuracy for these crops (McNairn et al. 2009). The following sub-chapters give an overview of commonly studied crop groups and features of each data source which were found to be valuable for their classification.

5.1. *Cereals*

Cereals are a group of crops that are widely cultivated throughout the world and were subject to almost all reviewed publications. Among cereals, the most frequently studied crops were maize (33 studies), wheat (31 studies), rice (18 studies) and barley (16 studies). Compared to other crops, rice was the only crop on which eight individual studies were focused exclusively. Due to the high similarity of spectral reflectance, plant structure and dielectric properties of different sub-types of cereals, their differentiation is a difficult task for both optical and SAR datasets (Larrañaga, Álvarez-Mozos, and Albizua 2011). Since often times strong misclassifications occur among cereal crops, several studies decided to group these crops into one class ‘cereals’ e.g. Feingersh, Gorte, and van Leeuwen (2001), Forkuor et al. (2015).

As it was stated by Blaes, Vanhalle, and Defourny (2005), for distinguishing cereal crops from non-cereals, SAR time series can be actively injected into processing stages. SAR backscatter is responsive to the changes in canopy structure of wheat crops (McNairn et al. 2002). The results of Sonobe et al. (2017) show that identification of wheat fields was straightforward because of the large difference in phenological stages which can easily be identified using Sentinel-1 and Sentinel-2 time series.

The cultivation areas of maize are growing due to the increasing use of corn for ethanol fuels in the world market (Soria-Ruiz et al. 2007). Skakun et al. (2016) reported that SAR images alone produce reliable classification results of corn using dual-polarization data with producer (PA) and user accuracies (UA) exceeding 90%. Nonetheless, addition of optical images to SAR images was critical in producing early season maps. Identification of corn was subject to many research studies, which showed that it is possible to successfully classify corn fields with the help of optical or SAR data only (Zhong et al. 2016). Nevertheless, when using only optical data, a high level of confusion between maize and grassland was reported by Soria-Ruiz, Fernandez-Ordoñez, and Woodhouse (2010). The classification results based on a classification of Landsat and RADARSAT-1C demonstrated acceptable accuracy for Central Mexican agricultural zones (Soria-Ruiz, Fernandez-Ordoñez, and Woodhouse 2010). Additionally to backscattering intensity, the combination of the HH/VV ratio and LAI values derived from optical data was shown to positively affect maize delineation (Dusseux et al. 2014).

Rice is one of the main crop types in many regions around the world. A recent study of Park et al. (2018) proposed the Paddy Rice Mapping Index (PMI) which takes into consideration spectral and phenological aspects of paddy rice. PMI is calculated using NIR and SAR backscattering information without any need of training data. Nonetheless, the performance of SVM and RF classifiers based on Landsat and RADARSAT combination outperformed the results obtained using PMI. The potential of the combined use of optical and weather independent SAR datasets in cloud-prone tropics and subtropical regions was discussed by Mansaray et al. (2017). With the integration of NDVI and modified NDWI with Sentinel-1 data, considerable increase in rice field identification was reported. Onojeghuo et al. (2018) could achieve a classification accuracy of 96.7% for paddy rice by using the RF classifier and a combination of multi-temporal VH polarization and NDVI data.

5.2. *Oilseed crops*

Oilseeds are widely cultivated crops all over the world, primarily for the oil contained in their seeds. Oilseeds are important for human diets and are used for various industrial products. Among oilseed crops, soybeans (15 studies), rapeseed (13 studies) and sunflower (9 studies) were the most frequently explored crop types in the reviewed literature. A number of studies arrived at the conclusion that adding SAR data increases the accuracy of oilseed identification (e.g. Ban, Hu, and Rangel 2010; Qiao et al. 2014; Villa et al. 2015; Salehi, Daneshfar, and Davidson 2017). Ban, Hu, and Rangel (2010) reported that an improvement of classification accuracy from 71% to 90% was possible for soybean crops after fusion of optical and SAR data at decision level. The classification of optical images showed a high degree of misclassification between soybeans and pastures, but adding of SAR data, which can easily separate these two agricultural classes based on their canopy structure, considerably improved final results. Furthermore, several studies highlighted the importance of polarization information for the classification of oilseeds. The result of Qiao et al. (2014) showed that the use of Freeman-Durden (FD) decomposition of RADARSAT-2 and RapidEye optical images improved classification of soybeans (UA = 100%, PA = 96.3%) compared to the combination of original quad-polarized images with optical data (UA = 96.2%, PA = 96.2%). The significant importance of polarization information (VV/VH polarization ratio) for the classification of soybeans was pointed out by McNairn, Champagne, and Shang (2007). Dissimilar plant structure of broad-leafed rapeseed and thin-leafed cereals results in different backscatter patterns in polarization, which in its turn heavily contribute to the distinction of these two classes (Lussem, Hütt, and Waldhoff 2016). Nevertheless, the results of Skakun et al. (2016) showed that Landsat-8 data alone can successfully discriminate winter rapeseed mainly because of image availability at rapeseed flowering stage, which provides specific color information.

Several studies found that sunflower classification results can be enhanced after adding SAR information to the classification chain (Lobo, Chic, and Casterad 1996; Larrañaga, Álvarez-Mozos, and Albizua 2011; Skakun et al. 2016). For large and dense sunflower canopies HH polarization has been reported to work much better than ratio- or cross-polarized images (McNairn et al. 2009).

5.3. *Sugar crops*

As a main source of sugar and fundamental element of alcohol and ethanol production, sugar crops are widely cultivated around the world. Sugar beet was subject to 11 of the reviewed studies. The majority of studies came to the common conclusion that SAR data in addition to optical data boosted the accuracy of sugar beet classification significantly (e.g Blaes, Vanhalle, and Defourny 2005; McNairn et al. 2009; Kussul et al. 2016a, 2016b). McNairn, Champagne, and Shang (2007) suggested that among optical and SAR features VV/HH dual polarization mode is the best suitable choice for classification of sugar beets. Controversially, the study of Ok and Akyurek (2012) showed that the addition of SAR data (Envisat ASAR) to multispectral Kompsat-2 data did not lead to significant improvements in the classification accuracy of sugar beet.

5.4. *Vegetables, nuts and tuber crops*

Studies on classification and mapping of vegetables, nuts and tuber crops were less than other crop types mentioned above. Tomatoes (Ok and Akyurek 2012) and asparagus (Larrañaga, Álvarez-Mozos, and Albizua 2011) were studied by a single study each. Classification of vegetables is a challenging task due to the constant human management interactions which may cause different responses. For instance, identification of asparagus is complex because of the deep furrows and application of plastic cover to protect plants from weeds and keep suitable temperature. This may lead to changes in reflectance or backscattering values which leads to misclassification (Larrañaga, Álvarez-Mozos, and Albizua 2011). The dramatic improvement (~25.55%) in classification accuracy of tomato class was observed when Envisat ASAR SAR data were integrated to Kompsat-2 optical segment-based classification approach (Ok and Akyurek 2012).

Classification of almonds performed by Sheoran and Haack (2013) showed 100% prodicer's accuracy when using radar texture and six Landsat bands. Fused optical data (Landsat TM) and radar texture (ALOS PALSAR) information produced the highest overall accuracy for all studied crops and land use types including alfalfa, fallow and almonds.

Among tuber or root crops, potatoes (6 studies) and yams (1 study) were the subjects of seven reviewed studies. Presutti et al. (2001) reported that adding radar texture derived from RADARSAT to Landsat optical data increases the classification accuracy by 25% of row crops such as potatoes and corn. The study of McNairn et al. (2009) conducted on test sites located across Canada, showed that multi-temporal VV polarization contained most relevant information for the discrimination of potato fields. This conclusion was also supported by Forkuor et al. (2014) where VV polarization data derived from TerraSAR-X was better suited for discrimination yams than VH.

6. Discussion

The approaches of a crop type classification with combined information from optical and radar remote sensing data were presented in the previous chapters. Advantages and drawbacks, current trends and possible future research directions together with the exciting knowledge gaps will now be discussed.

The increasing amounts of EO data, particularly time series data from optical and radar sensors, accelerating advanced computational capacities as well as emerging availability of cloud-based geospatial platform are the main triggers for the development of crop type mapping research in the direction of multi-sensor analysis. A continuous growth of research publications on the synergetic use of optical and radar data for crop type discrimination reflects the great advantage of multi-sensor and multi-temporal data analysis with respect to their information content for crop delineation. This interest might be also associated with the launch of several high and very high resolution optical and radar satellite data such as Landsat-7/8 (1999/2013), RADARSAT-1/2(1995/2007), SPOT 4–7 (starting in 1998), ERS-1/2 (1991/1995) and TerraSAR-X (starting from 2007). Given the limitations, with respect to spatial, temporal resolutions and frequencies a number of studies highlighted expectations about the future use of freely available satellite images with high temporal and spatial coverage from Sentinel-1 (starting from 2014) and Sentinel-2 (starting from 2015) missions. The open data policy of these missions expected to boost methodological developments and creation of new scientific approaches and techniques in various applications as it was the case with opening archives of Landsat data in 2008 (Wulder et al. 2012). Nonetheless, it has to be considered that the limitations in data storage and processing capabilities of big Earth Observation data are still a challenge in many countries with lower standards of technological equipment. Geoprocessing platforms such as Google Earth Engine or DIAS can help to at least partly overcome this issue.

The longest-running optical satellite mission Landsat was combined with radar data by more than half of the reviewed studies. The familiarity of the remote sensing community with Landsat datasets and their wide application could be a reason for this fact. Since the end of 2015, Sentinel-1 images, in combination with optical data were utilized by half of the reviewed studies. This shows the high interest in open access, high temporal and spatial resolution radar datasets. As it is shown in Figure 6, optical data was mainly combined with C-band radar data. After the launch of L-band ALOS POLSAR, X-band TerraSAR-X and COSMO-SkyMed they were actively used in the studies. Nevertheless, the combination of optical data with multi-frequency radar data was not fully covered by the reviewed studies. The study of Shang et al. (2008) demonstrated that combination of radar data with similar polarization but different frequencies (C-band and L-band) provides more information on the canopy structure and increases the classification accuracy. The vast majority of the studies used data from one radar satellite and concentrated more on the optical-radar data fusion aspect of the study.

Besides remote sensing data availability, one of the most important aspects in a crop type classification is the presence of trustworthy reference data. The majority of the studies performed field surveys in order to obtain the needed amount of training and validation data, which are expensive with regards to budget and time. This obstacle of field data absence could be taken to the next step with the support from governments and international organizations. Examples of such effective movements include the initiative of European Union Land Use and Coverage Area frame Survey (LUCAS) data, CropScape – cropland data layer from United States Department of Agriculture, Land

Parcel Identification System (LPIS) data collected in the European Union for distributing subsidies in the framework of the Common Agricultural Policy (CAP), etc. These datasets might lead to considerable improvement and new developments in methodological approaches in a crop monitoring and classification tasks.

Crowdsourcing as a source of ground reference data has to be also taken into account. Recent crowdsourcing compaign by Geo-Wiki showed the great potential of such activities which resulted in a global reference data set on croplands (Laso Bayas et al. 2017). Especially, in view of recent studies on advancement of the quality of geo-crowdsourced data (e.g. Foody et al. 2018) such data can assists global cropland mapping tasks.

It was observed that the study sites that up to now were covered by optical and radar data fusion studies for crop type mapping are on average still relatively small. More than one-third of the reviewed studies worked on study areas of less than 1,000 km^2. Almost all of the reviewed studies (73 studies out of 75) conducted their research in a particular region around the world, with no comparison of the performance of their methodology over spatially and climatically different regions. This fact might reflect that the handling and processing of large data amounts (multi-sensor, high spatial resolution and multi-temporal data) are challenging for the research community. The differences in agronomic practices, field sizes, climatic dissimilarity etc. are the major challenges for large scale mapping tasks. Another reason, however, could also be that training data availability for large areas and spatial transferability of classification models is still an issue. The spatial and temporal transferability of the models were not considered by the reviewed papers. However, recent articles with single source optical data show promising results when classifying a target agricultural crop year by a model trained on reference data of previous years (Tardy, Inglada, and Michel 2017; Cai et al. 2018). The study of Nelson et al. (2014) with SAR-based automated processing combined with knowledge-based parameter specification could achieve accurate classification of rice fields across multiple environments and managements types. Extending such approaches to the case of multi-sensor data would be particularly interesting. Spatial model transferability is not yet (sufficiently) addressed explicitly in the research community but is an interesting topic especially because of the previously mentioned limited reference data availability over larger areas.

Nonetheless, with open and free access to high resolution satellite data from Sentinel-1 and Sentinel-2 missions and open government data for agriculture together with available and upcoming EO data processing platforms such as Earth Engine and Copernicus Data and Information Access Services (DIAS), it is expected that synergetic multi-source (optical-SAR) data analysis approaches will be applied in large geographical areas. All of the reviewed studies reported the advancement of the classification accuracy using optical and radar data combination with different levels of improvement. The leading motivation for the majority of reviewed studies was performing multi-sensor fusion in order to identify if the fusion of optical and radar data can outperform the 'traditional' optical classification approach. Almost all the studies performed a comparison of optical alone, SAR alone and optical-SAR data classifications. The main drawback in the classification of data only from optical data is low quality due to extensive cloud cover. The cloud-free scene-based analysis was the main approach for the vast majority of the reviewed studies. However, in the context of large area mapping there is a need to create spatially contiguous data over large areas for analysis. This can be done by building best-available-pixel (BAP) (White et al. 2014; Frantz et al. 2017), spectro-temporal statistical metrics or interpolating data to fill missing data gaps (Inglada et al. 2015) can open up new opportunities in the crop type classification tasks.

Studies conducting fusion at the pixel level was mainly comparative studies (11 studies out of 13) which assessed the performance of various pixel level fusion techniques mentioned in sub-chapter 3.1. The choice of pixel level fusion techniques was not reasoned. In feature fusion level, combing original optical and radar datasets in stacked raster data was one of the main approaches (24 studies out of 54). Nonetheless, another half of the studies performed extraction of the features and included them to the stacked data cube. Random or pre-defined selection of optical and radar features was the case in many studies. The chaotic preferences and choice of features in the feature fusion approaches for all kind of crop classes and land use types indicates the lack of appropriate guidance or literature on this topic.

The performance of fusion at pixel, feature and decision levels was not compared in a reviewed literature. A comparative evaluation was performed by Gibril et al. (2017) which concludes that stacked-layers (fusion of features from two sensors) of optical and radar data outperforms in classification accuracy compared to pixel levels fusion techniques such as Brovey, Wavelet and Ehlers fusion.

Studies performing comparatively complex pixel level fusion in many cases gave preference to the parametric classifier as Maximum Likelihood (9 studies out of 13). The use of parametric classifiers for multi-source data which have different characteristics can be arguable choice. The existence of the conflict in the nature of input data and the choice of classification strategy shows the need for more studies on this topic.

As a classical approach of remote sensing image classification, pixel-based methods were mostly used. However, the interest in the object-based image analysis was present in reviewed studies. All studies which utilized advances of per-object or per-field classification reported better accuracy compared to the pixel-based approach. The effectiveness of object-based classification approach was proved by several studies (Ban, Hu, and Rangel 2010; Gibril et al. 2017; Salehi, Daneshfar, and Davidson 2017). But at the same time, the quality of the object-based classification strongly depends on the quality of the initial segmentation results. Since object-based approaches homogenize all pixel values inside an 'object' or prospective crop field if field or object boundaries were not properly defined this may lead to significant misclassifications. Another important point is a spatial resolution of input data. An object-based image analysis can be a powerful tool when using high resolution or very high resolution optical and radar images, but not for data with coarser spatial resolution. If the size of the pixel covers all agricultural field or half of the field, object-based classification methods cannot be applied. The study of Ban, Hu, and Rangel (2010) is a good example where all advantages of very high-resolution input data were successfully used in an object-based and rule-based classification approach. Nonetheless, the information presented in Figure 10 shows that a pixel-based classification is still the leading approach.

The reviewed studies reporting an advancement of the classification accuracy mainly highlighted the importance of using SAR data as complementary information about the physical and structural parameters of crops.

Table 7. An overview of the partly complementary capabilities (+) and limitations (-) of optical and SAR data in the context of crop type classification and monitoring.

Crop characteristics	Optical data	SAR data
Canopy structure		
– Leaf type	-	+
– HEIGHT	-	+
– density	+	+
– Geometry	-	+
Water content	+	+
Biomass estimation	+	+
Yield prediction	+	+
Spectral properties	+	-
– Pigments	+	-
– Flower colouring	+	-
– NIR reflc. strength	+	-
Phenological stages	+	+
Soil surface characteristics (e.g. ploughing lines, roughness)	-	+
Sources of data gap or noise		
Weather condition		
– Cloud cover	-	+
– Wind effect on canopy	+	-
– Atmospheric effects	-	+
Soil moisture/dry effect	+	+
Terrain variations effect	+	-

The collective ability of optical and radar data to classify crops found to be complementary, which allows using information about different perspectives of crops. In Table 7, we centralized all information about abilities and limitation of each sensor type with regards to crop type identification.

Each sensor type has its advantages and strength which are in many cases complementary to each other. It is particularly important in the studies of crop type classification and monitoring as the combination of optical and radar data allows to discriminate at the same time crops with differences in leaf type (e.g. broadleaf crops form herbaceous crops) using radar data and also enable to grasp information about pigments (e.g. flower color, chlorophyll content) using optical data. Additionally, information about crucial phases of agricultural management phases (e.g. tillage) and soil surface structure (e.g. water coverage in rice cropping) can also considerably improve the accuracy of crop type classification.

However, the most challenging issue is the variability of the cropping systems worldwide. The case studies underline that there an 'overall solution' in terms of data type, feature type or mapping approach, for all possible crop combinations that occur in reality under different management and ecological conditions is missing. One crop can be grown under completely different conditions. For instance, the discrepancies in the usefulness of features for detecting the same crop, or in separability studies underpin that one future direction for achieving transferability or standardization of mapping agricultural land may be the stratification of agricultural ecosystems. Do separation improvements of a combination of crop types, when including multi-source data, still hold for the neighbored cropping system, if only one crop is missing or added in the crop portfolio? Considerations are required if only major crops should be distinguished or if the entire cropping system should be analyzed.

Nonetheless, the majority of researchers worldwide still give preferences to 'traditional' single source image classification methods. But the growing number of publication in the topic of optical and radar data fusion for crop type classification is the best indicator of positively increasing interest to this approach.

7. Conclusion

In this review article, an overview of studies on crop type classification using integrated information from optical and radar data was given. Remote sensing image fusion methods and data classification strategies were described and presented. The key finding of this review can be summarized in the following five points. First, the interest towards optical and radar data fusion is rapidly growing. Second, the main motivation in using multi-sensor approaches was the advancement of crop classification accuracy. The majority of studies reported that fusion of optical and radar data remarkably improved the results of classification. From the findings of the reviewed studies, we can conclude that addition of radar and optical features (radar texture, vegetation indices, polarization ratio, etc.) to original bands increases the accuracy of classification. Many studies gave preference to the simple and straightforward approach of layer-stacking of optical and SAR bands. Third, comparative studies analyzing the performance of fusion levels and methods on the same input data are missing. Fourth, all studies performed classification on comparatively small study areas. Large area mapping was never the case. Fifth, the spatial and temporal transferability of the models was not covered and still remains as one of the main issues.

With all the upcoming and available open data resources and powerful processing and analyzing platforms there is great potential in fusing optical and radar data for crop type mapping.

Disclosure statement

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