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REVIEW

Research advances of SAR remote sensing for agriculture applications: A review

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Abstract

Synthetic aperture radar (SAR) is an effective and important technique in monitoring crop and other agricultural targets because its quality does not depend on weather conditions. SAR is sensitive to the geometrical structures and dielectric properties of the targets and has a certain penetration ability to some agricultural targets. The capabilities of SAR for agriculture applications can be organized into three main categories: crop identification and crop planting area statistics, crop and cropland parameter extraction, and crop yield estimation. According to the above concepts, this paper systematically analyses the recent progresses, existing problems and future directions in SAR agricultural remote sensing. In recent years, with the remarkable progresses in SAR remote sensing systems, the available SAR data sources have been greatly enriched. The accuracies of the crop classification and parameter extraction by SAR data have been improved progressively. But the development of modern agriculture has put forwarded higher requirements for SAR remote sensing. For instance, the spatial resolution and revisiting cycle of the SAR sensors, the accuracy of crop classification, the whole phenological period monitoring of crop growth status, the soil moisture inversion under the condition of high vegetation coverage, the integrations of SAR remote sensing retrieval information with hydrological models and/or crop growth models, and so on, still need to be improved. In the future, the joint use of optical and SAR remote sensing data, the application of multi-band multi-dimensional SAR, the precise and high efficient modeling of electromagnetic scattering and parameter extraction of crop and farmland composite scene, the development of light and small SAR systems like those onboard unmanned aerial vehicles and their applications will be active research areas in agriculture remote sensing. This paper concludes that SAR remote sensing has great potential and will play a more significant role in the various fields of agricultural remote sensing.

Keywords: crop, cropland, yield, soil roughness, soil moisture, LAI, crop height, scattering model, quantitative remote sensing, crop yield estimation, SAR

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1. Introduction

Agriculture is the cornerstone of the economy of a nation, and it is highly important to economic development and social stability. Food and fiber from agriculture especially farming system is an important strategic material related to human livelihood. Therefore, it is important to be able to monitor the growth status of crops in a timely manner and forecast the crop output. Accurate and timely crop mapping, planting area statistics and growth status monitoring are the requirements of sound agricultural management and policy-making.

Remote sensing technology is widely used in many fields, which collects a wide range of observations in a timely manner and uses less restricted data collection methods. Agriculture is one of the most important fields for remote sensing application and research. With remote sensing, a wide range of crop growth dynamic information can be obtained in a timely manner. The crop growth status acquired through remote sensing can provide a reference for the establishment of agricultural product regulation and control policies.

Current crop planting area estimation, growth monitoring and yield prediction are still largely based on optical remote sensing because the optical images are easily interpreted, especially for dry-land crops. Optical remote sensing methods for monitoring and studying crop growth status and yield are generally characterized by a combination of different bands/features that are used to build relationships with the crop bio-physical and/or eco-physiological parameters, such as leaf area index (LAI), biomass, chlorophyll content, plant water content, and so on.

Unfortunately, two-thirds of the earth's surface is often obscured behind clouds throughout the year (Wang *et al.* 2009). Some agricultural lands in the humid and semi-humid climate zone with abundant water resources, are often affected by the adverse weather conditions in remote sensing application. Therefore, in agricultural remote sensing, there are many challenging weather conditions to overcome to obtain high-quality optical remote sensing data. These challenges cause great difficulties in the establishment of crop monitoring practices, crop planting area extractions and parameter inversion methods. Compared with optical remote sensing, synthetic aperture radar (SAR) remote sensing has the following characteristics and advantages:

(1) SAR is an active remote sensing method, which makes it possible to continually collect data despite of light and weather conditions. Due to the cloud-penetrating property of microwaves, SAR can acquire "cloud-free" images in all weather conditions. It is also capable of night-time operation.

(2) SAR remote sensing is sensitive to the dielectric and geometrical characteristics of the plants. SAR has a penetrating property, and depending on the frequency, it can obtain information below the vegetation canopy cover.

(3) SAR remote sensing can use different imaging parameters, such as the incident angles and the polarization configurations of the sensor, to obtain a wealth of information.

Based on these characteristics and advantages, SAR remote sensing has considerable potential in the field of agricultural remote sensing.

In recent years, there have been great progresses in SAR sensor developments. Many new SAR satellites have been developed and launched, from the earlier Seasat, ERS-1/2, JERS-1, RADARSAT-1, and other single polarization space-borne sensors to the more recent ENVISAT/ASAR, SIR-C/X-SAR, ALOS/PALSAR, Sentinel-1, RADARSAT-2, TerraSAR-X, Cosmo-Skymed, GF-3, ALOS-2 multi-band, and multi-polarization satellite sensors. A brief summary of the main space-borne and air-borne SAR systems are presented in Tables 1 and 2. National Aeronautics and Space Administration of US (NASA), DLR (The German Aerospace Center), and the Canadian Space Agency (CSA) have proposed a number of new SAR missions, such as NASA's DESDynI mission, Germany's TanDEM-L mission, and Canada's radar satellite constellation (RCM) mission (Guo and Li 2011). Diversified sensor working modes (such as the double/multi-station/constellation observation, compact polarimetric SAR, polarization interferometry SAR, tomography SAR) can help us to obtain more detailed information. SAR plays an important role in the field of agricultural remote sensing because there are currently more data sources to choose from than ever before. In addition, with the development of light and small SAR systems like unmanned aerial vehicle SAR, the application of SAR in agriculture is with great potential in the future.

F-SAR system, which is suitable for agricultural applications, is taken as an example to show the characteristics of air-borne SAR system. The main design feature of F-SAR is the fully polarimetric operation in up to five frequency bands (X-, C-, S-, L-, and P-band) with the ability to acquire data in different bands and/or polarizations simultaneously. Furthermore, the system features two single-pass polarimetric interferometers at X-band (across and along-track) as well as one at S-band (across-track). The F-SAR System also has a very high spatial resolution of up to 25 cm at X-band (Horn *et al.* 2008). The primary technical parameters are shown in Table 3. Since its completion, F-SAR has been in heavy use for various SAR experiments and measurement campaigns, both for external customers and internal research purposes. About half of the campaigns are dedicated to establishing new imaging techniques, while the other half is carried out to provide standard SAR data products.

The basic theories of SAR remote sensing have been developed considerably in recent years. A variety of

Table 1 The main space-borne synthetic aperture radar systems

Satellite/Sensor	Band	Spatial resolution (m)	Imaging mode	Revisiting interval (d)	Polarization mode
ERS-1/AMI	C	30	StripMap	35	VV
JERS-1/SAR	L	18×24	StripMap	44	HH
ERS-2/AMI	C	30	StripMap	35	VV
RADARSAT-1	C	10–30	StripMap	24	HH
		50–100	ScanSAR		
ENVISAT/ASAR	C	10–30	StripMap	35	HH, VV, HH+VV, HH+HV, VV+VH
		150–1 000	ScanSAR		
ALOS/PALSAR	L	10–20	StripMap	46	HH, VV, HH+HV, VV+VH, HH+HV+VH+VV
		100	ScanSAR		
TerraSAR-X	X	1–2	SpotLight	11	HH, VV, HH+VV, HH+HV, VV+VH
		3	StripMap		
		16	ScanSAR		
RADARSAT-2	C	1	SpotLight	24	HH, VV, HV, VH
		3	StripMap		HH+HV, VV+VH
		50–100	ScanSAR		HH+HV+VH+VV
ALOS-2/PALSAR-2	L	1×3	SpotLight	14	HH, VV, HV, VH
		3–10	StripMap		HH+HV, VV+VH
		60–100	ScanSAR		HH+HV+VH+VV
Cosmo-Skymed	X	1	SpotLight	16	HH, VV
		5–15	StripMap		HH+VV,
		30–100	ScanSAR		HH+HV,
					VV+VH,
					HH, HV, VH, VV
Sentinel-1	C	5	Stripmap	12	HH+HV, VH+VV, HH, VV
		5×20	Interferometric wide swath		
		20×40	Extra wide swath		
		5	Wave mode		
GaoFen-3 (GF-3)	C	1	Spot light	29	Optional single polarization
		3	Ultra-fine strip		Optional single polarization
		5	Fine strip I		Optional dual polarization
		8	Full polarized strip I		Full polarization
		10	Fine strip II		Optional dual polarization
		10	Wave imaging		Optional dual polarization
		25	Standard strip		Optional dual polarization
		25	Full polarized strip II		Full polarization
		25	Extended low		Optional dual polarization
		25	Extended high		Optional dual polarization
		50	Narrow scan		Optional dual polarization
		100	Wide scan		Optional dual polarization
		500	Global		Optional dual polarization

new polarization parameters, polarization decomposition methods, and vegetation microwave scattering models have been proposed. The progress of SAR theories and technologies has further promoted the application of SAR remote sensing in the field of agriculture. Using these new techniques and methods, the accuracy of crop identification, crop/soil parameters extraction, and crop yield estimation are continuously being improved. The potential of SAR remote sensing has been further revealed in recent years.

This paper reviews the research advances of SAR remote sensing for agricultural applications and analyses the problems and future development trends. This paper begins with a brief description of the development of crop identification, crop acreage statistics, crop mapping, crop growth monitoring, and crop/soil parameter extraction using SAR data. Then, the development and studies of crop yield estimation based on SAR data assimilation methods are introduced and analyzed. At the end of the paper, the existing problems in SAR remote sensing for agriculture applications are analyzed, and the future research foci and development directions are summarized.

2. Crop identification and crop planting area mapping

Crop identification and crop planting area mapping are the

Table 2 The main air-borne synthetic aperture radar (SAR) system

Name	Nation	Platform	Band	Polarization mode
AIRSAR	USA	DC-8	P/L/C	Full polarization
UAVSAR	USA	Gulfstream G3	L	Full polarization
DO-SAR	Germany	Dornier DO-228	C/X/Ka	Full polarization
E-SAR/F-SAR	Germany	Dornier DO-228	P/L/C/X	Full polarization
RAMSES	France	Transall C160	P–W	Full polarization
EMISAR	Denmark	Gulfstream G3	L/C	Full polarization

Table 3 Primary technical parameters of F-SAR (synthetic aperture radar) system

Band	Frequency (MHz)	Polarization	Bandwidth (MHz)	Peak power (W)	PRF (kHz)	Resolution (m)
X	9600	Full polarization	760	2500	5	0.25
C	5300	Full polarization	384	1000	5	0.5
S	3250	Full polarization	300	1250	5	0.6
L	1325	Full polarization	150	750	10	1.0
P	350/435	Full polarization	100/50	750	10	2.0/4.0

most basic applications of agricultural SAR remote sensing. Locations and distributions of crops are essential for many applications, such as crop parameter estimation and crop yield forecasting, as well as drought, flood and disease risk analysis (Inoue *et al.* 2002; Stankiewicz 2006; Kussul *et al.* 2017). Therefore, timely and accurate monitoring of the spatial distributions of crop species and their extents are considered the most important applications in agricultural remote sensing. With the rapid development of SAR systems, the new generation of SAR sensors makes the multi-polarization and multi-temporal density high spatial resolution SAR data available for crop identification and crop planting area mapping. SAR data have a considerable potential for use in crop type identification and mapping due to the availability of several high-quality SAR data sources. In this section, we review the studies on crop identification and mapping with SAR remote sensing between 2001 and 2017. The existing studies on crop identification and mapping can be broadly classified into two categories: studies that use SAR data alone and studies that use both SAR and optical data.

2.1. Crop identification and mapping with SAR remote sensing alone

SAR signals backscattered from crops are affected by the biomass structure, soil condition, surface roughness and sensor configurations (frequency, polarization and incident angle) (Stankiewicz 2006). Crops with structures that change across the growing season have different scattering responses for the various polarizations and various frequencies. It has been suggested that crop identification accuracy will be improved with the use of multiple polarizations (Stankiewicz 2006; Chen *et al.* 2007; Mcnairn *et al.* 2009). Phenology temporal variation is the most prominent characteristic for crop identification. A number of studies found that better results are yielded for crop identification and crop growth monitoring when using multi-temporal, multi-polarization and multi-frequency SAR imagery (Stankiewicz 2006; Chen *et al.* 2007; Mcnairn *et al.* 2009; Lopez-Sanchez *et al.* 2011, 2012). Generally, backscattering coefficients from different polarizations/bands are compared for crop identification and multi-polarimetric SAR data with high temporal density are used to determine the crop types in light of their phenological variations.

Different polarization/frequency combinations for crop identification and mapping The radar backscattering from crops is sensitive to the structure of the crop canopy and the underlying soil condition (Lopez-Sanchez *et al.* 2012), and the radar backscattering changes with the SAR sensor polarization modes and wavelengths. SAR systems with different wavelengths have different penetration abilities. Higher biomass crops have been successfully classified using L-band PALSAR data, and lower biomass crops have been accurately classified using C-band data (Mcnairn *et al.* 2009). The differences between the HH- and VV-polarization results are moderate. However, the efficiencies of various polarizations differ between crop types. Lee *et al.* (2001) evaluated the classification efficiency of fully polarimetric, dual-polarization and single-polarization SAR data with C-, L-, and P-bands to classify 9 crop types and concluded that the fully polarimetric mode performed best at both the C- and L-bands. The same conclusion was obtained by Hoekman and Vissers (2003) using a single acquisition style for 14 crop types. Frate *et al.* (2003) noted that joining cross-polar backscattering information to the single co-polar information improved the classification accuracy from 55 to 85%. They also found that joining the phase information to the co-polar information improved the crop classification accuracy to a lesser extent. It was reported that the HH polarization was the most accurate for identifying alfalfa and that the HV was the most accurate for identifying corn and wheat (Mcnairn and Brisco 2004). The differential attenuation of grain crops in a linearly co-polarized response (HH or VV) and the ratio (or difference) of the co-polarized radar backscatter have been reported to be useful for discriminating grain crops (Moran *et al.* 2012). The VV polarization was found to discriminate crop types better than the VH polarization (Forkuor *et al.* 2014).

Multi-temporal sar data for crop identification and mapping Some studies have successfully demonstrated the potential of backscattering coefficients derived from multi-temporal SAR data for identifying crop types. The temporal variation of SAR backscatter can be regarded as a striking characteristic for crop monitoring. Moran *et al.* (2012) revealed that the addition of multi-polarization and multi-temporal data clearly improved crop classification, although their results varied. Therefore, the temporal variation of SAR backscatters makes SAR data more valuable for crop mapping and crop condition monitoring (Shao *et al.* 2001; Nguyen *et al.* 2015). Blaes *et al.* (2005) performed a classification using 15 SAR (ERS and Radarsat) images and three optical Landsat TM images and found that the accuracy had been improved when using the SAR data compared to the three optical images alone. A number of studies revealed that the time series SAR data produce more accurate results than the results produced from a single temporal SAR dataset (Wang *et al.* 2010; Skriver 2012). Wang *et al.* (2010) investigated a method using multi-temporal, multi-polarization ENVISAT ASAR data to identify crops, and the results showed that the multi-temporal, multi-polarization ASAR images performed very well for crop mapping. Skriver (2012) used multi-temporal acquisitions of EMISAR data to assess the performance of different polarization (single, dual and full polarization) modes for crop classification and found that the dual and full polarization modes were better than the single polarization mode, and the best overall results were obtained using multi-temporal information. Mcnairn *et al.* (2014) developed a multi-temporal filtering approach to reduce the speckle noise of SAR data, and the result indicated that the classification accuracies were nearly 90% or exceeding 90% for each of the individual classes. Jiao *et al.* (2014) found that multi-temporal polarimetric decomposition parameters produced more accurate results than linear polarizations.

2.2. Crop identification and mapping by the integration of SAR and optical remote sensing

It is difficult to interpret and understand the SAR image due to the coherent noises. Therefore the crop classification accuracy was influenced and resulted in lower accuracy. Optical sensor data can help these defects in crop recognition to a certain extent. Recently, many study results have indicated that the integrated use of optical and SAR data can significantly improve classification accuracy. Forkuor *et al.* (2014) investigated the efficiency of crop classification *via* integrating multi-temporal optical (RapidEye) data and dual-polarized SAR (TerraSAR-X) data to map crops. Their results indicated that the integration of the RapidEye and TerraSAR-X data improved classification accuracy by 10–15% over the use of the optical RapidEye data alone. Mcnairn *et al.* (2009) developed a methodology to integrate SAR (Envisat-ASAR) data and optical (SPOT-4) data and clearly demonstrated that the SAR-optical combined dataset (two Envisat ASAR images and one optical image) could classify crops successfully in a variety of cropping systems across Canada with acceptable accuracy (75–90%). Villa *et al.* (2015) proposed an expert-based decision tree to combine Landsat 8 and X-band COSMO-SkyMed SAR time series data for identifying 7 crop types during their respective seasons and achieved an overall accuracy greater than 86%, highlighting the contribution of the X-band backscatter in improving mapping accuracy. Skakun *et al*. (2016) investigated the use of C-band Radarsat-2 dual polarimetric images together with Landsat 8 time series in preparation for the upcoming availability of Sentinel-1 images. Inglada *et al.* (2016) used 9 Sentinel-1 SAR images and 11 Landsat 8 images for crop classification and found that the optical data outperformed the SAR time series, although there was a specific period in which the SAR data performed better than the optical data when ploughing occurs before sowing winter crops. They also found that the joint use of SAR and optical data yielded better results than using optical data alone.

Many classification approaches have been used for crop identification with SAR remote sensing data. These methods are broadly divided into two categories: pixel-based methods and object-oriented methods. Most studies have used pixel-based methods, such as support vector machines, decision tree classifier, maximum likelihood classifier, neural network classifier, and random forest classifier (Hoekman and Vissers 2003; Stankiewicz 2006; Mcnairn *et al.* 2009, 2014; Wang *et al.* 2010), and some studies have used an adaptive threshold method (Satalino *et al.* 2014). In summary, some studies investigated the performance of SAR-based crop identification, which tries to exploit the polarization, frequency and temporal characteristics of the various SAR sensor datasets to identify crops of different cropping systems. Studies were conducted to integrate the optical and SAR datasets. Pixel-based methods classify each pixel individually, and the resultant maps are often with a lot of noise speckles due to the coherent nature of SAR imagery. These methods often result in low classification accuracy. However, object-oriented classification, which first merges pixels into objects and then classifies each object, can reduce the SAR data noise. In general, the object-oriented classifications may be more favorable in the SAR data classification (Ok and Akyurek 2012; Jiao *et al.* 2014).

3. Crop and cropland parameter extraction

3.1. Crop parameter estimation

Crop growth monitoring and yield estimation are the core products of agricultural radar remote sensing. Crop growth monitoring and yield estimation are realized by studying physiological and structural parameters that are closely related to crop growth conditions. Therefore, the main work of crop growth monitoring and yield estimation is parameter inversion. Quantitative remote sensing of crop and cropland parameters supports regional agricultural monitoring and provides an effective technical approach to monitor crop growth status.

In the early stages of crop parameter inversion, the correlation between crop parameters and radar backscattering coefficients was established through statistical analyses. Later, scientists developed many microwave backscattering models, of which the vegetation scattering models are most widely used. Ulaby and Jedlicka (1984) and Ulaby and Wilson (1985) systematically studied the effects of the dielectric, attenuation and structural characteristics of the vegetation on the radar backscattering properties and developed a well-known microwave vegetation scattering model, the Michigan Microwave Canopy Scattering (MIMICS) model (Ulaby *et al.* 1990; Mcdonald and Ulaby 1993). MIMICS model has provided theoretical support for studying the various scattering mechanisms in vegetation-covered surfaces. Although MIMICS model was initially established for forested areas, many studies found that it can also be suitable for crops such as wheat, maize and castor after simple model modifications (Toure *et al.* 2002; lin *et al.* 2009). Later, to increase the practicality of MIMICS model, many simplified versions were proposed, such as the water cloud model (WCM) proposed by Attema and Ulaby (1978). The water cloud model describes vegetation as a mass of water-bearing di-electrical spheres in space. This model has been successfully applied over many agricultural fields (Graham and Harris 2002; Harris and Graham 2003; Dabrowska-Zielinska *et al.* 2007).

MIMICS model describes the crop scattering components in detail but does not have the ability to simulate the phase information. Coherent scattering models can acquire phase information in various polarization modes and have been a research frontier in recent years. Lin and Sarabandi (1999) used the fractal theory to construct the tree structure and established a coherent scattering model for forested areas. Chiu and Sarabandi (1998) considered the coherent effect due to the phase difference between the scattered fields from various particles and proposed a coherent scattering model for short branching vegetation. Cloude and Williams (2003) used coherent scattering models to simulate the L- and P-band SAR polarimetric responses from trees. The vegetation microwave scattering models mainly studied the interaction mechanisms of the electromagnetic waves and vegetation. These models have greatly improved the understanding of the physical scattering mechanisms in vegetation. Therefore, many researchers have used the vegetation scattering models to analyze the relationship between crop parameters and radar signals and to retrieve vegetation parameters from SAR data. However, as a practical matter, many electromagnetic backscattering models are too complicated and computationally expensive to execute, so some inversion methods for complex models have been proposed. For example, Yuzugullu *et al.* (2017a, b) put forward a novel approach for determining the growth stage of rice fields from SAR data using a parameter space search algorithm, therefore a surrogate metamodel-based inversion was proposed for the growth stage estimation (Yuzugullu *et al.* 2017a, b).

In addition to the research on the scattering model, in recent years, the SAR interferometry technique, polarimetric interferometry and SAR tomography technique have been greatly developed. Many scholars used interferometry techniques to study the physical structures of agricultural vegetation and retrieve the biophysical parameters of crops. In this part, we will mainly introduce the recent advances of the inversion of crop parameters. These parameters are primarily crop height, crop LAI and crop biomass.

Crop height estimation Sonobe *et al.* (2014) measured the height, moisture content and dry matter of the crops during nearly the same interval time as the collection of the TerraSAR-X data in the same area and studied the relationships between the measured parameters and the SAR data, including the sigma naught and coherence. The results confirmed that the X-band SAR data possessed great potential for the development of an operational system for monitoring wheat growth (Sonobe *et al.* 2014). In the extraction of crop height using high-resolution interferometric SAR, Rossi *et al.* (2014) used a stack of 16 dual-pol TanDEM-X images to generate 32 digital elevation models (DEMs) over their study area. The quality of the data allows the use of the interferometric phase as a state variable capable to estimate the crop heights for almost all the growing stages. The validation with reference data demonstrates the capability to establish a direct relationship between the interferometric phase and rice growth (Rossi and Erten 2014). Erten *et al.* (2015) studied the interaction between the SAR signal and the canopy height using a single polarization. In particular, the vertical and horizontal wave polarizations were compared, and their performance in the temporal mapping of the crop height was analyzed. The results showed that there are differences between the height measurements of the TanDEM-X HH and VV channels, depending on the different attenuations of the polarized channels (Erten *et al.* 2015).

Polarization interferometry techniques combine the characteristics of polarization and interferometry and can fully extract multi-level information of plants (Cloude and Papathanassiou 1998, 2003; Papathanassiou and Cloude 2001). Ballester-Berman *et al.* (2005) proposed an algorithm to retrieve the biophysical parameters of agricultural crops using polarimetric SAR interferometry. The retrieval algorithm provides estimates of the ground vertical position and the crop height (Ballester-Berman *et al.* 2005). In another article, these authors reviewed the potentials of the polarimetric SAR interferometry for agriculture monitoring (Lopez-Sanchez and Ballester-Berman 2009). In addition, SAR tomography is a powerful approach to investigate the relationship between 3-D radar backscattering and the physical structure of agricultural vegetation (Joerg *et al.* 2014). Joerg *et al.* (2015, 2016) investigated the application of TomoSAR techniques for the retrieval of the vertical structure of agricultural vegetation and analyzed the orientation effects of crop vegetation volumes using SAR tomography at different frequencies. Pichierri *et al.* (2016) presented a novel model-based inversion scheme that takes advantage of the multi-baseline extended observation space to estimate the entire set of the oriented volume over ground (OVoG) structural parameters. The proposed algorithm is significantly stable over changes of the crop structure and robust against nonvolumetric decorrelation sources (Pichierri *et al.* 2016).

Crop LAI estimation LAI is a basic representation of vegetation canopy structure and is directly related to the growth stage and yield of crops. LAI is an excellent indicator of crop development and health and is used as an input variable for many crop growth and yield forecasting models (Jiao *et al.* 2011; Hosseini *et al.* 2015). Many experimental studies have been carried out to investigate the sensitivity of SAR to crop LAI. There are two main groups of algorithms used to estimate crop LAI from SAR imagery: methods based on empirical models and semi-empirical models.

The methods based on empirical models use regressive analysis to estimate LAI from SAR backscattering coefficients. Paloscia *et al.* (2002) analyzed the relationship between multi-frequency and multi-polarization SAR data with crop LAI. An empirical relationship between the backscattering coefficient for the P-, L-, and C-bands in HV polarization and the LAI of some crop types was established (Paloscia 1995). Chen *et al.* (2009) investigated the relationship between the LAI of rice and the ENVISAT ASAR VV/HH polarization ratio. The results suggested that ASAR alternating polarization data can be used to estimate the LAI of rice. Jiao *et al.* (2010, 2014) analyzed the response of TerraSAR dual-polarized X-band data, RASARSAT-2 quad-polarized C-band data and ALOS PALSAR dual-polarized L-band data to corn and soybean LAI. The result of their study showed that the lower frequency bands, such as L and C, were closely correlated with LAI. Fontanelli *et al.* (2013) analyzed the sensitivity of X-band SAR to wheat and barley LAI in the Merguellil Basin using the COSMO-SkyMed and TerraSAR-X data. These authors found a clear sensitivity of the backscatter coefficient to the LAI of wheat and barley for both HH and VV polarizations.

Empirical models were established for particular areas and crops and may have limited application scopes (Beauregard *et al.* 2016). Recently, the WCM has been the most widely used semi-empirical model to estimate crop LAI from SAR. Semi-empirical models combined physical scattering models with statistical analysis, which have wider application areas than empirical models. Beriaux *et al.* (2013) investigated the inversion of retrieving maize LAI from C-band and VV-polarized SAR data using the WCM. Hosseini *et al.* (2015) used the multi-polarization RADARSAT-2 and L-band Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) to estimate LAI. A new LAI estimation approach was developed though the coupling of two existing models, the WCM and the Ulaby soil moisture model. Beriaux *et al.* (2015) used the water cloud model and a Bayesian fusion method to estimate maize LAI, and the result showed that this method has great potential in improving the accuracy and reliability of LAI retrieval using C-band SAR data.

Crop biomass estimation Plant biomass plays an important role in ecosystem mechanisms. In the field of agriculture, biomass reflects the healthy condition of a crop ecosystem. Therefore, the studies of biomass have received extensive attention in agricultural remote sensing.

Optical data can only retrieve information of the surface of the crops. This limits the application of optical data in the inversion for biomass. SAR has considerable potential for use in estimating crop biomass because of its penetration capability. Many studies have used SAR data to estimate crop biomass. Generally, methods in crop biomass estimation using SAR data can be classified into methods that use backscatter values and methods that use interferometric coherent properties. De Matthaeis *et al.* (1995) combined L- and C-bands of AIRSAR data to estimate crop biomass using backscatter values, and the results indicated that the HV polarizations, circular co-polarization and 45° cross polarizations are important for biomass estimation. Previous studies show that L-band backscattering exhibited a high sensitivity to biomass of crops with large leaves (e.g., corn and sunflowers), and higher frequency C- and X-bands were in good agreement with the development of crops with narrow leaves (e.g., wheat) (Ferrazzoli *et al.* 1997; Macelloni *et al.* 2001). Ferrazzoli *et al.* (1997) analyzed the potential of multifrequency polarimetric radar data collected with AIRSAR and SIR-C in assessing agricultural biomass. The results indicated that the L-band appears to be good for crops with low plant density, while both L- and C-bands are useful for crops with high plant density. Paloscia *et al.* (2002) discussed and compared the sensitivity of the backscattering coefficient, measured with the ERS-1, JERS-1 and AIRSAR radars, to the vegetation biomass and found that the best results were achieved when using multifrequency polarimetric AIRSAR data. Jia *et al.* (2014) used fully polarimetric backscattering S-band data to estimate rice biomass based on neural networks. The study found that multi-temporal backscattering coefficients were very sensitive to the changes of biomass, and multi-temporal observations were suitable for paddy detection in the early growth period. Wiseman *et al.* (2015) examined the relationship between the C-band RADARSAT-2 polarimetric SAR data and dry crop biomass from canola, corn, soybean, and spring wheat fields in Manitoba, Canada. This study demonstrated that polarimetric SAR responds to the accumulation of dry biomass and that several radar parameters can uniquely identify changes in crop structure and phenology.

SAR interferometry, polarization interferometry and tomographic SAR can reflect the elevations of the scatters through the phase difference information. These methods are sensitive to the vertical profile of the scatters and have been widely used in forest biomass monitoring (Mette *et al.* 2004; Cartus *et al.* 2011; Minh *et al.* 2013). In crop biomass monitoring, due to the rapid growth of crops and other complex environmental factors, there are relatively fewer studies.

In general, the crop parameter inversion methods based on SAR data can be mainly divided into two categories. Multi-band, multi-polar radar backscatter information and polarimetric decomposition parameters are used to establish empirical relationships with crop parameters; crop parameter inversion is based on these empirical relationships, and scattering mechanisms are analyzed using a semi-empirical model to extract crop physiological parameters. With the diversification of SAR imaging modes and the continuous improvement in SAR data quality, the precision of SAR crop parameter extraction is increasing.

Optical observations can offer an accurate interpretation of the photosynthetic and non-photosynthetic components of plants, and SAR is much more sensitive to plant structure and soil moisture. Both of these techniques can describe the growing status of vegetation. Integration of optical and SAR observations may provide higher-precision results. Recently, merging optical data and SAR data to retrieve the biophysical parameters of crops has become more common. This approach can resolve some limitations in using single-sensor data. For example, Svoray and Shoshany (2002) suggest that based on a modified water cloud model, the synergism of ERS-2 SAR data and Landsat TM data can be applied to the estimation of areal aboveground biomass of herbaceous vegetation in a semi-arid environment. The RADARSAT-2 data were combined with HJ-1 data to retrieve maize structure parameters to overcome the saturation limitation (Gao *et al.* 2013). ASAR and TM data were used for biomass estimation in a mixed vegetation area (Xing *et al.* 2014). Combining multi-temporal optical and radar parameters, Jin *et al.* (2015) investigated the estimation of the LAI and biomass of winter wheat using HJ and RADARSAR-2 data. Fieuzal and Baup (2016) demonstrated the usefulness of radar satellite data to complement the optical data for sunflower height and LAI monitoring. Based on a neural network (NN) inversion technique, Baghdadi *et al.* (2016) developed an approach for estimating soil moisture and the leaf area index in irrigated grasslands by coupling C-band polarimetric SAR and optical data.

3.2. Cropland parameter estimation

The cropland parameters extracted using SAR remote sensing are mainly the cropland surface roughness and soil moisture. Surface roughness is an important parameter for distinguishing different crop types. Changes in soil surface roughness conditions are related to agricultural practice or to precipitation and wind effects (Marzahn and Ludwig 2008). Surface roughness is an input parameter of many microwave scattering models, and it is also the key input parameter in many soil moisture acquisition models. Estimation of the soil moisture content is the key research objective of other disciplines, such as meteorology, hydrology, ecology and agriculture. Soil moisture is an important hydrological and ecological modelling parameter. The process of ecosystem vegetation is also affected by the effects of the temporal changes in soil moisture. The successful SAR mapping of soil moisture under vegetation canopies would be a boon to agriculture, global climate change studies, water resource management and other areas (Marzahn and Ludwig 2008). In this part of the paper, we will give a brief review of the main SAR inversion methods related to the surface roughness and soil moisture under the vegetation cover.

Surface roughness inversion Surface roughness is an important parameter affecting radar backscattering. In past studies, the surface roughness has been considered a signal-disturbing effect, and conditions for minimizing the roughness effect were investigated. However, surface roughness is important information that is required in different application areas such as agronomy, pedology, weather and climate forecasting, and geology (Mattia *et al.* 1997). Surface roughness has a special significance in the field of agricultural remote sensing; it has a strong relationship with cropland farming methods.

Currently, there are the following main methods to extract the surface roughness from the SAR imagery. A promising approach for the extraction of surface parameters started with the investigation of second-order surface scattering statistics. In 1997, Mattia *et al.* (1997) analyzed the dependence of the co-polarized correlation coefficient on the surface roughness and moisture states. The correlation coefficient can be derived for any set of orthogonal polarizations to investigate the polarization effect. The results indicated an enhanced sensitivity of the correlation coefficient on roughness using circular polarizations. Cloude (1999) studied the extraction of surface roughness parameters from the eigenvalue and eigenvector parameters calculated from polarimetric coherent decomposition and found a good linear relationship between the polarization scattering anisotropy (A) and surface root mean square (RMS) height. Hajnsek *et al.* (2003) studied the surface parameter extraction problem using polarimetric SAR images. These authors used the H, A, and α parameters obtained from the Cloude decomposition to separate the surface roughness parameters from the soil moisture parameters. They also proposed an improved model, called the X-Bragg model, since the SPM (small perturbation method) model cannot describe the cross-polarization and depolarization features very accurately.

Schuler *et al.* (2002) found that the real part of the circular polarization correlation coefficient is more efficient in surface roughness calculations and can use polarization data to extract topographical information. Allain *et al.* (2003) combined the polarization eigenvalue decomposition method with the physics-based integral equation model (IEM) and improved IEM (AIEM) surface scattering models and used a look-up table method to conduct a surface roughness inversion. Park *et al.* (2009) investigated three types of roughness inversion algorithms based on IEM, semiempirical, and extended-Bragg models to retrieve the roughness parameters of intertidal mudflats. The results indicated that the fully polarimetric approach is more useful to monitor geophysical parameters from space than the dual polarimetric approach. The fully polarimetric method applies to a wider range of surface roughness. Marzahn and Ludwig (2008) investigated the potential of multi-parametric polarimetric SAR data for soil surface roughness estimation and evaluated its potential for hydrological modelling. The resulting micro-DSMs were analyzed to correlate a soil surface roughness index to three well-established polarimetric roughness estimators. Well-correlated results were obtained for the Re[ρRRLL] and RMS height, for areas with a polarimetric alpha angle $\alpha<40°$.

Apart from the inversion of surface roughness, many scholars have studied new descriptors of surface roughness. In addition to the classic descriptors of the mean standard deviation height (s) and the correlation length (l). Zribi and Dechambre (2003) proposed an original roughness parameter, Z_s. In the same article, these authors also put forward a new empirical model to retrieve the bare soil moisture content and the surface roughness characteristics from radar measurements, at a field scale. Later, Zribi *et al.* (2014) proposed another new description of the soil surface roughness for microwave applications. It was found that the parameter Z_g has a high potential for the analysis of surface roughness using radar measurements, and it combines the three most commonly used soil parameters, namely, root mean surface height, correlation length, and correlation function shape, into one parameter.

In summary, many of the current methods are aimed at estimating a small range of surface roughness or identifying a particular type of cropland surface. Regarding croplands with large surface roughness or croplands with special surface structures, these surface roughness inversion methods may not be appropriate. Moreover, further studies on how to depict cropland surface roughness more accurately are also needed because the characterization of soil surface roughness is a key requirement for the accurate analysis of radar backscattering behavior.

Soil moisture inversion Soil moisture is an important factor to describe the water and energy exchange in the soil surface, and it plays an important role in the water cycle. Soil moisture is a basic condition for crop survival and development and has become an important basis for estimating the crop yields. Soil moisture data acquisition is of great significance for drought monitoring and can be used as an indicator of crop health.

Currently, in the bare soil areas, the commonly used semi-empirical models for soil moisture inversion are Oh, Chen, Dubois and Shi models (Oh *et al*. 1992; Chen *et al*. 1995; Dubois *et al*.1995; Shi *et al*. 1997). The widely used theoretical models are SPM, IEM, and AIEM (Fung *et al*.

1992; Fung and Chen 2004).

In cropland with vegetation cover, the contribution of the vegetation layer to radar backscatter is an important factor that affects the sensitivity of radar to surface soil moisture. Studies have shown that vegetation type, coverage, geometric structure (including height, branch and leaf shapes, and density distribution) and water content will have an influence on radar backscattering and radar wave transmittance in the vegetation canopy. When using the theoretical and semi-empirical models for bare land surfaces, the occurrence of vegetation cover will lead to an underestimation of soil moisture. To eliminate the impact of the vegetation layer for radar backscatter and to retrieve soil moisture content more accurately, scholars have proposed multi-angle, multi-polarization and multi-temporal radar data inversion algorithms. Srivastava *et al.* (2009) proposed a methodology for soil moisture estimation over a large area using a pair of low- and high-incidence-angle RADARSAT-1 SAR datasets. The proposed methodology offers an approach to incorporate the effects of surface roughness, crop cover, and soil texture into the soil moisture retrieval model from the space platform, without making any assumptions on the distributions of these parameters or without knowing the actual values of these parameters on the ground. Balenzano *et al.* (2011) investigated the potential of multi-temporal C- and L-band SAR data acquired within a short revisiting time (1–2 weeks) to map the temporal changes in the surface soil moisture content (mv) underneath crops. Observations indicated that rationing of the multi-temporal radar backscatter can be a simple and effective way to decouple the effect of vegetation and surface roughness from the effect of soil moisture changes, when volume scattering is not dominant. Wang *et al.* (2011) studied a method to simultaneously obtain surface roughness parameters (standard deviation of surface height, σ, and correlation length, cl) along with soil moisture from multi-angular ASAR images using a two-step retrieval scheme based on the AIEM. It was demonstrated that the proposed method achieves a reliable estimation of the soil water content.

To effectively remove the vegetation layer effect on the soil moisture inversion, many scholars carried out studies based on the polarimetric decomposition methods. SAR polarimetry allows for the decomposition of the scattering signature into canonical scattering components and their quantification. The main scattering types included in cropland areas are surface, dihedral, and vegetation scattering, which can be used to model and interpret scattering processes in cropland. Using polarimetric decomposition, the obtained surface and dihedral components can then be used to retrieve the surface soil moisture. Hajnsek *et al.* (2009) discussed the performance and modifications of the individual scattering components for surface, dihedral, and vegetation scattering. Then, these authors used SAR polarimetry theory to decompose the scattering signature into canonical scattering components to retrieve the surface soil moisture in the presence of agricultural vegetation using L-band PolSAR images. An improvement in the estimates of the soil moisture was observed with the use of surface backscattering coefficients for the bare soil and sparsely vegetated fields instead of the total backscattering (Charbonneau 2012). This creates a major increase in the inversion rate for soil moisture estimation. Ballester-Berman *et al.* (2013) proposed a two-component polarimetric model for soil moisture estimation in vineyards using C-band radar data. These authors used a combined X-Bragg/Fresnel approach to characterize the polarized direct soil response. High inversion rates are reported for various phenological stages of vines (Ballester-Berman *et al.* 2013). Jagdhuber *et al.* (2009) investigated the estimation of volumetric soil moisture under low agricultural vegetation from L-band fully polarimetric SAR data using a multi-angular polarimetric decomposition method. This approach combined, for the first time, polarimetric decomposition techniques with the concept of multi-angularity. Later, Jagdhuber *et al.* (2013, 2014) developed a generalized hybrid polarimetric decomposition with a physically constrained volume intensity component and applied it for an inversion of soil moisture under vegetation cover. The algorithm does not need an empirical calibration or to be fit with auxiliary data. When L-band fully polarimetric datasets acquired with the DLR's E-SAR sensor were used, the achieved root mean square error (RMSE) levels are between 4.0 and 4.4% (volume percent for soil moisture) for all three sites tested, across various vegetation and soil types across the entire phenological cycle (Jagdhuber *et al.* 2013, 2014). Wang *et al.* (2016) investigated a simplified polarimetric decomposition for soil moisture retrieval over agricultural fields using the polarimetric UAVSAR data. To overcome the coherent superposition of the backscattering contributions from the vegetation and underlying soils, a simplification of an existing polarimetric decomposition was proposed. The results showed that the performance of the soil moisture retrieval depends on both the crop types and the crop phenological stage. Huang *et al.* (2016b) proposed an integrated surface parameter inversion scheme (ISPIS) to invert for the surface parameters in agricultural fields based on the analysis of H-α parameters at the early crop growing stages. The calibrated integral equation model (CIEM) was adopted to invert for the surface parameters for bare soils, and an adaptive two-component decomposition combined with the CIEM and a simplified adaptive volume scattering model was developed for fields with crop residues and below low vegetation cover (Huang *et al.* 2016b). These authors also developed an adaptive two-component decomposition (ATCD) method that considers the surface and volume scattering caused by the soil and crop canopy to improve the existing model-based decomposition methods to estimate the soil moisture from C-band RADARSAT-2 data. The surface scattering adopted was an X-Bragg scattering, whereas the volume scattering model was constructed based on the *n*th power of sine and cosine probability distribution functions (Huang *et al.* 2016a).

Another category of soil moisture retrieval under vegetated areas in SAR remote sensing is based on the existing microwave scattering models. After the acquisition of the vegetation layer information, the parameters of the scattering models can be corrected, and the vegetation effects on the radar backscattering can then be removed. The semi-empirical water cloud model, proposed according to the actual crop vegetation types and coverage, is suitable for the description of the scattering mechanism in low vegetation coverage areas. This model is very concise and has been continuously improved by other researchers. Currently, this model is the most widely used model in the study of soil moisture under low vegetation cover. On the basis of the scattering models, many researchers use SAR data to carry out the retrieval of soil moisture under the vegetation cover, and there are also many researchers using multi-source remote sensing data to remove the influence of vegetation on the retrieval of the surface soil moisture content.

Specifically, in the use of SAR data to establish a model for the retrieval of soil moisture under vegetation cover, De Roo *et al.* (2001) proposed a semi-empirical forward scattering model for soil moisture inversion under a soybean canopy. This forward scattering model was based on the first-order radiative transfer solution, similar to MIMICS model. The results showed that the combination of L-band VV polarization and C-band HV and VV polarizations can achieve a regression coefficient of R^2=0.898 and volumetric soil moisture RMSE of 1.75%. Joseph *et al.* (2010) discussed the effects of vegetation on C-band (4.75 GHz) and L-band (1.6 GHz) backscattering and applied two methods to the retrieval of soil moisture, which are the semi-empirical water cloud model and an alternative novel method. To correct for vegetation, this alternative method uses the empirical relationships between the vegetation water content (W) and the ratio of the bare soil and the measured σ_o. It is found that this alternative method is superior in reproducing the measured σ_o and retrieving the soil moisture. Gherboudj *et al.* (2011) analyzed the depolarization ratio (χ_v), the co-polarized correlation coefficient (ρ_{vvhh}) and the ratio of the absolute value of the cross polarization to crop height (Λ_{vh}) derived from RADARSAT-2 data with respect to changes in soil surface roughness, crop height, soil moisture and vegetation water content. This sensitivity analysis allowed for the development of empirical relationships for estimation of the soil surface roughness, crop height and crop water content, regardless of crop type. The estimations were then used to correct the semi-empirical water cloud model for soil surface roughness and vegetation effects to retrieve the soil moisture data. The soil moisture retrieval algorithm was evaluated over mature crop fields (wheat, pea, lentil, and canola) using ground measurements. Kim *et al.* (2014) developed physical models for radar backscattering coefficients for the global land surface at L-band to apply to the soil moisture retrieval from the upcoming soil moisture active passive mission data. The land surface classes include 12 vegetation types and four major crops (wheat, corn, rice and soybean). Although this paper focuses on presenting the forward models, the retrieval algorithms need to be tested and refined in the future using experimental data for diverse land cover types. A new algorithm for surface soil moisture mapping using L-band SAR observations was developed by Narvekar *et al.* (2015). These authors used the radar vegetation index (RVI), from radar measurements alone, to account for the variable vegetation effect and introduced a new radar roughness index (RRI), which was also formed from radar observations alone, to account for the variable roughness effects and to construct an approach independent of ancillary data (Narvekar *et al.* 2015). Stamenković *et al.* (2015) simulated the time series of the L-band SAR signals over agricultural fields using a discrete radiative transfer model (RTM). Then, soil moisture was estimated using a nonlinear inversion technique called support vector regression. Full growth cycles of winter wheat, maize, and sugar beet fields were considered in their research. Martino *et al.* (2016) proposed a polarimetric two-scale two-component model (PTSTCM) for the retrieval of soil moisture under moderate vegetation with SAR L-band data. In particular, the PTSM was used to describe the surface scattering component, and a randomly oriented (uniformly, vertically, or horizontally) thin dipole model was used to describe the volume scattering contribution from the vegetation layer that covers the scattering surface.

In addition, many researchers use the multi-source data for soil moisture inversion under vegetation cover to combine the advantages of optical and SAR remote sensing. Dabrowska-Zielinska *et al.* (2007) investigated the applicability of three different vegetation descriptors to the semi-empirical water cloud model using C- and L-band SAR data: leaf area as expressed in the leaf area index, the dielectric properties of leaf surface as expressed in the leaf water area index (LWAI) and the vegetation water mass (VWM). The results demonstrated that the C-band data with small incident angles are useful in soil moisture estimation. Zribi *et al.* (2011) used the water cloud model for vegetation correction and to retrieve soil moisture from the radar signal. These authors implemented this analysis over areas in the "non-irrigated olive tree" land use class and wheat fields. Moisture mapping over wheat fields shows a high variability between the irrigated and non-irrigated wheat covers. With the PALSAR and MODIS data, Prakash *et al.* (2012) developed an algorithm for soil moisture retrieval in vegetation-covered areas. A normalized scattering-based empirical model was also developed. The scattering coefficient of bare soil with HH and VV polarization is provided with the developed empirical relationship, and these values were subsequently used in Dubois model to calculate volumetric soil moisture content regardless of the roughness value. Said *et al.* (2012) mapped soil moisture from ERS-2 SAR images by minimizing the effect of vegetation on the backscatter coefficient. These authors analyzed the performances of the prominent crop descriptors (i.e., crop height, leaf area index, and plant water content). A semi-empirical water cloud model was used to eliminate the vegetation effects on the backscatter coefficient. The results showed that the water cloud model based on the LAI estimated the crop-covered backscatter coefficient more accurately than the other crop descriptors (Said *et al.* 2012). Hajj *et al.* (2016b) simulated a coupling scenario between SAR and optical images through the water cloud model. An inversion technique based on the multi-layer perceptron neural networks (NNs) was used to invert the water cloud model to estimate the surface soil moisture from X-band SAR data over irrigated grassland areas. The investigated vegetation descriptors were the normalized difference vegetation index (NDVI), leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR), and the fractional vegetation cover (FCOVER).

With the emergence of new SAR imaging modes, some studies extensively analyzed the new SAR imaging models for soil moisture inversion under vegetation cover. For example, Lahlou *et al.* (2014) used polarimetric tomographic synthetic aperture radar (PolTomSAR) data to spatially determine and characterize the ground signature under a vegetation layer. The influence of the various scattering mechanisms on the ground response was analyzed and a new algorithm was proposed to use the double bounce response to characterize the soil response and to estimate the soil moisture. Ponnurangam *et al.* (2016) assessed the capability of the hybrid PolSAR data to estimate the soil moisture on bare and vegetated agricultural soils. A new methodology based on combining a compact polarimetric decomposition with a surface component inversion was developed to retrieve surface soil moisture.

Generally, to obtain the backscattering information representative of the soil surface, the mainly used methods can be divided into two categories. One category of methods is based on the polarimetric decomposition to obtain the surface and dihedral components, and the other is based on the microwave scattering models, which in many cases are needed to be combined with the use of optical and SAR data to eliminate the vegetation effects on the backscatter coefficient. When the backscattering information representative of the soil surface is obtained, the soil moisture can then be retrieved from it. The current inversion methods are mainly based on the airborne SAR data, and C-band satellite SAR data. With ALOS-2 satellite data, it is worth studying the use of the L-band satellite SAR satellite data to carry out a wide range of soil moisture detection under crop coverage.

4. Crop yield estimation methods based on SAR data assimilation

Most of the crop yield estimation methods primarily depend on the agricultural meteorological methods and empirical statistical methods. However, these empirical methods cannot accurately describe the process of crop growth. In recent years, crop growth models have been rapidly developed due to the development of computer technology and the expanded understanding of the physiological process mechanisms of the crops. Presently, the most widely used crop growth models are Holland's WOFOST model and the United States' DSSAT model and EPIC model, as well as Australia's APSIM model. These models can accurately predict crop yield at the field scale. However, due to the input data, model parameters, model structures and so on, the accuracy of these models is not satisfactory when applied to regional areas (Chen *et al.* 2010; Jégo *et al.* 2012). The method of data assimilation can integrate multi-source observational data (especially quantitative remote sensing data), and adjust the model trajectory to reduce the forecast error of the system (Xu *et al.* 2015). Therefore, the data assimilation technology provides an important theory and method for real-time monitoring of crop growth and improving crop yield forecasting accuracy. The current method of data assimilation is mainly based on the optical remote sensing data.

Recent studies on the estimation of crop yields using SAR data assimilation are as follows. Dente *et al.* (2004) found a strong correlation between multi-temporal series of C-band HH/VV backscatter ratios acquired at a 40° incidence angle and the wheat biomass, and they investigated the effect of the assimilation of the radar-retrieved information into the CERES-wheat crop model. Tan *et al.* (2012) assimilated the biomass information retrieved from SAR data into the crop growth model to describe biomass changes with crop growth. The results showed that simulated biomass values using the revised model introduced SAR data and the measured values were consistent, and the estimated biomass profile had been significantly improved. Dotzeler *et al.* (2013) studied the possibility of using TerraSAR-X (TSX) data for mapping crop growth and showed, for the first time, that X-band data can be used to identify the spatial heterogeneities in wheat fields and TSX data can be used successfully to complement the optical data for yield modelling. Rinaldi *et al.* (2013) assimilated a time series of LAI maps derived from the COSMO-SkyMed SAR images acquired over the Capitanata plain (Puglia region) in 2010 and 2011 using a forcing procedure in AQUATER and assessed the improvements of its predictions. The results indicated that the LAI assimilation leads to significant improvements in the yield forecast of sugar beet and tomato crops.

It is difficult to interpret and understand SAR images, since there are always serious coherent noise interferences in the SAR images. Compared with radar remote sensing, optical sensor data are easily understood and may have higher spatial resolutions. Many studies have successfully applied the optical domain data to crop monitoring but optical remote sensing may have data acquisition problems because many critical growth stages of crops are under cloud cover, which contaminates the data. Radar remote sensing is less affected by weather conditions and is very sensitive to the structure geometry and water content of crops. In crop monitoring, optical remote sensing and SAR remote sensing have their respective advantages. The knowledge acquired in the field of optical remote sensing, coupled with recent advances in SAR remote sensing, has led researchers to evaluate the combined contribution of these two sources of data by assimilating them into crop growth and agro-meteorological models (Betbeder *et al.* 2017).

There have been many studies on estimating crop yield with the assimilation of SAR data and optical data. Betbeder *et al.* (2017) used an agro-meteorological model controlled by optical and/or SAR multi-polarized satellite images to estimate soybean yield. A vegetation index was derived from the optical images, and backscattering coefficients and polarimetric indicators were computed from the full quad-pol Radarsat-2 images. The feasibility of assimilating LAI and/or dry biomass derived from optical and/or SAR time series into a simplified agro-meteorological model to estimate soybean yields was evaluated, which demonstrated the complementary of optical and SAR data. Clevers and Leeuwen (1996) combined optical and microwave remote sensing data for crop growth monitoring. These authors analyzed the synergistic effect of using both optical and radar data for estimating LAI by studying different data acquisition scenarios, and the remote sensing models were inverted to obtain LAI estimates during the growing season to calibrate the crop growth model to actual growing conditions. They found that in the absence of optical remote sensing data, radar data yielded a significant improvement in the yield estimation compared with not using remotely observed information. Jongschaap and Schouten (2005) used optical remote sensing satellite data (SPOT HRV XS and Landsat 5 TM) to estimate the winter wheat coverage in a 5 km×5 km pilot test area in the southeast of France and used ERS SAR data to estimate the regional wheat flowering dates to calibrate a wheat growth simulation model used to calculate wheat yields. These results demonstrated that the results from point-based simulation models can be applied at spatially higher levels with the aid of remote sensing data. Dente *et al.* (2008) presented a method to assimilate the leaf area index retrieved from ENVISAT ASAR and MERIS data into the CERES-wheat crop growth model, with the objective to improve the accuracy of the wheat yield predictions at the catchment scale. The results indicate that the LAI maps retrieved from the MERIS and ASAR data can be effectively assimilated into the CERES-wheat model. Hajj *et al.* (2016a) studied the feasibility, merits and limitations of forcing remote-sensing derived parameters (initial and maximal LAI values and harvest and irrigation dates) in the PILOTE crop model, targeting the predictions of biomass production. The results show that the use of LAI values and harvest dates derived from optical sensors and the irrigation dates derived from SAR sensors are effective as inputs to crop models (such as PILOTE) to estimate and monitor the yield during vegetation growth.

In summary, the study of the assimilation of remote sensing data into crop growth models started very late. The research results are scattered, and there are not many mature and unified research results. The assimilation of optical remote sensing data is now mainstream. Current studies are focused on selecting appropriate assimilation and optimization algorithms to improve simulation efficiency and accuracy (Jiang *et al.* 2014). There are a few studies on crop growth monitoring and yield estimation that combine SAR data and crop growth models.

5. The present research state and problems

In-depth studies of rice and other aquatic crops have been conducted by researchers who came to a series of valuable conclusions, and the agreement in the literature is relatively high. Compared with rice, the scattering mechanisms of wheat, maize, and other dry land crops are more complex because they are affected by the underlying heterogeneous soil surface. The highly accurate identification and classification methods of the dry land crops are still being studied. Currently, most of the crop monitoring studies are based on backscattering information, and so far, only a few studies have been conducted that consider the other features or characteristics, for instance, the texture or the shape information.

The development of precision agriculture put forward more requirements for the spatial resolution and revisiting cycle of the SAR satellite sensor design. Currently, the main SAR remote sensing data cannot meet the spatial and temporal resolution requirements of precision agriculture, and there is still plenty of room for improvements in spatial and temporal resolution.

Regarding information acquisition, with the richness of SAR data types and imaging modes of the sensors, we can acquire more abundant information than ever before. The new SAR sensors generally have dual- or multi-station observation, polarization interferometry, high-resolution wide-range mapping and three-dimensional imaging abilities, and therefore have great advantages in obtaining the crop height and biomass parameters. How to make full use of the multi-dimensional information provided by the new SAR imaging models for crop monitoring has become a problem that agricultural SAR remote sensing studies need to solve.

The present studies are mainly focused on one or several of the crop growth periods. The current research of crop identification methods and radar scattering mechanisms in different growth periods is insufficient. In fact, the radar scattering mechanisms of crops during various growth periods are quite different, which will create many differences in crop identification and extraction methods. In the future, efforts should be devoted to this topic to expand these identification and extraction methods for the entire crop growth period.

Presently, the main crop parameter inversion methods are based on empirical or semi-empirical models. The lack of awareness of the scattering mechanisms brings a certain blindness to parameter inversion. The methods use statistical analysis to establish the quantitative relationships between the radar scattering coefficient and crop parameters only for certain regions, and cannot be applied directly in other regions. In addition, in the research of the microwave scattering models, the early vegetation scattering models are mainly non-coherent scattering models, which can only simulate the intensity information of vegetation backscattering. These models do not have the ability to simulate phase information. With further development of the full polarimetric SAR, the coherent scattering models that have the ability to simulate phase information will be the hotspots for the future development of SAR scattering models. Research on scattering mechanisms using numerical simulations will also be a frontier because of its high precision since it is based on the numerical simulations of vegetation structures and the computational electromagnetics.

In the polarization decomposition-based extraction methods for crops and cropland parameters, an assumption is that the vegetation layer is composed of uniform particles, and these particles meet a specific orientation distribution function. The real vegetation canopy structures are more complex than this assumption (e.g., the vegetation layer may be not uniform vertically) and are difficult to accurately portray. Some of the existing methods are aimed at specific vegetation types, crop growth stages, degrees of soil moisture content and soil roughness ranges. The models are not universal. In addition, further analysis of the effects of topographic factors on inversion results is needed.

Currently, most of the current SAR-based parameter retrieval studies have only been evaluated up to the parameter inversion and verification step. Studies to combine the parameter inversion results with hydrological, meteorological, agricultural and meteorological models are still needed. SAR remote sensing is sensitive to the physiological structures of crops, so the combination of SAR remote sensing with crop growth models for crop yield estimation has considerable potential for development.

6. The new research foci and development directions

Optical remote sensing and SAR remote sensing are two different means of obtaining ground surface parameters. They reflect the information of crop LAI, vegetation water content and soil moisture from different angles. It is difficult to retrieve LAI, vegetation water content and soil moisture based on a single data with high accuracy. SAR is mainly sensitive to the geometrical and dielectric properties of targets, and optical remote sensing is mainly based on the spectral characteristics of targets. The combined inversion of LAI, the water content of vegetation layer and soil moisture with the advantages of optical and microwave remote sensing, can help to improve the coverage and accuracy of remote sensing inversion. Due to the different advantages of optical and SAR remote sensing data for crop identification, the combination of these two data types can improve crop identification and mapping precision. The use of various characteristic parameters (such as spectral characteristics, texture features, shape features, vegetation indexes, polarization indexes, radar scattering components and radar vegetation indexes) extracted using optical and SAR remote sensing data for crop identification and classification is worthy of study. At the same time, proper methods are needed to effectively synthesis these multi-dimensional parameters. In addition, in agricultural remote sensing, the development of advanced models using multi-source data is important for reducing uncertainties in parameter retrieval. Using synthetic SAR and optical remote sensing data, and choosing a suitable model with which to carry out parameter inversion based on multi-source data are also worthy of study. Although many scholars have completed related studies, such as the joint use of optical and SAR remote sensing data to retrieve LAI and soil moisture simultaneously, they are mainly based on the simplified vegetation models such as the water cloud model. More accurate microwave scattering models will be needed in future studies.

With the increasing availability of SAR imaging modes (e.g., PolSAR, Compact SAR, PolInSAR, Two-station/Multi-station SAR, TomoSAR, and 3D/4D SAR), the SAR data sources available for agricultural remote sensing are increasingly growing. The new generation of SAR can solve many problems that the traditional SAR faced, such as a long revisit cycle, a low spatial resolution, and only obtaining the backscattering information. The application of high-resolution SAR data can improve the accuracy and application range of crop identification, and the application of high time-resolution SAR data can improve the timeliness of crop growth monitoring. The use of new higher spatial and temporal resolution SAR data to develop new crop monitoring methods is worth studying. In addition, a variety of new polarization decomposition theories and microwave scattering models have been put forward. Therefore, the use of new data and new theories to establish more effective crop parameter inversion models, which would then better correspond to the crop growth and cropland parameters, is also worthy of further study. For example, some scholars have preliminarily studied the retrieval of vegetation height and vegetation extinction from polarimetric synthetic aperture radar interferometry for agricultural areas (Jagdhuber 2012), and included these parameters in PolSAR volume scattering models. Tebaldini *et al.* (2009, 2010) studied the decomposition of vegetation and ground scattering components using polarimetric SAR tomography, to retrieve the backscattered signature, which originate predominantly from the soil.

Many of the existing research methods are aimed at the smaller field scale. When these methods are applied to a larger area, the accuracy is not ideal because there are big differences of vegetation types and terrain structures across the croplands. The methods of crop planting area extraction and crop growing status monitoring in regional areas should be further studied.

Many of the polarization decomposition methods and scattering models are proposed for specific object types (such as forests), and if they are directly applied to agricultural remote sensing, the accuracy of the results may be limited. Crops have different planting densities and growth structures, which can result in very different scattering mechanisms. Further research is needed to establish the polarization decomposition methods and the electromagnetic scattering models for specific crops.

There is great potential in the combination of SAR remote sensing and crop growth models for the crop growth monitoring and yield estimation. More work is needed in selecting the appropriate remote sensing inversion algorithms, assimilation algorithms and crop models to carry out crop yield estimation research based on SAR data. Various methods of data integration and better selection and quantification of the variables used in the assimilation models are the frontiers for future research. Using multi-source remote sensing data based on a unified assimilation scheme to improve the stability, accuracy and efficiency of assimilation simulation is also worth studying in the future.

7. Conclusion

The various agricultural remote sensing applications using SAR data was reviewed in this paper, emphasizing the limitations and the prospects linked to these techniques. Due to the dynamic nature of the agriculturally related parameters, the use of remote sensing technology is an attractive tool for agricultural applications. SAR has a significant advantage over optical sensors because it can acquire data in poor weather conditions; therefore, it has special value in the field of agricultural remote sensing. In this paper, we classified SAR agriculture applications into three main categories: crop identification and crop planting area mapping, crop and cropland biophysical parameter extraction, and crop yield estimation. A systematic summary of the recent developments was presented, and the existing problems and the future development directions were also discussed and proposed, respectively. Recently, the imaging modes of SAR sensors are more and more abundant, which can provide various types of data sources for agricultural remote sensing applications. These new sensors will allow the further development of SAR applications in agriculture, particularly in crop type mapping, crop condition assessment, soil moisture estimation and crop yield estimation. SAR will play a more and more important and irreplaceable role in the field of agricultural remote sensing.

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