

Review

Soil Moisture Retrieval from Active Spaceborne Microwave Observations: An Evaluation of Current Techniques

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Received: 17 June 2009; in revised form: 1 July 2009 / Accepted: 2 July 2009 /

Published: 7 July 2009

Abstract: The importance of land surface-atmosphere interactions, principally the effects of soil moisture, on hydrological, meteorological, and ecological processes has gained widespread recognition over recent decades. Its high spatial and temporal variability however, makes soil moisture a difficult parameter to measure and monitor effectively using traditional methods. Microwave remote sensing technology has demonstrated the potential to map and monitor relative soil moisture changes over large areas at regular intervals in time and also the opportunity of measuring, through inverse modelling, absolute soil moisture values. This ability has been demonstrated under a variety of topographic and land cover conditions using both active and passive microwave instruments. The purpose of this paper is to review the current status of soil moisture determination from active microwave remote sensing systems and to highlight the key areas of research that will have to be addressed to achieve routine use of the proposed retrieval approaches.

Keywords: soil moisture; active microwave remote sensing; retrieval approaches; change detection

1. Introduction

Surface soil moisture is a key parameter that influences numerous environmental processes that occur over a large range of spatial and temporal scales, yet despite its importance, soil moisture measurements are not routinely included in the modelling of these processes. This is due to the fact that soil moisture is difficult to measure on a large scale in a cost-effective and routine manner. In the past both optical, microwave and even Global Positioning System (GPS) reflected signals [1-5] have been explored and shown to be sensitive to the soil dielectric constant. Microwave remote sensors are particularly favoured, not only due to their sensitivity to variations in certain surface parameters but also because of their ability to penetrate most cloud cover conditions and their independence of solar illumination. They can provide recurrent and consistent surface soil moisture measurements which can benefit *inter alia* climate sensitive socio-economic activities such as agriculture and sustainable water management, and also measures such as flood and drought forecasting and monitoring, by extending the capability to predict water availability and seasonal climate [6] through improved modelling capabilities.

Microwave remote sensing encompasses both active and passive forms, depending on the sensor and its mode of operation. Passive sensors (radiometers) detect the naturally emitted microwave radiation within their field of view (all physical objects with a temperature above absolute zero (0 K/-273 °C) emit energy of some magnitude) and operate in a similar manner to thermal sensors, measuring the emanating electromagnetic radiation from the earth's surface or objects. In order to detect the low quantities of emitted microwave radiation [7], the field of view for passive sensors must be large enough to detect sufficient energy to record a signal, resulting in a low spatial resolution (generally greater than 1 km). Active microwave sensors on the other hand provide their own source of illumination and measure the difference in power between the transmitted and received electromagnetic radiation. Active sensors can be divided into two distinct categories: imaging (radar) and non-imaging sensors (altimeters and scatterometers). Scatterometers are generally used to obtain information on wind speed and direction over ocean surfaces [8], although numerous applications to soil moisture measurement have been used in the past [9-15]. Altimeters are primarily used to determine height measurements, traditionally over in the oceans and cryosphere, although applications in geodesy, hydrology and the atmospheric sciences have also been explored.

The sensitivity of active microwave sensors to soil moisture content has been successfully demonstrated in numerous studies [16-21] as too have passive sensors [22-25]. Similarly, a number of large scale field experiments have been carried out attempting to correlate the spatial and temporal variability of surface soil moisture under various land cover types to various airborne and satellite microwave measurements: ISLSCP Field Experiment (FIFE 87-89) [26]; Washita' 92 [27], HAPEX-Sahel [28], Washita 1994 [29], Southern Great Plains 1997 [30] & 1999 [31], SMEX02 [32], SMEX03 [33], SMEX04 [34], SMEX05, AgriSAR2006 [35], SMOSREX [36] and SMAPVEX08. Although it can be argued that most progress has been made with passive microwave sensors [37], only active sensors meet the spatial resolution and coverage required for many of the applications of consistent soil moisture data. The main characteristics of the currently operating spaceborne Synthetic Aperture Radar (SAR) sensors along with some past and future sensors are summarised in Table 1. All (satellite) microwave sensors previous to 2002 were capable only of single configuration observations

where the influence of surface roughness and vegetation on the backscatter could not be easily differentiated from that of soil moisture. The launch of ENVISAT marked the beginning of the trend towards multi-configuration sensors, with the Advanced Synthetic Aperture Radar (ASAR) featuring greater capability in terms of coverage, range of incidence angles, polarisation and modes of operation than any of its predecessors. The increasing number of SAR satellites now available and the higher spatial resolution along with shorter revisit intervals offers greater potential than ever to improve the quality with which surface soil moisture can be retrieved from radar data [38].

Table 1. Characteristics of major spaceborne SAR systems.

Platform	Sensor	Band	Polarisation	Highest Spatial Resolution(m)	Swath Width (km)	Mission
SEASAT	SAR	L	HH	25	100	June-Oct 1978
SIR-A	SAR	L	HH	40	50	Nov 12-15th 1981
SIR-B	SAR	L	HH	25	30	Oct 5-13th 1984
Almaz-1	SAR	S	HH	13	172	Mar 31st 1991- Oct 17th 1992
ERS-1	AMI	C	VV	30	100	July 17th 1991- Mar 10th 2000
JERS-1	SAR	L	HH	18	75	Feb 11th 1992- Oct 12th 1998
SIR-C/X-SAR	SIR-C X-SAR	L,C,X	VV,HH,HV, VH, HH	30	10-200	April 1994 Oct 1994
ERS-2	AMI	C	VV	30	100	April 21 st 1995-
RADARSAT-1	SAR	C	HH	10	100-170	Nov 28 th 1995-
SRTM	C-SAR X-SAR	C,X	VV,HH HH	30	50	Feb 11 th – 22 nd 2000
ENVISAT	ASAR	C	VV,HH,HH/VV HV/HH,VH/VV	30	100-400	Mar 1st 2002-
ALOS	PALSAR	L	Quad-pol	10	70	Jan 24 th 2006-
TerraSAR-X	X-SAR	X	Quad-pol	1	10-100	June 15 th 2007-
RADARSAT-2	SAR	C	Quad-pol	3	10-500	Dec 14 th 2007-
COSMO/ SkyMed Series	SAR-2000	X	Quad-pol	1	10-200	June 8 th & Dec 8 th 2007-
TecSAR	SAR	X	HH, HV, VH, VV	1	40-100	21 st Jan 2008
SAR-Lupe	SAR	X	-	<1	-	Dec 2006 & Jul 2008-
Kondor-5	SAR	S	HH,VV	1	-	2009
TanDEM-X	SAR	X	Quad-pol	1	10-150	2009
RISAT	SAR	C	Quad-pol	3	30-240	2009
HJ-1C	SAR	S	HH, VV	20	-	2009
ARKON-2	SAR	X, L, P	-	2	-	2011
Sentinel-1	C-SAR	C	Quad-pol	5	80-400	2011
MapSAR	SAR	L	Quad-pol	3	20-55	2011
KompSAT-5	SAR	X	HH, HV, VH, VV	20	100	2011
SAOCOM-1	SAR	L	Quad-pol	7	50-400	2011
RADARSAT Constellation Mission	SAR	C	Quad-pol	3	20-500	2012 – 2014
SMAP	SAR	L	HH, HV, VV	3km	30-1000	2012
DESDynI	SAR	L	Quad-pol	25	>340	2015

In spite of recent advances, development of robust methods for estimating surface soil moisture has proven to be extremely complicated. As a result, many different approaches have been developed to retrieve surface soil moisture content from various modes of SAR measurements. For the purpose of this paper, the emphasis of the discussion is on spaceborne active microwave remote sensing for

surface soil moisture determination. A concise review of the physical basis behind SAR for soil moisture retrieval is presented along with a comprehensive exploration of all the major retrieval approaches as detailed in the literature to date.

1.1. Theory behind microwave remote sensing of soil moisture

Soil is a mixture of soil particles, air and both bound and free water [39]. As soil moisture increases, water is able to move more freely around the soil particles and it is this free water that has a dominant effect on the dielectric constant (ϵ). The theory behind microwave remote sensing of soil moisture is based on the large contrast between the dielectric properties of liquid water ($\epsilon \approx 80$) and dry soil ($\epsilon \approx 6$) which results in a high dependency of the complex dielectric constant on volumetric soil moisture (m_v). Given this dependency, it is possible to estimate soil moisture by measuring the dielectric constant which is in turn related to the intensity of the radar backscattering coefficient.

1.2. Factors affecting the microwave signal

The backscattering coefficient (σ^0) is the fraction that describes the amount of average backscattered energy compared to the energy of the incident field. The intensity of σ^0 is a function of the physical and electrical properties of the target, along with the wavelength (λ), polarisation and incidence angle (θ) of the radar. Therefore, interpreting the microwave signal from a soil surface and determining how much of that signal is actually from the soil water content is extremely difficult and can often be referred to as an ‘ill-posed problem’. Vegetation is probably the most important factor because a thick enough layer can totally obscure the soil surface from observation [40]. Vegetation above a soil surface absorbs and scatters part of the microwave radiation incident on it as well as the reflected microwave energy from underneath the soil surface. The amount that the vegetation absorbs is mainly a result of its water content while the scattering is influenced by its geometry. The effect of vegetation on backscattering decreases with increasing wavelength [41]. Shorter wavelengths (X-band, 3 cm) reflect from the upper surfaces of the vegetation canopy while longer wavelengths (L-band, 24 cm) penetrate further through the canopy and reflect from the soil surface. Intermediate wavelengths (C-band, 6 cm) generally reflect from both the canopy and soil surface. It has been shown by Brown *et al.* [42] that C-band data can penetrate the vegetation better when the vegetation is drier. Nonetheless, for optimum soil moisture retrieval, Ulaby *et al.* [39] recommended that longer wavelengths (L-band) with low incidence angles be used as they can minimise the effect of vegetation and surface roughness.

Surface roughness (expressed statistically in terms of *rms* height, correlation length and autocorrelation function) is another major limiting factor in soil moisture retrieval for which simple correction procedures are extremely difficult to develop. Altese *et al.* [43] studied the sensitivity of the radar signal to various land surface parameters over a short grass canopy and found that the most influencing parameter appeared to be the surface roughness. The effect of surface roughness can often be equal to or greater than the effects of soil moisture content on the backscatter [44,45] and therefore determining these parameters and separating them from their contribution to the total backscatter is perhaps one of the most challenging aspects for active microwave soil moisture estimation.

Ulaby *et al.* [16] found that for incidence angles greater than 10°, the energy scattered back to the sensor increases with increasing surface roughness. In addition, precise field measurement of surface roughness is often difficult and becomes impractical and prohibitively expensive when larger areas are considered. Rahman *et al.* [46] suggests the long-established pin meter may be inadequate to characterise surface roughness due to its inability to measure subsurface rock fragments that have been shown to have an influence on the radar backscatter [47].

Since natural surface parameters (soil moisture and surface roughness) cannot be controlled, many studies have focussed on how best to configure the radar sensor parameters for optimum soil moisture retrieval. Rao *et al.* [48] found multi-frequency measurements of σ^0 provided better estimates of soil moisture over those derived from single frequency. Srivastava *et al.* [49] and Baghdadi *et al.* [50] found SAR data (C-band) acquired at both low and high incidence angles produced better results in soil moisture estimates in comparison with results using a single incidence angle. Low to medium incidence angles (20°-37°) were found by Holah *et al.* [51] to be optimal for soil moisture estimation, with HH polarisation more sensitive than HV to volumetric soil moisture content but less sensitive than VV, in agreement with studies by Li *et al.* [52] and Zhang *et al.* [53], while Autret *et al.* [54] and Chen *et al.* [55] reported that the influence of surface roughness can be minimised using the co-polarised ratio (HH/VV). Using multiple polarisations should, in theory, improve estimates. However, some studies disagree; for example Baghdadi *et al.* [50] concluded that the accuracy of soil moisture estimates did not improve when using two polarisations (HH & HV) instead of just one. Nonetheless, the general consensus from the literature is that low incidence angles, long wavelengths (L-band) and either HH or HV polarisation are the pre-eminent sensor parameters for soil moisture estimation.

To take account of the various sensor configurations and surface parameters, many backscattering models [11,56,57] have been developed over the past 30 years to help determine the relationship between the radar signal and certain biophysical parameters, where numerous studies have been carried out to further the understanding of the effect of surface roughness [58-60] and vegetation [60-63] in soil moisture estimation. These models are generally categorised into three groups; theoretical, empirical and semi-empirical models.

2. Model-Based Retrieval Approaches

2.1. Soil moisture retrieval using theoretical scattering models

Developing direct theoretical or physical models by simulating the backscattering coefficients in terms of soil attributes such as the dielectric constant and the surface roughness, for an area with known characteristics, is one of the most common approaches used to develop models for soil moisture retrieval [64]. In principle, the dielectric constant of the soil surface and hence the soil moisture content can be estimated from the mathematical inversion of these models. The standard theoretical backscattering models are the Kirchhoff Approximation (KA), which consist of the geometrical optics model (GOM) and physical optics model (POM), and the small perturbation model (SPM) [39]. These models can be applied in the case of specific roughness conditions and assume that the *rms* height, the correlation length and the dielectric constant are known. Generally, the geometrical optics model is

best suited for very rough surfaces, the physical optics model for surfaces with intermediate roughness, and the small perturbation model for very smooth surfaces.

The integral equation model (IEM) is a physically based radiative transfer model developed by Fung and Chen [56] that unites the Kirchhoff models and the small perturbation model, making it more applicable to a wider range of roughness conditions, and in theory, not limited to any one location. The parameters required by the IEM to compute the backscattering coefficient are the sensor parameters, radar frequency, polarisation and incidence angle and surface parameters, dielectric constant, *rms* surface height, correlation length and the autocorrelation function. The IEM essentially quantifies (or simulates) the backscattering coefficient as a function of the unknown soil moisture content and surface roughness and known radar configuration and is given as follows:

$$\sigma_{pp}^o = \frac{k^2}{2} \exp[-2k_z^2 s^2] \sum_{n=1}^{\infty} s^{2n} |I_{pp}^n|^2 \frac{W^{(n)}(-2k_x, 0)}{n!} \tag{1}$$

where *p* is H or V polarisation, *k* is the wave number (where $k = 2\pi/\lambda$), $k_z = k \cos\theta$, $k_x = k \sin\theta$, θ is the incidence angle, and *s* is the *rms* surface height. In the equations below, ϵ_r is the dielectric constant of the soil, μ_r is the relative permeability, I_{pp}^n depends on *k* and *s* and on R_h and R_v , the Fresnel reflection coefficients in H and V polarisations respectively (see (6) and (7)), and is given by:

$$I_{pp}^n = (2k_z)^n f_{pp} \exp(-k_z^2 s^2) + \frac{k_z^n [F_{pp}(-k_x, 0) + F_{pp}(k_x, 0)]}{2} \tag{2}$$

where:

$$f_{hh} = \frac{-2R_h}{\cos\theta} \quad \& \quad f_{vv} = \frac{2R_v}{\cos\theta} \tag{3}$$

$$F_{hh} = 2 \frac{\sin^2 \theta}{\cos \theta} \left[4R_h - \left(1 - \frac{1}{\epsilon_r} \right) (1 + R_h)^2 \right] \tag{4}$$

$$F_{vv} = 2 \frac{\sin^2 \theta}{\cos \theta} \left[\left(1 - \frac{\epsilon_r \cos^2 \theta}{\mu_r \epsilon_r - \sin^2 \theta} \right) (1 - R_v)^2 + \left(1 + \frac{1}{\epsilon_r} \right) (1 + R_v)^2 \right] \tag{5}$$

$$R_h = \frac{\cos \theta - \sqrt{\epsilon_r (1 - \sin^2 \theta)}}{\cos \theta + \sqrt{\epsilon_r (1 - \sin^2 \theta)}} \tag{6}$$

$$R_v = \frac{\cos \theta - \sqrt{\frac{1}{\epsilon_r} (1 - \sin^2 \theta)}}{\cos \theta + \sqrt{\frac{1}{\epsilon_r} (1 - \sin^2 \theta)}} \tag{7}$$

$W^{(n)}$ is the Fourier transform of the *n*th power of the surface correlation coefficient, given as:

$$W^n(k_x, k_y) = \frac{1}{2\pi} \iint p^n(x, y) \exp(jk_x x + jk_y y) dx dy \quad (8)$$

where $p(x, y)$ is the surface correlation function whose distribution is Gaussian for high surface roughness values or exponential for low surface roughness values. The Fresnel reflection equations simulate the surface reflection coefficient (R_H & R_V) as a function of the dielectric constant (ϵ_r) and the incidence angle (θ) based on the polarisation of the sensor. Using the reflection coefficient the dielectric constant can be estimated.

Since the IEM is valid only for single scattering terms attributable to surface scattering, the model is generally only used to invert soil moisture from bare soil surfaces [44,65] where second order scattering is not considered, although in a later effort, Fung *et al.* [66] improved the model to take into account multiple scattering terms. However, due to the complexity of the model, the original version is rarely used and often replaced by approximate solutions [67]. Whereas the complete version describes the backscattering process from a bare soil surface without any limitation on frequency and roughness, the approximate solutions are only valid for low to medium frequencies and surfaces with low roughness. Many approximate solutions (and improvements) to the original version of the IEM have been developed [44,57,68-71] and used in numerous studies with varying results [72,73]. Baghdadi *et al.* [74] proposed a semi-empirical calibration of the IEM by replacing the required correlation length (l) with a calibration parameter derived from SAR data and field measurements and found the calibrated IEM to agree well with SAR backscatter measurements, as did Sahebi *et al.* [75]. This calibrated IEM was later modified by Baghdadi and Zribi [76] to include C-band HH and VV polarisation and found by Alvarez-Mosos *et al.* [77] to also show good agreement with the measured SAR backscattering coefficients. Some studies have found the original IEM to perform well even in vegetated areas [78].

In order to invert the IEM and directly relate σ^0 to the model predictions over both bare and sparsely vegetated surfaces, several algorithms have been devised based on the fitting of IEM numerical simulations for a variety of soil moisture and roughness conditions, including Look Up Tables (LUTs) [79-81], Neural Networks (NN) [75,82-84], Bayesian approaches [85-87] and minimisation techniques (Nelder-Mead minimisation method devised by Nelder and Mead [88,89] and later adapted by Paloscia *et al.* [89]). Santi *et al.* [90] compared the performances of three of these approaches (Bayes, Neural Networks and Nelder-Mead minimisation) and found them to yield satisfactory results, although the Nelder-Mead minimisation tended to slightly overestimate soil moisture values. Similarly Paloscia *et al.* [89] compared the same three approaches with experimental data and found again all three to produce soil moisture values very close to the measured ones, but NN were found to be most suitable in terms of accuracy and computational speed.

However, some studies have reported poor correlations between the IEM simulations and σ^0 retrieved from SAR data [91,92]. Thoma *et al.* [93] found the IEM to perform poorly when used to estimate soil moisture over a semi-arid rangeland, possibly explained by the large amount of near surface rock fragments that had the effect of reducing the sensitivity of the backscatter to the volumetric soil moisture. Jackson *et al.* [46] confirmed the same effect and concluded that sub-surface rock fragments can cause the radar-perceived roughness to be much larger than ground measured surface roughness due to the multiple bounce effect caused by the rock fragments in addition to the scattering of the surface.

Since *a priori* information on the surface roughness is required, the use of the IEM for soil moisture retrieval over large areas is cumbersome due to the difficulty of describing the natural surface roughness conditions over such large areas, as those covered in radar image swaths. Additionally, due to the restrictive assumptions made when deriving them, they can seldom be used to invert data to a high degree of accuracy when measured over natural surfaces [6].

2.2. Soil moisture retrieval using empirical scattering models

The difficulty encountered in the application of theoretical models has led to the development of empirical and semi-empirical models [94]. Empirical backscattering models have been employed to gain insight into the interaction of microwaves with natural surfaces through simple retrieval algorithms, with varying degrees of success [51,95,96]. At the same time, Baghdadi *et al.* [97] have reported no relationship between the backscattered signal and the measured soil moisture, even at three different incidence angles; 23°, 39°, and 47°, citing low moisture content values and surface roughness as the probable cause. Due to the fact that these types of models are generally derived from specific data sets and in most cases, are valid only to the area under investigation, due to limitations in observation frequency, incidence angles and surface roughness, empirical models may not be applicable for data sets other than those used in their development [55]. As a result, there is no physical basis behind the models, therefore undermining their robustness. Another limitation of empirical models is that many *in situ* soil moisture measurements are required over time. Collecting high quality reference data and the compilation of SAR databases can be challenging and many studies have not produced meaningful results due largely to the lack of statistically significant databases. As a result, large databases over a variety of study sites are essential to ensure that developed (and proposed) models are robust and transferable to other datasets, irrespective of surface conditions and sensor configuration [98].

2.3. Soil moisture retrieval using semi-empirical scattering models

Semi-empirical backscattering models represent a compromise between the complexity of the theoretical models and simplicity of empirical models and may be applied when little or no information about the surface roughness is available [99]. They are an improvement on empirical models in so much as they start from a physical background and then use simulated or experimental data sets to simplify the theoretical backscattering model [6]. The main advantage of these types of models is that they are not site dependent- a problem more associated with empirical backscattering models. The most widely used semi-empirical models include those developed by Oh *et al.* [10], Dubois *et al.* [11] and Shi *et al.* [57].

The Oh model [10] relates the ratios of backscattering coefficients in separate polarisations to volumetric soil moisture and surface roughness using the following equation:

$$p = \frac{\sigma_{HH}^o}{\sigma_{VV}^o} = \left[1 - \left(\frac{2m_v}{\pi} \right)^{\frac{1}{3\Gamma_o}} \exp(-ks) \right]^2 \quad (9)$$

$$q = \frac{\sigma_{HV}^o}{\sigma_{VV}^o} = 0.23\sqrt{\Gamma_o}[1 - \exp(-ks)] \quad (10)$$

where p and q represent the co- and cross-polarised backscatter ratios, Γ_o is the Fresnel reflectivity of the surface at nadir given by:

$$\Gamma_o = \left| \frac{1 - \sqrt{\varepsilon}}{1 + \sqrt{\varepsilon}} \right|^2 \quad (11)$$

and σ^o is the backscattering coefficient in HH, HV and VV polarisation, m_v is the volumetric soil moisture, ks is the normalised *rms* surface roughness and ε is the complex permittivity (dielectric constant). The model has an estimated validity range of $9 \leq m_v \leq 31\%$ & $0.1 \leq ks \leq 6$. The radar measurements used for the Oh model were obtained using a truck-mounted polarimetric scatterometer operating at three frequencies (C-, L- and X-band) with an incidence angle range from 10° to 70° . The model addresses both the co- and cross-polarised backscatter coefficient but does not account for multiple or secondary scattering processes. The later presented and improved Oh model [100] was shown to agree well with experimental observations over a wider range of ks than the original model and also agreed with the IEM within its restricted range of validity. The primary advantage of the Oh models is that only one surface parameter (*rms* height) is required and, when multi-polarised data are available, both the dielectric constant and surface roughness can be inverted without the need for field measurements [101]. Although the model is based on truck-mounted scatterometer measurements, it has been applied successfully to airborne and spaceborne SAR measurements [102]. However, other studies have found the model not to produce such promising results [29,103].

The Dubois model [11] accounts for co-polarised backscatter only and was formulated using scatterometer data collected at six frequencies between 2.5 GHz and 11 GHz:

$$\sigma_{HH}^o = 10^{-2.75} \left(\frac{\cos^{1.5} \theta}{\sin^5 \theta} \right) 10^{0.028\varepsilon \tan \theta} (ks \cdot \sin \theta)^{1.4} \lambda^{0.7} \quad (12)$$

$$\sigma_{VV}^o = 10^{-2.37} \left(\frac{\cos^3 \theta}{\sin^3 \theta} \right) 10^{0.046\varepsilon \tan \theta} (ks \cdot \sin \theta)^{1.1} \lambda^{0.7} \quad (13)$$

The inversion of these Equations (12) and (13), expresses the dielectric constant as a function of the HH and VV polarised backscatter and specific radar configuration parameters (wavelength and incidence angle). The estimated validity range of the retrievable surface parameters are $m_v \leq 35\%$ and $ks \leq 2.5$ for incidence angles greater than 30° . Studies using the Dubois model [64,94] have generally found best results were achieved over bare to sparsely vegetated surfaces. The model only accounts for the co-polarised backscattering coefficients since they are less sensitive to system noise and are generally easier to calibrate and thus more accurate than cross-polarised backscattering coefficients. Additionally, given that only two polarisations are required, the model can be applied to dual polarised systems and not just fully polarimetric systems, as is the case for the Oh model. Furthermore, Ji *et al.* [103] found the Dubois model to produce better results than either the Oh or the IEM in both

C- and L-band while Baghdadi *et al.* [76] found that the Oh, Dubois and IEM all tended to overestimate the radar response.

The model developed by Shi [57] is not as commonly used as the previous models and is based on a regression analysis of simulated backscattering coefficients using the single scattering term of the IEM. The Shi model aims to provide a simplification of the IEM to make its implementation more practical and the model easier to invert. Unlike the Oh and Dubois models, the Shi algorithm was derived using only L-band measurements (both airborne and spaceborne) with an incidence angle range of 25° to 70°, but similar to the Dubois model, is valid only for co-polarised terms.

The semi-empirical models mentioned hitherto are, strictly speaking, only valid for bare soil surfaces. In some studies, the models have been shown to be quite accurate under sparsely vegetated soil surfaces [32], although the errors increase with growing vegetation cover. On the other hand, the semi-empirical water cloud model, devised by Attema & Ulaby [104], has been shown in various studies [105-107] to adequately represent the backscatter from a vegetation canopy as well as the underlying soil during the crop's phenological cycle. According to the model, the total backscatter at a co-polarised channel qq (σ_{qq}°), is the incoherent sum of the contribution from the vegetation (σ_{veg}°) and the soil (σ_{soil}°), and the two way attenuation of the vegetation layer (τ^2). For a given incidence angle, the co-polarised backscatter can be given by:

$$\sigma_{qq}^{\circ} = \sigma_{veg}^{\circ} + \tau^2 \sigma_{soil}^{\circ} \quad (14)$$

with:

$$\sigma_{veg}^{\circ} = A \cdot W_1 \cdot \cos \theta (1 - \tau^2) \quad (15)$$

and:

$$\tau^2 = e^{(-2B \cdot W_2 / \cos \theta)} \quad (16)$$

and:

$$\sigma_{soil}^{\circ} = C + D \cdot m_v \quad (17)$$

where $W_{1\&2}$ are vegetation descriptors, θ is the incidence angle, and A, B, C and D represent different vegetation and soil parameters determined during the fitting of the model.

The water cloud model has been modified and implemented differently by various authors [108-111] and despite its inconsistency during model implementation, it has found widespread use among the radar modelling community [112] with varying results. Dabrowska-Zielinska *et al.* [113] found the soil moisture contribution to the backscattering coefficient to be predominant over that from the vegetation for C-band, $\theta = 23^\circ$, while for L-band $\theta = 35^\circ$, the backscattering coefficient was more sensitive to the vegetation contribution. Conversely, Stolz *et al.* [114] found the model to be inadequate for reliable soil moisture estimation, possibly due to a poor model parameterisation. Since most natural surfaces are not bare and periodically covered throughout the year with some type of vegetation, the development of a robust canopy model is essential for reliably estimating spatially distributed soil moisture content.

2.4. Dielectric mixing models

The aforementioned models yield dielectric constant values as output (or require them as input, depending on the model and whether forward or inverse mode is used). To convert between these values and volumetric soil moisture a dielectric mixing model is required. The phenomenological Cole-Cole [115] and Debye [116] models relate the frequency behaviour of materials to the relaxation times and as a result need recalibration for each particular material or surface. In terms of soil dielectric properties, it is difficult to use these models to describe dielectric differences between varying soil types [117] as each new soil composition requires refinement of the model [118].

Among the most common dielectric mixing models used in microwave remote sensing are the semi-empirical ones developed by Topp *et al.* [119], Wang and Schmugge [120], Dobson *et al.* [121] and Perplinski *et al.* [122]. The model by Topp *et al.* [119] is the most widely used and does not account specifically for the soil properties or the dielectric constants of soil constituents. As a result it requires only values of dielectric constant as inputs into the model. In contrast, the model by Wang & Schmugge [120], accounts for soil texture, bulk density and wilting point and these variables are required as inputs for the model. The semi-empirical dielectric mixing model developed by Dobson *et al.* [121] covers a broad frequency range, between 1.4 and 18 GHz, and provides both the real and imaginary components of the dielectric constant in terms of the soil texture (%sand, silt and clay), bulk density and volumetric soil moisture. The model by Perplinski *et al.* [122] is essentially an extension of that by Dobson *et al.* [121] to cover the 0.3–1.4 GHz range.

2.5. SAR data fusion

SAR data fusion or synthesis studies have come about as a direct result of the difficulties encountered in discriminating between the multiple influences on the radar backscatter and that from soil moisture. Most studies deal with either a) an integration of active (SAR) and passive (radiometer) microwave technologies or b) a combination of SAR and optical data, although some studies have estimated surface soil moisture from the synergistic use of two active microwave instruments. For example, Zribi *et al.* [123] developed an algorithm using a high temporal resolution scatterometer combined with the high spatial resolution SAR and observed high correlations ($R^2 > 0.8$) when soil moisture estimates were compared with ground measurements. Concerning a), this technique generally takes the form of using the high resolution SAR σ^0 for determining surface roughness and vegetation biomass and then combining this with coarse resolution radiometer brightness temperature (T_B) for estimating soil moisture content [124]. Studies by Li *et al.* [25], O'Neill *et al.* [125], Njoku *et al.* [126], Narayan *et al.* [127], and Narayan *et al.* [128] found an integration of active and passive observations to be best for deriving estimates of soil moisture.

Similarly, a study by Bindlish and Barros [129] investigated the compatibility of SAR and ESTAR (Electronically Scanned Thinned Array Radiometer) to determine sub-pixel variability of retrieved soil moisture, successfully downscaling values from 200 m to 40 m. This technique will undoubtedly receive new attention when products from ESA's SMOS (Soil Moisture Ocean Salinity) mission become available and indeed from later planned missions such as NASA's SMAP (Soil Moisture Active Passive) mission [a successor to the cancelled HYDROS (Hydrosphere State) mission].

Alternatively, Wang and Qi [130,131] developed an approach using an ERS-2/Landsat TM synergy to minimise surface roughness and vegetation effects and extract soil moisture in sparsely to moderately vegetated areas. The ratio between two different SAR images (wet and dry seasons) was used to reduce the effect of surface roughness while Landsat data were used to calculate the normalised difference vegetation index (NDVI) to account for the influence of vegetation. Moran *et al.* [132] and Notarnicola *et al.* [133] used a similar data fusion approach and recommended the use of multi-temporal SAR/optical fusion for soil moisture studies.

3. Soil Moisture Retrieval Using a Change Detection Approach

The ability to detect temporal changes of certain surface phenomena can be seen as the main reason behind the increasing attractiveness of spaceborne satellite sensors for retrieving geo-and bio-physical information of the earth's surface, given their high spatial and temporal resolution. The very nature of SAR imaging (and all imaging) is that the surface or target under study can be described only at that one particular instance when the image was acquired. While many change detection techniques have been proposed and utilised for the analysis of images acquired by optical sensors, less attention has been devoted to change detection using SAR data [134] due to its inherent complexity in terms of processing and in the development of effective data analysis techniques to minimise speckle [135,136].

All the models described above are based on retrieving surface soil moisture from a single image. In the following, different change detection techniques for the retrieval of soil moisture from multi-date SAR imagery are discussed. While wavelet based change detection techniques for multitemporal SAR have been presented [136,137], the discussion in this paper is limited to the methods most commonly used for soil moisture retrieval; namely, differencing and ratioing, Principal Components Analysis (PCA), and interferometric coherence.

3.1. Image differencing and ratioing

Image differencing and ratioing are two of the simplest and most commonly used methods for change detection. Differencing involves the subtraction of backscatter intensity values between two different date images while ratioing divides the intensity values between the two dates, usually followed by a thresholding operation. The advantage of these techniques is that, in cases where surface roughness and vegetation remain time-invariant, the difference in backscatter between two dates can be related solely to a change in the dielectric properties of the surface i.e., the surface soil moisture content. The ratio method is usually preferred and generally more effective as it is more robust to calibration errors [135], as shown in Villasenor *et al.* [138]. Shoshany *et al.* [139] introduced the normalised radar backscatter soil moisture index (NBMI), similar to the normalised difference vegetation index (NDVI) concept, obtained from the backscatter measurements at two different times (t_1 and t_2) over the same location, expressed as:

$$\text{NBMI} = \frac{\sigma_{t_1}^0 + \sigma_{t_2}^0}{\sigma_{t_1}^0 - \sigma_{t_2}^0} \quad (18)$$

An image difference technique originally proposed by Thoma *et al.* [93] and later adapted by Thoma *et al.* [79], known as the delta index (or Δ -index), is similar to image differencing except that the backscatter difference is divided by the ‘dry’ reference backscatter image, thereby scaling the index to the soil moisture range. The delta index is defined as:

$$\Delta - \text{index} = \left| \frac{\sigma_{\text{wet}}^{\circ} - \sigma_{\text{dry}}^{\circ}}{\sigma_{\text{dry}}^{\circ}} \right| \quad (19)$$

where : $\sigma_{\text{wet}}^{\circ}$ = average backscatter from wet soil
 $\sigma_{\text{dry}}^{\circ}$ = average backscatter from dry soil

The Δ -index, like the basic differencing method, accounts for surface features such as roughness and vegetation, provided that they remain unchanged between image acquisitions. Additionally, imagery must be acquired with the same wavelength and viewing geometry (incidence angle and footprint). The resulting backscatter changes between repeat passes can therefore be attributed to changes in soil moisture. This approach has been used successfully used [79,93,140] where two techniques, the theoretical IEM and the Δ -index for retrieving surface soil moisture were compared and the Δ -index was found to be a better predictor of soil moisture content.

3.2. Principal components analysis (PCA)

Principal components analysis (PCA) or eigenvector analysis is a powerful statistical technique that enhances key spatial patterns in multi-dimensional datasets by transforming a number of correlated variables into a reduced number of uncorrelated variables or components. In terms of remote sensing, PCA is used to generate new image datasets that compress the information contained in a series of multi-temporal images into a reduced number of images [141], leading to a more parsimonious description of the original data. PCA has traditionally been constrained to multi-spectral optical datasets [142-144] though its utility when applied to SAR has become more recognised [145-147]. Verhoest *et al.* [148] used PCA on a winter time series of C-band SAR images and found the second principal component to be related to soil moisture, indicating that it was possible to separate soil moisture content from the other factors influencing the signal such as topography and vegetation. Similarly Kong and Dorling [149] performed a PCA on ASAR wide swath data, spanning two years, demonstrating that a PCA could be used to monitor soil moisture on surfaces throughout the growing season, at different levels of roughness and vegetation cover.

3.3. Interferometric techniques

The soil moisture retrieval approaches discussed above concern only the amplitude of the SAR signal. Repeat-pass SAR interferometry (InSAR), introduced originally for topographic mapping by Graham [150], makes use of the phase information to calculate the interferometric coherence between two or more SAR scenes to provide additional information, complimentary to that contained in the

amplitude of the backscattering coefficient. The phase (φ) of a single SAR image is a measure of the two-way path length of the radar signal from transmitter to ground target back to receiver and is of no practical use on its own. However, when two or more SAR images from slightly different imaging geometries are available, their phase difference ($\varphi_1 - \varphi_2$) can be used to generate topographic products such as Digital Elevation Models (DEMs). The interferometric coherence can be used in addition to the amplitude information to increase the accuracy of surface parameter estimates [151]. Previous studies investigating the relationship between InSAR coherence and relative soil moisture content have found promising results [53,152-154]. The coherence is a measure of the phase correlation between two co-registered complex SAR images, I_1 and I_2 and is defined as the correlation coefficient:

$$\gamma = \frac{\langle I_1 \cdot I_2^* \rangle}{\sqrt{\langle I_1 \cdot I_2^* \rangle \cdot \langle I_2 \cdot I_1^* \rangle}} \quad (20)$$

where γ is the coherence, ranging from 0 (no coherence) to 1 (perfect coherence), the brackets $\langle \rangle$ denote the ensemble average and * denotes the complex conjugate. Several different factors however, contribute to the phase decorrelation of the backscattered signal [155]. For the repeat-pass configuration, the changes in the viewing geometry (baseline) and changes of the surface scatterers between acquisitions (temporal) are the main factors affecting the interferometric phase. The baseline decorrelation is caused by the difference in orbit position from one satellite pass to the next. Temporal decorrelation results from variations in the complex reflection coefficient, which in turn is due to changes in the soil moisture content and/or vegetation. The temporal changes of soil moisture causing decorrelation are, on the one hand, a serious source of error for generating topographic products but, on the other hand, provide valuable information on the moisture changes where a quantitative relationship between the complex correlation coefficient and phase shift induced by soil moisture changes can be established [156,157]. Other laboratory experiments investigating the decorrelation and phase shift of backscatter due to soil moisture variations also showed that changes in soil moisture caused decorrelation [158]. Luo *et al.* [159] found similar results and field experiments by Srivastava and Jayaraman [160] also deduced that the decorrelation of the radar signal is mainly due to surface moisture variability. Since temporal decorrelation increases rapidly with frequency according to the expression from [155]:

$$\gamma = \exp\left\{-\frac{1}{2}\left(\frac{4\pi}{\lambda}\right)^2\left(\sigma_y^2 \sin^2 \theta + \sigma_z^2 \cos^2 \theta\right)\right\} \quad (21)$$

Where σ_y and σ_z are the variances of the random motion components in ground range (y) and height (z), the temporal effects are stronger at C-band than at L-band (since the number of scatterers in a resolution cell decreases for increasing wavelength and phase sensitivity to surface deformation is lower at lower frequencies). Consequently, C-band SAR images are dependent on variations of features similar to that of its wavelength such as crop structure and foliage, whereas L-band SAR images, with their longer wavelengths are more dependent on larger scale vegetation characteristics such as tree branch and trunk structures.

In contrast, Hajnsek *et al.* [161,162] investigated the extraction of surface parameters (soil moisture and surface roughness) from interferometric coherences at different polarisations using the

decorrelation caused by the additive signal-to-noise ratio (γ_{SNR}) in two interferometric images (from a single pass interferometric system thereby ignoring temporal decorrelation) and found a high sensitivity of the interferometric coherences to soil moisture variations, especially for low roughness values; $0.2 < ks < 0.5$. Topographic variations are, however, not the only factor contributing to the path-length changes and therefore the InSAR phase. Surface displacement also has a considerable effect and can be measured by slightly extending the capabilities of InSAR. These two contributing components can be separated using a technique known as Differential Interferometry (DInSAR) where, typically, two interferograms are subtracted from one another, one of which is a synthetic interferogram containing only topographic information (DEM) resulting in an Interferogram containing only deformation phase information.

DInSAR is the process of producing interferograms from which the topographic phase contribution has been removed, extending the capability of InSAR for the measurement of small ground or surface deformations. Gabriel *et al.* [163] were the first to propose the technique of Differential Interferometric SAR (DInSAR) for soil moisture estimation using L-band Seasat data over agricultural test sites. They found that the spatial variations in soil moisture could be explained by the phase differences between the separate fields based on the hypothesis that increases and decreases in water content caused expansion or contraction of the soil, thereby causing a change in elevation and thus the SAR scattering centers within the soil. Nolan *et al.* [164,165] supported this theory (i.e., that a soil moisture phase signal exists within the interferograms), using C-band for both cultivated and uncultivated land, but could not conclusively verify the hypothesis. Furthering this Hajnsek *et al.* [166] investigated the use of DInSAR and Polarimetric SAR (PolSAR) at L-band in a fully polarimetric mode using airborne data to estimate surface soil moisture under vegetation cover. However, despite the encouraging results of [163], where a decrease in phase was correlated to an increase in soil moisture, very few studies have been carried out that were dedicated to the detection of soil moisture using DInSAR. For such studies, the requirement for high coherence tends to limit the study to areas with very little or no vegetation. It is envisaged, however that this constraint may be overcome in future studies by the use of Polarimetric Interferometry (POLInSAR), as discussed below.

4. Soil Moisture Retrieval Using Polarimetric Parameters

An alternative and more recent technique to address the soil moisture retrieval problem is to use polarimetric parameters, such as coherence (γ), entropy (H), and alpha angle (α). Fully polarimetric SAR (PolSAR) and also Compact Polarimetric SAR [167-170] measurements have been used to study the dependence of the polarimetric signature on land cover changes and on surface parameters such as soil moisture and surface roughness. The major advantage of using PolSAR over traditional SAR is its ability to measure all the polarisation characteristics of a surface target simultaneously. Conventional spaceborne SARs operate with a single fixed polarisation for both transmission and reception (e.g., Radarsat-1, ERS-1 & 2) while now, most current sensors operate with dual (ENVISAT ASAR) or fully (Radarsat-2, TerraSAR-X) polarimetric capabilities, i.e., can measure a target's reflectivity in all combinations of the two linear polarisations: HH, HV, VH and VV (in the case of fully Polarimetric radars). As a result, fully polarimetric radar can describe the complete complex scattering from within an imaged cell, given as [171]:

$$[S] = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \quad (22)$$

where S is the scattering matrix consisting of S_{pq} ($p = H, V; q = H, V$) complex components. For monostatic radars (i.e., have the same antenna for both transmitting and receiving signals), $S_{HV} = S_{VH}$ can be assumed under the law of scattering reciprocity. From the vectorisation of the scattering matrix the (Pauli) scattering vector $\vec{k}p$ is obtained:

$$\vec{k}p \approx \frac{1}{\sqrt{2}} [S_{HH} + S_{VV} \quad S_{HH} - S_{VV} \quad 2S_{HV}]^T \quad (23)$$

By averaging the outer product of $\vec{k}p$, with the assumption that $S_{HV} = S_{VH}$, the Coherency matrix $[T]$ is formed which describes the scattering effects that cannot be described by $[S]$ [172,173].

$$[T] = \frac{1}{2} \begin{bmatrix} \langle |S_{HH} + S_{VV}|^2 \rangle & \langle (S_{HH} + S_{VV})(S_{HH} - S_{VV})^* \rangle & 2\langle (S_{HH} + S_{VV})S_{HV}^* \rangle \\ \langle (S_{HH} - S_{VV})(S_{HH} + S_{VV})^* \rangle & \langle |S_{HH} - S_{VV}|^2 \rangle & 2\langle (S_{HH} - S_{VV})S_{HV}^* \rangle \\ 2\langle S_{HV}(S_{HH} + S_{VV})^* \rangle & 2\langle S_{HV}(S_{HH} - S_{VV})^* \rangle & 4\langle |S_{HV}|^2 \rangle \end{bmatrix} \quad (24)$$

The main characteristic of polarimetric SAR is that it permits the discrimination of the different types of scattering mechanisms within an imaged cell. In comparison to conventional single channel SAR, PolSAR can lead to significant improvements in the quality of data analysis and the accuracy of results achieved. A major limitation, however, for the extraction of surface soil moisture from fully polarimetric SAR is the same as that from single polarisation SAR; the presence of vegetation. Two main approaches that have been used to separate the different scattering mechanisms (and thus compensate for the vegetation effects) are target decomposition algorithms and polarimetric SAR interferometry (PolinSAR). The aim of using decomposition theorems is to repress the influence of secondary scattering processes by breaking down the backscattered signature into the various different scattering contributions coming from the imaged cell. A comprehensive and detailed appraisal of the implementation of all decomposition theorems can be found in [174,175] however the two main decomposition theorems that are widely used are the Freeman decomposition [176] and the Cloude-Pottier or eigenvector decomposition [174,177].

The eigenvector approach uses the diagonalisation of the coherency matrix $[T]$ (24) in order to represent the received backscatter as the sum of three scattering mechanisms, where the first component represents the surface scattering and the second and third components represent secondary or multiple scattering contributions. Following decomposition, the extended Bragg or X-Bragg model, developed by Hajnsek [173] can be used for the quantitative estimation of soil moisture and surface roughness from the surface scattering component of the signal. This model is an extension of the SPM, assumes reflection symmetry, and accounts for cross-polarisation as well as depolarisation effects. The model has been shown in Hajnsek *et al.* [178,179] to agree well between inverted and ground measured data. Additionally, the retrieval of surface parameters from the derived entropy (H), anisotropy (A), and alpha angle (α) of the Cloude-Pottier decomposition has been demonstrated in

several studies. Hajnsek *et al.* [161] and Cloude *et al.* [180] found the anisotropy to be sensitive to surface roughness while the entropy and alpha angle polarimetric parameters have been found effective in estimating surface soil moisture [181]. Cloude [182] developed a dual polarized version of the above-mentioned entropy/alpha decomposition, expanding its use beyond that of only fully polarimetric data. Williams [183] also used compact polarimetry successfully to retrieve soil moisture and roughness for bare soil surfaces.

In addition to the above methods, incorporating polarimetric phase information in the form of complex correlation coefficients has been shown to be sensitive to surface parameters. For example, Mattia *et al.* [184] determined a significant relationship between the circular polarisation coherence $|\gamma_{RRLL}|$ (25) and surface roughness while minimising the impact of the dielectric constant. This was also shown in studies by Hajnsek *et al.* [178], Schuler *et al.* [185] and Malhotra *et al.* [186].

$$\gamma_{RRLL} = \frac{|S_{LL} \cdot S_{RR}^*|}{\sqrt{\langle |S_{LL} \cdot S_{LL}^*| \rangle \langle |S_{RR} \cdot S_{RR}^*| \rangle}} \quad (25)$$

Similarly the linear polarisation coherence $\gamma_{(HH+VV)(HH-VV)}$ approach [173] has been found to be correlated to surface roughness and be independent of soil moisture content [161], whereas Cloude & Corr [187] developed a new ratio for soil moisture estimation from polarimetric backscattering coefficients that is non sensitive to surface roughness variations.

5. Discussion and Conclusions

“Even though the existence, quantity, and nature of all life forms in our planet are highly linked to the distribution and phase of water in the Earth’s Biosphere, we have no means today for mapping the spatial distribution or the temporal variability of soil moisture on even a local scale” [188]. Although this quotation is more than 10 years old, its message is just as compelling today as it was then. Despite the technological and analytical advances of the past decade, obtaining accurate and reliable measurements of soil moisture from current and past sensors continues to challenge the scientific community. While the most significant progress has been made with large scale (regional and global) soil moisture retrieval [189,190], fine scale (field) soil moisture products are still some time away from becoming operational [140,191,192].

The preference of microwave remote sensors over optical and thermal sensors for soil moisture estimation is due largely to their longer wavelengths compared to visible and infrared radiation and the fact that microwaves are largely unaffected by cloud cover, haze, rainfall, and aerosols and so are not susceptible to atmospheric scattering, which affects the shorter optical wavelengths [193]. The sensitivity of microwave scattering to the dielectric properties and geometric structure of the soil surface has also made radar remote sensing an attractive technique to address a wide range of environmental problems related to the natural surface condition. Two parameters of particular interest that have been the subject of intensive studies for many decades are surface soil moisture and surface roughness. A major limiting factor in the quantitative estimation of soil moisture and surface roughness from SAR is the separation of their individual scattering effects that contribute to the

backscattered signal. In addition, the return signal is not only a function of the physical and electrical properties of the target, but also of the wavelength, polarisation and incidence angle of the radar sensor.

As discussed, various theoretical and semi-empirical methods have been developed to try and unravel the scattering problem of electromagnetic waves from randomly rough (or natural) surfaces. The most common theoretical approximate methods are the Kirchoff Approximation (KA) and the Small Perturbation Model (SPM). The SPM [194] assumes that variations in surface height are small compared to the system wavelength and is therefore not suitable for applications using short wavelengths (X and C-band) but more appropriate for longer wavelengths, at L- and P-band [195]. Several empirical and semi-empirical algorithms [10-11,57] have been developed to extend the applicability of these theoretical models using a less complex implementation. These models, using only the magnitude of the backscatter generally show accuracies of $\pm 5\%$. Despite this, the insufficiency of these models in predicting secondary scattering and depolarisation effects generally results in imprecise soil moisture estimates [162]. Alternative approaches to address the scattering problem and separate soil moisture and roughness effects include the use of multi-configuration parameters, multi-temporal analysis, and interferometric and polarimetric techniques.

Given that the roughness effect on the scattering process is scaled by wavelength, the combination of two or more frequencies ensures a wider coverage of natural surfaces and a more robust estimation [195]. For example, Moran *et al.* [196] used a dual frequency approach of Ku-band (14.8 GHz) and C-band (5.3 GHz) SAR backscatter to estimate soil moisture. Using this approach, Ku-band was used to estimate Leaf Area Index (LAI) for input into the water cloud model to facilitate measuring soil moisture using C-band (as C-band backscatter can be strongly attenuated by increasing LAI). However there are no dual frequency sensors on board currently orbiting satellites. Until such time as they become available, the alternative of exploiting SAR data though fusion with data from optical sensors can offer significant improvements for soil moisture retrieval. Similarly, change detection approaches such as the Δ -index show potential and account for surface features such as roughness and vegetation, provided that they remain unchanged between image acquisitions. A caveat in this type of analysis is this implicit assumption, coupled with the fact that some sensors (e.g., PALSAR) can have repeat cycles as long as 46 days, a condition that can easily violate the Δ -index assumptions and have a substantial effect on the retrieval accuracy.

The use of InSAR and also differential techniques has produced positive results in soil moisture determination using a range of interferometric products, from simply using the coherence to identify areas of unchanged geometry, i.e., constant surface roughness, whereby the changes in backscattering for those places can be related solely to soil moisture variations; to using the temporal decorrelation and also the signal-to-noise decorrelation of the phase shifts to determine soil moisture content. Furthermore, studies utilising DInSAR have indicated that the measurable change in SAR microwave path lengths could also be caused by changes in the penetration depth (and not just surface deformation), which are strongly influenced by soil moisture. However, concerning InSAR, the difficulty in establishing a unified relationship between the average phase shift and soil moisture changes makes the prospect of deriving absolute values of soil moisture complicated using single frequency and single polarisation sensors. Again, it is envisaged that multi-frequency polarimetric sensors will assist in resolving some of these ambiguities [158] and may be the most suitable approach to provide consistent and reliable information on the surface soil moisture content. This, along with the

continued progression of Polarimetric SAR Interferometry (POLinSAR) is a promising advance in accurate bio-physical parameter retrieval.

Table 2. Summary of soil moisture retrieval techniques from SAR data.

Approach	Characteristics	Advantages	Disadvantages	Examples
1. Modelling				
• Empirical	Regression fits between <i>in situ</i> measurements and σ^0	Simple and straightforward	No physical basis behind the model. Usually only valid for the area under investigation	[51,95-97]
• Semi-empirical	Based on theoretical models but have been extended according to empirical observations.	Offer a good compromise between the simplicity of empirical and complexity of theoretical models.	Each model has certain validity ranges. Generally only valid for bare soil surfaces (apart from Water Cloud Model)	[10,11,57,104]
• Theoretical	Simulates σ^0 as a function of m_v and <i>rms</i> and known radar configurations.	Not site dependent	Only accounts for single scattering terms. Many input parameters required making model implementation extremely complex.	[56,197]
2. Change Detection				
• Image Differencing (& Ratioing)	Subtraction (& division) of intensity values from different dates	Differences in σ^0 can be related directly to soil moisture	Assumes surface roughness and vegetation remain time-invariant between dates	[79,93,135,138-140]
• PCA	Reduces the number of variables in a multi-dimensional dataset.	Enhances key patterns in the data. Change can be detected in the new 'components'.	Assumes multi-temporal data are highly correlated.	[145-149]
• Coherence	Temporal (phase) decorrelation of σ^0 can be related to soil moisture changes.	Compliments the information contained in the amplitude of σ^0	Several different factors contribute to the phase decorrelation of σ^0 .	[152-154,156-160]
3. SAR Data Fusion				
• Active & Passive	Integrates active (SAR) and passive (radiometer) measurements to help discriminate between the multiple influences on σ^0 .	Vegetation (volume scattering term can be separated) and roughness effects can be minimised. Fine and coarse resolution data can be combined.	Issues in scaling and validation. Sub-pixel variability (passive data).	[31,125-128]
• SAR & Optical	Same as above but with SAR and optical measurements.	Vegetation and roughness effects can be minimised.	Issues in scaling and validation	[130-133]

Table 2. Cont.

4. Differential SAR Interferometry	Topographic phase contribution is removed. Decrease in phase (surface displacement) is correlated to an increase in soil moisture.	Potential for estimating soil moisture with increased accuracies.	Requirement for high coherence limits the application to sparsely or non-vegetated surfaces. Very few studies using this technique have been carried out to date.	[163-165]
5. SAR Polarimetry	Uses all polarisations to describe the complete complex scattering from within an imaged cell.	Can separate the different types of scattering mechanisms within the imaged cell.	Limited by presence of vegetation (target decomposition theorems and PolinSAR can be used to compensate for these)	[162,173,178-183]

Accurate soil moisture retrieval from SAR remains an enigma. As discussed in this review, a variety of approaches have been developed and analysed. Table 2 gives a brief summary of the five core approaches with their respective advantages and disadvantages. Selection of a certain technique requires careful consideration of the specific research purpose, the major impact factors and the accuracies required, along with some prior knowledge of the study area conditions. Consequently, and despite the considerable progress made in recent decades, there exists no ‘all-purpose’ technique for wide scale soil moisture estimation using active microwave sensors. The scientific challenge, therefore, for accurate soil moisture retrieval, is to develop techniques that can describe and account for the complex natural surface in its varying states of transition with relative simplicity and precision while minimising the confounding influences of both target and sensor characteristics. Validation of such techniques represents a further challenge in that there lacks suitable datasets with appropriate time-series. Despite these obstacles, the current generation of space borne SAR sensors, (e.g., ALOS PALSAR, TerraSAR-X and Radarsat-2) operating in fully polarimetric mode in three respective frequencies (L-, X-, and C-bands) along with future planned sensors (see table 1) offer a potential to gain a more in-depth knowledge of soil surface dynamics and ultimately improve soil moisture estimates in the future.

Acknowledgements

This review has been prepared as part of the Science, Technology, Research and Innovation for the Environment (STRIVE) Programme. The programme is financed by the Irish Government under the National Development Plan (NDP) 2007-2013 and is administered by the Environmental Protection Agency (EPA).

References and Notes

1. Larson, K.M.; Small, E.E.; Gutmann, E.; Bilich, A.; Axelrad, P.; Braun, J. Using GPS multipath to measure soil moisture fluctuations: initial results. *GPS Solutions* **2008**, *12*, 173-177.
2. Masters, D.; Katzberg, S.; Axelrad, P. Airborne GPS bistatic radar soil moisture measurements during SMEX02. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '03)*, Toulouse, France, 21-25 July, 2003; pp. 896-898.
3. Masters, D.; Zavorotny, V.; Katzberg, S.; Emery, W. GPS signal scattering from land for moisture content determination. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Honolulu, HI, USA, 2000; pp. 3090-3092.
4. Katzberg, S.J.; Torres, O.; Grant, M.S.; Masters, D. Utilizing calibrated GPS reflected signals to estimate soil reflectivity and dielectric constant: Results from SMEX02. *Remote Sens. Environ.* **2006**, *100*, 17-28.
5. Larson, K.M.; Small, E.E.; Gutmann, E.D.; Bilich, A.L.; Braun, J.J.; Zavorotny, V.U. Use of GPS receivers as a soil moisture network for water cycle studies. *Geophys. Res. Lett.* **2008**, *35*, L24405, doi:10.1029/2008GL036013.
6. Walker, J.P.; Houser, P.R. Requirements of a global near-surface soil moisture satellite mission: accuracy, repeat time, and spatial resolution. *Adv. Water Resour.* **2004**, *27*, 785-801.
7. Campbell, J.B.; Bonnet, R. *Introduction to Remote Sensing*. Taylor & Francis: London, 2002.
8. Elachi, C.; van Zyl, J.J. *Introduction to the physics and techniques of remote sensing*. 2nd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2006.
9. Batlivala, P.P.; Dobson, C.; Ulaby, F.T. *Soil moisture experiment (Kansas): documentation of radar backscatter and ground truth data*. University of Kansas Center for Research: Gainesville, Florida, FL, USA, 1976.
10. Oh, Y.; Sarabandi, K.; Ulaby, F.T. An empirical model and an inversion technique for radar scattering from bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 370-381.
11. Dubois, P.C.; van Zyl, J.; Engman, T. Measuring soil moisture with imaging radars. *IEEE Trans. Geosci. Remote Sens.* **1995**, *33*, 915-926.
12. Benallegue, M.; Taconet, O.; Vidal-Madjar, D.; Normand, M. The use of radar backscattering signals for measuring soil moisture and surface roughness. *Remote Sens. Environ. (USA)* **1995**, *53*, 61-68.
13. Wagner, W.; Noll, J.; Borgeaud, M.; Rott, H. Monitoring soil moisture over the Canadian Prairies with the ERS scatterometer. *IEEE Trans. Geosci. Remote Sens.* **1999**, *37*, 206-216.
14. Woodhouse, I.H.; Hoekman, D.H. Determining land-surface parameters from the ERS wind scatterometer. *IEEE Trans. Geosci. Remote Sens.* **2000**, *38*, 126-140.
15. Scipal, K.; Wagner, W.; Trommler, M.; Naumann, K. The Global Soil Moisture Archive 1992-2000 from ERS scatterometer data: first results. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '02)*, Toronto, ON, Canada, 2002; p. 28.
16. Ulaby, F.T.; Batlivala, P.P. Optimum radar parameters for mapping soil moisture. *IEEE Trans. Geosci. Electron.* **1976**, *14*, 81-93.

17. Ulaby, F.T.; Batlivala, P.P.; Dobson, M.C. Microwave backscatter dependence on surface roughness, soil moisture, and soil texture: Part I-bare soil. *IEEE Trans. Geosci. Electron.* **1978**, *16*, 286-295.
18. Jackson, T.J.; Chang, A.; Schmugge, T.J. Active microwave measurements for estimating soil moisture. *Photogramm. Eng. Remote Sens.* **1981**, *47*, 801-805.
19. Wang, J.R.; Engmen, E.T.; Shiue, J.C.; Rusek, M.; Steinmeier, C. The SIR-B observations of microwave backscatter dependence on soil moisture, surface roughness, and vegetation covers. *IEEE Trans. Geosci. Remote Sens.* **1986**, *24*, 510-516.
20. Dobson, M.C.; Ulaby, F.T. Active microwave soil moisture research. *IEEE Trans. Geosci. Remote Sens.* **1986**, *24*, 23-36.
21. Rombach, M.; Mauser, W. Multi-annual analysis of ERS surface soil moisture measurements of different land uses. In *Proceedings of the Third ERS Symposium: Space at the Service of our Environment*, Florence, Florence, ESA-SP-414: 1997; pp. 27-34.
22. Jackson, T.J. Measuring surface soil moisture using passive microwave remote sensing. *Hydrol. Process.* **1993**, *7*, 139-152.
23. Wigneron, J.P.; Schmugge, T.; Chanzy, A.; Calvet, J.C.; Kerr, Y. Use of passive microwave remote sensing to monitor soil moisture. *Agronomie* **1998**, *18*, 27-43.
24. Du, Y.; Ulaby, F.T.; Dobson, M.C. Sensitivity to soil moisture by active and passive microwave sensors. *IEEE Trans. Geosci. Remote Sens.* **2000**, *38*, 105-114.
25. Li, Z.; Shi, J.; Guo, H. Measuring soil moisture change with vegetation cover using passive and active microwave data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '02)*, Toronto, ON, Canada, 2002; pp. 3071-3073.
26. Sellers, P.J.; Hall, F.G.; Asrar, G.; Strebel, D.E.; Murphy, R.E. An overview of the first international satellite land surface climatology project (ISLSCP) field experiment (FIFE). *J. Geophys. Res. Atmosph.* **1992**, *97*, 18345-18371.
27. Jackson, T.J.; Le Vine, D.M.; Swift, C.T.; Schmugge, T.J.; Schiebe, F.R. Large area mapping of soil moisture using the ESTAR passive microwave radiometer in Washita'92. *Remote Sens. Environ.* **1995**, *53*, 27-37.
28. Goutorbe, J.P.; Lebel, T.; Tinga, A.; Bessemoulin, P.; Brouwer, J.; Dolman, A.J.; Engman, E.T.; Gash, J.H.C.; Hoepffner, M.; Kabat, P. HAPEX-Sahel: a large-scale study of land-atmosphere interactions in the semi-arid tropics. *Ann. Geophys.* **1994**, *12*, 53-64.
29. Wang, J.R.; Hsu, A.; Shi, J.C.; O'Neill, P.E.; Engman, E.T. A comparison of soil moisture retrieval models using SIR-C measurements over the Little Washita River watershed. *Remote Sens. Environ.* **1997**, *59*, 308-320.
30. Le Vine, D.M.; Jackson, T.J.; Swift, C.T.; Isham, J.; Haken, M.; Hsu, A. Passive microwave remote sensing with the synthetic aperture radiometer, ESTAR, during the Southern Great Plains experiment. In *Proceedings of IEEE International Geoscience and Remote Sensing Symposium (IGARSS'98)*, Seattle, WA, USA, 1998; pp. 2606-2608.
31. Bolten, J.D.; Lakshmi, V.; Njoku, E.G. Soil moisture retrieval using the passive/active L-and S-band radar/radiometer. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 2792-2801.

32. van Zyl, J.J.; Njoku, E.G.; Jackson, T.J. Quantitative analysis of SMEX'02 AIRSAR data for soil moisture inversion. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS'03)*, Toulouse, France, 2003; pp. 404-406.
33. Jackson, T.J.; Bindlish, R.; Gasiewski, A.J.; Stankov, B.; Klein, M.; Njoku, E.G.; Bosch, D.; Coleman, T.L.; Laymon, C.A.; Starks, P. Polarimetric scanning radiometer C- and X-band microwave observations during SMEX03. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 2418-2430.
34. Vivoni, E.R.; Gebremichael, M.; Watts, C.J.; Bindlish, R.; Jackson, T.J. Comparison of ground-based and remotely-sensed surface soil moisture estimates over complex terrain during SMEX04. *Remote Sens. Environ.* **2008**, *112*, 314-325.
35. Pauwels, V.R.N.; Timmermans, W.; Loew, A. Comparison of the estimated water and energy budgets of a large winter wheat field during AgriSAR 2006 by multiple sensors and models. *J. Hydrol.* **2008**, *349*, 425-440.
36. De Rosnay, P.; Calvet, J.C.; Kerr, Y.; Wigneron, J.P.; Lemaître, F.; Escorihuela, M.J.; Sabater, J.M.; Saleh, K.; Barrié, J.; Bouhours, G. SMOSREX: A long term field campaign experiment for soil moisture and land surface processes remote sensing. *Remote Sens. Environ.* **2006**, *102*, 377-389.
37. Moran, M.S.; McElroy, S.; Watts, J.M.; Peters Lidard, C.D. Radar remote sensing for estimation of surface soil moisture at the watershed scale. In *Proceedings of ARS/INIFAP Binational Symposium on Modeling and Remote Sensing in Agriculture*, Aguascalientes, Mexico, 2006; pp. 91-106.
38. Baghdadi, N.; Cerdan, O.; Zribi, M.; Auzet, V.; Darboux, F.; Hajj, M.E.; Kheir, R.B. Operational performance of current synthetic aperture radar sensors in mapping soil surface characteristics in agricultural environments: Application to hydrological and erosion modelling. *Hydrol. Process.* **2008**, *22*, 9-20.
39. Ulaby, F.T.; Moore, R.K.; Fung, A.K. *Microwave Remote Sensing: Active and Passive. Volume Scattering and Emission Theory, Advanced Systems and Applications*. Dedham, MA, USA, 1986.
40. Schmugge, T.J.; Kustas, W.P.; Ritchie, J.C.; Jackson, T.J.; Rango, A. Remote sensing in hydrology. *Adv. Water Resour.* **2002**, *25*, 1367-1385.
41. Ulaby, F.T.; Dobson, M.C.; Bradley, G.A. Radar reflectivity of bare and vegetation-covered soil. *Adv. Space Res.* **1981**, *1*, 91-104.
42. Brown, R.J.; Pokier, S.; Manore, M.J. Correlations between X, C and L-band imagery within an agricultural environment. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '88)*, Edinburgh, Scotland, UK, 1988; pp. 1279-1280.
43. Lin, D.; Wood, E.; Beven, K.; Saatchi, S.S. Soil moisture estimation over grass covered areas using AIRSAR. *Int. J. Remote Sens.* **1994**, *15*, 2323-2343.
44. Altese, E.; Bolognani, O.; Mancini, M.; Troch, P.A. Retrieving soil moisture over bare soil from ERS 1 synthetic aperture radar data: Sensitivity analysis based on a theoretical surface scattering model and field data. *Water Resour. Res.* **1996**, *32*, 653-661.
45. Satalino, G.; Mattia, F.; Davidson, M.W.J.; Thuy Le, T.; Pasquariello, G.; Borgeaud, M. On current limits of soil moisture retrieval from ERS-SAR data. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 2438-2447.

46. Rahman, M.M.; Moran, M.S.; Thoma, D.P.; Bryant, R.; Holifield Collins, C.D.; Jackson, T.; Orr, B.J.; Tischler, M. Mapping surface roughness and soil moisture using multi-angle radar imagery without ancillary data. *Remote Sens. Environ.* **2008**, *112*, 391-402.
47. Jackson, T.J.; Kostov, K.G.; Saatchi, S.S. Rock fraction effects on the interpretation of microwave emission from soils. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 610-616.
48. Rao, K.S.; Raju, S.; Wang, J.R.; Center, N.; Greenbelt, M.D. Estimation of soil moisture and surface roughness parameters from backscattering coefficient. *IEEE Trans. Geosci. Remote Sens.* **1993**, *31*, 1094-1099.
49. Srivastava, H.S.; Patel, P.; Manchanda, M.L.; Adiga, S. Use of multiincidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 1638-1640.
50. Baghdadi, N.; Holah, N.; Zribi, M. Soil moisture estimation using multiincidence and multipolarization ASAR data. *Int. J. Remote Sens.* **2006**, *27*, 1907-1920.
51. Holah, N.; Baghdadi, N.; Zribi, M.; Bruand, A.; King, C. Potential of ASAR/ENVISAT for the characterization of soil surface parameters over bare agricultural fields. *Remote Sens. Environ.* **2005**, *96*, 78-86.
52. Li, Z.; Ren, X.; Li, X.; Wang, L. Soil moisture measurement and retrieval using Envisat ASAR imagery. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '04)*, Anchorage, AK, USA, 2004; pp. 3539-3542.
53. Zhang, T.; Zeng, Q.; Li, Y.; Xiang, Y. Study on relation between InSAR coherence and soil moisture. In *Proceedings of the ISPRS Congress*, Beijing, China, 3-11th July, 2008.
54. Autret, M.; Bernard, R.; Vidal-Madjar, D. Theoretical study of the sensitivity of the microwave backscattering coefficient to the soil surface parameters. *Int. J. Remote Sens.* **1989**, *10*, 171-179.
55. Chen, K.S.; Yen, S.K.; Huang, W.P. A simple model for retrieving bare soil moisture from radar-scattering coefficients. *Remote Sens. Environ.* **1995**, *54*, 121-126.
56. Fung, A.K.; Li, Z.; Chen, K.S. Backscattering from a randomly rough dielectric surface. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 356-369.
57. Shi, J.; Wang, J.; Hsu, A.Y.; O'Neill, P.E.; Engman, E.T. Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 1254-1266.
58. Oh, Y.; Kay, Y.C. Condition for precise measurement of soil surface roughness. *IEEE Trans. Geosci. Remote Sens.* **1998**, *36*, 691-695.
59. Davidson, M.W.J.; Thuy Le, T.; Mattia, F.; Satalino, C.; Manninen, T.; Borgeaud, M. On the characterization of agricultural soil roughness for radar remote sensing studies. *IEEE Trans. Geosci. Remote Sens.* **2000**, *38*, 630-640.
60. Mattia, F.; Le Toan, T.; Picard, G.; Posa, F.I.; D'Alessio, A.; Notarnicola, C.; Gatti, A.M.; Rinaldi, M.; Satalino, G.; Pasquariello, G. Multitemporal C-band radar measurements on wheat fields. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 1551-1560.
61. Macelloni, G.; Paloscia, S.; Pampaloni, P.; Marliani, F.; Gai, M. The relationship between the backscattering coefficient and the biomass of narrow and broad leaf crops. *IEEE Trans. Geosci. Remote Sens.* **2001**, *39*, 873-884.

62. Macelloni, G.; Paloscia, S.; Pampaloni, P.; Ruisi, R.; Dechambre, M.; Valentin, R.; Chanzy, A.; Prévot, L.; Bruguier, N. Modelling radar backscatter from crops during the growth cycle. *Agronomie* **2002**, *22*, 575-579.
63. Della Vecchia, A.; Ferrazzoli, P.; Guerriero, L.; Blaes, X.; Defourny, P.; Dente, L.; Mattia, F.; Satalino, G.; Strozzi, T.; Wegmuller, U. Influence of geometrical factors on crop backscattering at C-band. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 778-790.
64. Sikdar, M.; Cumming, I. A modified empirical model for soil moisture estimation in vegetated areas using SAR data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '04)*, Anchorage, AK, USA, 2004; pp. 803-806.
65. Su, Z.; Troch, P.A.; De Troch, F.P. Remote sensing of bare surface soil moisture using EMAC/ESAR data. *Int. J. Remote Sens.* **1997**, *18*, 2105-2124.
66. Fung, A.K.; Dawson, M.S.; Chen, K.S.; Hsu, A.Y.; Engman, E.T.; O'Neill, P.O.; Wang, J. A modified IEM model for: scattering from soil surfaces with application to soil moisture sensing. In *Proceedings of the IEEE Transactions on Geoscience and Remote Sensing Symposium (IGARSS '96)*, Lincoln, NB, USA, 1996; Vol. 2, pp. 1297-1299.
67. Hsieh, C.Y.; Fung, A.K.; Nesti, G.; Sieber, A.J.; Coppo, P. A further study of the IEM surface scattering model. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 901-909.
68. Chen, K.S.; Tzong-Dar, W.; Mu-King, T.; Fung, A.K. Note on the multiple scattering in an IEM model. *IEEE Trans. Geosci. Remote Sens.* **2000**, *38*, 249-256.
69. Licheri, M.; Floury, N.; Borgeaud, M.; Migliaccio, M. On the scattering from natural surfaces: the IEM and the improved IEM. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '01)*, Sydney, Australia, 2001; Vol. 6, pp. 2911-2913.
70. Baghdadi, N.; King, C.; Bonnifait, A. An empirical calibration of the integral equation model based on SAR data and soil parameters measurements. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '02)*, Toronto, ON, Canada, 2002; pp. 2646-2650.
71. Fan, Y.; Song, K.; Zhou, X. Empirically adopted IEM for retrieval of soil moisture from radar backscattering coefficients. *IEEE Trans. Geosci. Remote Sens.* **2009**, *in press*.
72. Sano, E.E.; Huete, A.R.; Troufleau, D.; Moran, M.S.; Vidal, A. Relation between ERS-1 synthetic aperture radar data and measurements of surface roughness and moisture content of rocky soils in a semiarid rangeland. *Water Resour. Res.* **1998**, *34*, 1491-1498.
73. Alvarez, J.; Verhoest, N.E.C.; Casali, J.; Gonzalez-Audicana, M.; Lopez, J.J. RADARSAT based surface soil moisture retrieval on agricultural catchments of Navarre (Spain). In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS'04)*, Anchorage, AK, USA, 2004.
74. Baghdadi, N.; Gherboudj, I.; Zribi, M.; Sahebi, M.; King, C.; Bonn, F. Semi-empirical calibration of the IEM backscattering model using radar images and moisture and roughness field measurements. *Int. J. Remote Sens.* **2004**, *25*, 3593-3623.
75. Sahebi, M.R.; Bonn, F.; Bénié, G.B. Neural networks for the inversion of soil surface parameters from synthetic aperture radar satellite data. *Can. J. Civil Eng.* **2004**, *31*, 95-108.
76. Baghdadi, N.; Zribi, M. Evaluation of radar backscatter models IEM, OH and Dubois using experimental observations. *Int. J. Remote Sens.* **2006**, *27*, 3831-3852.

77. Alvarez-Mozos, J.; Gonzalez-Audicana, M.; Casali, J.; Larranaga, A. Effective versus measured correlation length for radar-based surface soil moisture retrieval. *Int. J. Remote Sens.* **2008**, *17*, 5397-5408.
78. Bindlish, R.; Barros, A.P. Multifrequency soil moisture inversion from SAR measurements with the use of IEM. *Remote Sens. Environ.* **2000**, *71*, 67-88.
79. Thoma, D.P.; Moran, M.S.; Bryant, R.; Rahman, M.; Holifield-Collins, C.D.; Skirvin, S.; Sano, E.E.; Slocum, K. Comparison of four models to determine surface soil moisture from C-band radar imagery in a sparsely vegetated semiarid landscape. *Water Resour. Res.* **2006**, *42*, 1-12.
80. van Oevelen, P.J.; Hoekman, D.H. Radar backscatter inversion techniques for estimation of surface soil moisture: EFEDA-Spain and HAPEX-Sahel case studies. *IEEE Trans. Geosci. Remote Sens.* **1999**, *37*, 113-123.
81. Saich, P.; Lewis, P.; Disney, M.I. Biophysical parameter retrieval from forest and crop canopies in the optical and microwave domains using 3D models of canopy structure. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '03)*, Toulouse, France, 2003; *6*, pp. 3546-3548.
82. Baghdadi, N.; Gaultier, S.; King, C. Retrieving surface roughness and soil moisture from synthetic aperture radar (SAR) data using neural networks. *Can. J. Remote Sens.* **2002**, *28*, 701-711.
83. Notarnicola, C.; Angiulli, M.; Posa, F. Soil moisture retrieval from remotely sensed data: neural network approach versus bayesian method. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 547-557.
84. Pasquariello, G.; Satalino, G.; Mattia, F.; Casarano, D.; Posa, F.; Souyris, J.C.; Le Toan, T. On the retrieval of soil moisture from SAR data over bare soils. In *Proceedings of the IEEE International Geoscience and Remote Sensing (IGARSS '97)*, Singapore, 1997; Vol. 3, pp. 1272-1274.
85. Haddad, Z. S.; Dubois, P. Bayesian estimation of soil parameters from remote sensing data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '94)*, Pasadena, CA, USA, August 8-12, 1994; Vol. 3, pp. 1421-1423.
86. Paloscia, S.; Santi, E.; Pettinato, S.; Angiulli, M. Soil properties estimates from SAR data by using a bayesian approach combined with IEM. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '04)*, Anchorage, AK, USA, 2004; pp. 819-822.
87. Paloscia, S.; Pampaloni, P.; Pettinato, S.; Poggi, P.; Santi, E. The retrieval of soil moisture from ENVISAT/ASAR data. *EARSeL eProc.* **2005**, *4*, 44-51.
88. Nelder, J.A.; Mead, R. A simplex method for function minimization. *Comput. J.* **1965**, *7*, 308-313.
89. Paloscia, S.; Pampaloni, P.; Pettinato, S.; Santi, E. A comparison of algorithms for retrieving soil moisture from ENVISAT/ASAR images. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 3274-3284.
90. Santi, E.; Paloscia, S.; Pampaloni, P.; Pettinato, S.; Poggi, P. Retrieval of soil moisture from ENVISAT/ASAR images: A comparison of inversion algorithms. In *Proceedings of the ESA ENVISAT/ERS Symposium*, Salzburg, Austria, 2004.

91. Rakotoarivony, L.; Taconet, O.; Vidal-Madjar, D.; Bellemain, P.; Benallegue, M. Radar backscattering over agricultural bare soils. *J. Electromagnet. Wave.* **1996**, *10*, 187-209.
92. Bryant, R.; Thoma, D.; Moran, M.S.; Holifield, C.D.; Goodrich, D.C.; Keefer, T.O.; Paige, G.; Williamd, D.; Skirvin, S.M. Evaluation of hyperspectral, infrared temperature and RADAR measurements for monitoring surface soil moisture. In *Proceedings of the First Interagency Conference on Research in the Watersheds Symposium*, Benson, AZ, USA, Oct. 27-30, 2003; pp. 528-533.
93. Thoma, D.; Moran, M.; Bryant, R.; Collins, C.H.; Rahman, M.; Skirvin, S. Comparison of two methods for extracting surface soil moisture from C-band radar imagery. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '04)*, Anchorage, AK, USA, 2004; pp. 827-830.
94. Neusch, T.; Sties, M. Application of the Dubois-model using experimental synthetic aperture radar data for the determination of soil moisture and surface roughness. *ISPRS J. Photogramm. Remote Sens.* **1999**, *54*, 273-278.
95. Wickel, A.; Jackson, T.; Wood, E. Multitemporal monitoring of soil moisture with RADARSAT SAR during the 1997 Southern Great Plains hydrology experiment. *Int. J. Remote Sens.* **2001**, *22*, 1571-1583.
96. Mathieu, R.; Sbih, M.; Viau, A.; Anctil, F.; Parent, L.; Boisvert, J. Relationships between Radarsat SAR data and surface moisture content of agricultural organic soils. *Int. J. Remote Sens.* **2003**, *24*, 5265-5281.
97. Baghdadi, N.; King, C.; Bourguignon, A.; Remond, A. Potential of ERS and Radarsat data for surface roughness monitoring over bare agricultural fields: Application to catchments in Northern France. *Int. J. Remote Sens.* **2002**, *23*, 3427-3442.
98. Baghdadi, N.; Zribi, M.; Loumagne, C.; Ansart, P.; Anguela, T.P. Analysis of TerraSAR-X data and their sensitivity to soil surface parameters over bare agricultural fields. *Remote Sens. Environ.* **2008**, *112*, 4370-4379.
99. D'Urso, G.; Minacapilli, M. A semi-empirical approach for surface soil water content estimation from radar data without a-priori information on surface roughness. *J. Hydrol.* **2006**, *321*, 297-310.
100. Oh, Y.; Sarabandi, K.; Ulaby, F.T. Semi-empirical model of the ensemble-averaged differential Mueller matrix for microwave backscattering from bare soil surfaces. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 1348-1355.
101. Álvarez-Mozos, J.; Gonzalez-Audicana, M.; Casalí, J. Evaluation of empirical and semiempirical backscattering models for surface soil moisture estimation. *Can. J. Remote Sens.* **2007**, *33*, 176-188.
102. Zribi, M.; Taconet, O.; Le Hégarat-Masclé, S.; Vidal-Madjar, D.; Emblanch, C.; Loumagne, C.; Normand, M. Backscattering behavior and simulation comparison over bare soils using SIR-C/X-SAR and ERASME 1994 data over Orgeval. *Remote Sens. Environ.* **1997**, *59*, 256-266.
103. Ji, J.; van der Keur, P.; Thomsen, A.; Skriver, H. Soil moisture retrieval using the Danish L- & C-band polarimetric SAR. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '96)*, Lincoln, NB, USA, 1996; Vol. 2, pp. 1300-1302.
104. Attema, E.P.W.; Ulaby, F.T. Vegetation modelled as a water cloud. *Radio Science* **1978**, *13*, 357-364.

105. Taconet, O.; Vidal-Madjar, D.; Emblanch, C.; Normand, M. Taking into account vegetation effects to estimate soil moisture from C-band radar measurements. *Remote Sens. Environ.* **1996**, *56*, 52-56.
106. Prevot, L.; Poenaru, V.; Voicu, P.; Vintila, R.; DeBoissezon, H.; Pourthie, N.; Lisah, I.; Montpellier, F. Surface soil moisture estimation from SAR data over wheat fields during the ADAM project. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, IGARSS'03*, Toulouse, France, 2003.
107. Maity, S.; Patnaik, C.; Chakraborty, M.; Panigrahy, S. Analysis of temporal backscattering of cotton crops using a semiempirical model. *IEEE Trans. Geosci. Remote Sens.* **2004**, *42*, 577-587.
108. Ulaby, F.T.; Allen, C.T.; Eger, G.; Kanemasu, E. Relating the microwave backscattering coefficient to leaf area index. *Remote Sens. Environ.* **1984**, *14*, 113-133.
109. Prévot, L.; Champion, I.; Guyot, G. Estimating surface soil moisture and leaf are index of a wheat canopy using a dual-frequency(C and W bands) scatterometer. *Remote Sens. Environ.* **1993**, *46*, 331-339.
110. van Leeuwen, H.J.C.; Clevers, J.G.P.W.; Rijckenberg, G.J. Synergetic use of optical and microwave remote sensing data using models and specific features with respect to the sugar beet crop. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '94)*, California, CA, USA, August 8-12, 1994; Vol. 2, pp. 827-831.
111. Champion, I. Simple modelling of radar backscattering coefficient over a bare soil: variation with incidence angle, frequency and polarization. *Int. J. Remote Sens.* **1996**, *15*, 783-800.
112. Graham, A.J.; Harris, R. Extracting biophysical parameters from remotely sensed radar data: a review of the water cloud model. *Prog. Phys. Geog.* **2003**, *27*, 217-229.
113. Dabrowska-Zielinska, K.; Gruszczynska, M.; Kowalik, W.; Inoue, Y.; Hoscilo, A. Retrieval of crop parameters and soil moisture from ENVISAT ASAR based on model analysis. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '05)*, Seoul, Korea, July 25-29, 2005; pp. 2149-2152.
114. Stolz, R.; Schneider, K.; Schouten, L.; van Leeuwen, H.; Bach, H. Combining the microwave model CLOUD and the growth model PROMET-V for soil moisture retrieval. In *Proceedings of ERS-ENVISAT-Symposium*, Gothenburg, Sweden, October 16-20, 2000.
115. Cole, K.S.; Cole, R.H. Dispersion and absorption in dielectrics II. Direct current characteristics. *J. Chem. Phys.* **1942**, *10*, 98-105.
116. Debye, P. *Polar molecules*. Dover Publications Inc.: New York, NY, USA, 1929.
117. van Dam, R.L.; Borchers, B.; Hendrickx, J.M. Methods for prediction of soil dielectric properties- A review. In *Proceedings of the SPIE*, Orlando, FL, USA, March 28- April 1, 2005; pp. 188-197.
118. Lisichkin, V.; Shvedov, S. Comparative analysis of models of the dielectric properties of soil in self-excited oscillator measurements of moisture content. *Meas. Techniq.* **2008**, *51*, 213-218.
119. Topp, G.C.; Davis, J.L.; Annan, A.P. Electromagnetic determination of soil water content: measurements in coaxial transmission lines. *Water Resour. Res.* **1980**, *16*, 574-582.
120. Wang, J.R.; Schmugge, T.J. An empirical model for the complex dielectric permittivity of soils as a function of water content. *IEEE Trans. Geosci. Remote Sens.* **1980**, *18*, 288-295.

121. Dobson, M.C.; Ulaby, F.T.; Hallikainen, M.T.; El-Rayes, M.A. Microwave dielectric behavior of wet soil-part II: Dielectric mixing models. *IEEE Trans. Geosci. Remote Sens.* **1985**, *23*, 35-46.
122. Peplinski, N.R.; Ulaby, F.T.; Dobson, M.C. Dielectric properties of soils in the 0.3-1.3-GHz range. *IEEE Trans. Geosci. Remote Sens.* **1995**, *33*, 803-807.
123. Zribi, M.; Le Hégarat-Masclé, S.; Ottlé, C.; Kammoun, B.; Guerin, C. Surface soil moisture estimation from the synergistic use of the (multi-incidence and multi-resolution) active microwave ERS Wind Scatterometer and SAR data. *Remote Sens. Environ.* **2003**, *86*, 30-41.
124. Moran, M.S.; Peters-Lidard, C.D.; Watts, J.M.; McElroy, S. Estimating soil moisture at the watershed scale with satellite-based radar and land surface models. *Can. J. Remote Sens.* **2004**, *30*, 805-826.
125. O'Neill, P.; Chauhan, N.; Jackson, T. Use of active and passive microwave remote sensing for soil moisture estimation through corn. *Int. J. Remote Sens.* **1996**, *17*, 1851-1865.
126. Njoku, E.G.; Wilson, W.J.; Yueh, S.H.; Dinardo, S.J.; Li, F.K.; Jackson, T.J.; Lakshmi, V.; Bolten, J. Observations of soil moisture using a passive and active low-frequency microwave airborne sensor during SGP99. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 2659-2673.
127. Narayan, U.; Lakshmi, V.; Jackson, T.J. High-resolution change estimation of soil moisture using L-band radiometer and Radar observations made during the SMEX02 experiments. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 1545-1554.
128. Narayan, U.; Lakshmi, V.; Njoku, E.G. Retrieval of soil moisture from passive and active L/S band sensor (PALS) observations during the Soil Moisture Experiment in 2002 (SMEX02). *Remote Sens. Environ.* **2004**, *92*, 483-496.
129. Bindlish, R.; Barros, A.P. Subpixel variability of remotely sensed soil moisture: an inter-comparison study of SAR and ESTAR. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 326-337.
130. Wang, C.; Qi, J. Soil moisture extraction in sparse vegetated area using SAR and TM data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2000)*, Honolulu, HI, USA, 2000; Vol. 3, pp. 1265-1267.
131. Wang, C.; Qi, J.; Moran, S.; Marsett, R. Soil moisture estimation in a semiarid rangeland using ERS-2 and TM imagery. *Remote Sens. Environ.* **2004**, *90*, 178-189.
132. Moran, M.S.; Hymer, D.C.; Qi, J.; Sano, E.E. Soil moisture evaluation using multi-temporal synthetic aperture radar (SAR) in semiarid rangeland. *Agr. Forest Meteorol.* **2000**, *105*, 69-80.
133. Notarnicola, C.; Angiulli, M.; Posa, F. Use of radar and optical remotely sensed data for soil moisture retrieval over vegetated areas. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 925-935.
134. Engman, E.T.; Chauhan, N. Status of microwave soil moisture measurements with remote sensing. *Remote Sens. Environ.* **1995**, *51*, 189-198.
135. Rignot, E.J.M.; van Zyl, J.J. Change detection techniques for ERS-1 SAR data. *IEEE Trans. Geosci. Remote Sens.* **1993**, *31*, 896-906.
136. Bovolo, F.; Bruzzone, L. A detail-preserving scale-driven approach to change detection in multitemporal SAR images. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 2963-2972.
137. Bao, M. Backscattering change detection in SAR images using wavelet techniques. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '99)* Hamburg, Germany, 1999; pp. 1561-1563.

138. Villasenor, J.D.; Fatland, D.R.; Hinzman, L.D. Change detection on Alaska's North Slope using repeat-pass ERS-1 SAR images. *IEEE Trans. Geosci. Remote Sens.* **1993**, *31*, 227-236.
139. Shoshany, M.; Svoray, T.; Curran, P.J.; Foody, G.M.; Perevolotsky, A. The relationship between ERS-2 SAR backscatter and soil moisture: generalization from a humid to semi-arid transect. *Int. J. Remote Sens.* **2000**, *21*, 2337.
140. Thoma, D.P.; Moran, M.S.; Bryant, R.; Rahman, M.M.; Collins, C.D.H.; Keefer, T.O.; Noriega, R.; Osman, I.; Skrivin, S.M.; Tischler, M.A.; Bosch, D.D.; Starks, P.J.; Peters-Lidard, C.D. Appropriate scale of soil moisture retrieval from high resolution radar imagery for bare and minimally vegetated soils. *Remote Sens. Environ.* **2008**, *112*, 403-414.
141. Jensen, J.R. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice Hall: Englewood Cliffs, New Jersey, NJ, USA, 1986.
142. Byrne, G.F.; Crapper, P.F.; Mayo, K.K. Monitoring land-cover change by principal component analysis of multitemporal landsat imagery. *Remote Sens. Environ.* **1980**, *10*, 175-184.
143. Fung, T.; LeDrew, E. Application of principal components analysis to change detection. *Photogramm. Eng. Remote Sens.* **1987**, *53*, 1649-1658.
144. Piwowar, J.M.; LeDrew, E.F. Principal components analysis of Arctic ice conditions between 1978 and 1987 as observed from the SMMR data record. *Can. J. Remote Sens.* **1996**, *22*, 390-403.
145. Lee, J.S.; Hoppel, K. Principal components transformation of multifrequency polarimetric SAR imagery. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 686-696.
146. Baronti, S.; Carla, R.; Sigismondi, S.; Alparone, L. Principal component analysis for change detection on polarimetric multitemporal SAR data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '94)*, Pasadena, CA, USA, August 8-12, 1994; Vol. 4, pp. 2152-2154.
147. Henebry, G.M. Advantages of principal components analysis for land cover segmentation from SAR image series. In *Proceedings of the 1st ERS Symposium 'Space at the Service of our Environment'*, ESA SP: Florence, Italy, 1997; pp. 175-178.
148. Verhoest, N.E.C.; Troch, P.A.; Paniconi, C.; De Troch, F.P. Mapping basin scale variable source areas from multitemporal remotely sensed observations of soil moisture behavior. *Water Resour. Res.* **1998**, *34*, 3235-3244.
149. Kong, X.; Dorling, S.R. Near-surface soil moisture retrieval from ASAR Wide Swath imagery using a Principal Component Analysis. *Int. J. Remote Sens.* **2008**, *29*, 2925-2942.
150. Graham, L.C. Synthetic Interferometer radar for topographic mapping. *Proc, IEEE* **1974**, *62*, 763-768.
151. Ichoku, C.; Karnieli, A.; Arkin, Y.; Chorowicz, J.; Fleury, T.; Rudant, J.P. Exploring the utility potential of SAR interferometric coherence images. *Int. J. Remote Sens.* **1998**, *19*, 1147-1160.
152. Borgeaud, M.; Wegmueller, U. On the use of ERS SAR interferometry for the retrieval of geo- and bio-physical information. In *Proceedings of the 'Fringe 96' Workshop on ERS SAR Interferometry*, ESA SP-406, Zurich, Switzerland, 1996; pp. 83-94.
153. Wegmüller, U. Soil moisture monitoring with ERS SAR interferometry. In *Proceedings of the Third ERS Symposium: Space at the Service of our Environment*, ESA-SP-414: Florence, Italy, 1997; pp. 47-52.

154. Lu, Z.; Meyer, D.J. Study of high SAR backscattering caused by an increase of soil moisture over a sparsely vegetated area: implications for characteristics of backscattering. *Int. J. Remote Sens.* **2002**, *23*, 1063-1074.
155. Zebker, H.A.; Villasenor, J. Decorrelation in interferometric radar echoes. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 950-959.
156. Nesti, G.; Sieber, A.J.; de Grandi, G.D.; Fortuny-Guasch, J.; Ohlmer, E. Recent advances at the european microwave signature laboratory. In *Proceedings of SPIE: Microwave Instrumentation and Satellite Photogrammetry for Remote Sensing of the Earth* Rome, Italy, 26 September 1994.
157. Nesti, G.; Tarchi, D.; Rudant, J.P. Decorrelation of backscattered signal due to soil moisture changes. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '95)*, Toulouse, France, October 1995; pp. 2026-2028.
158. Nesti, G.; Tarchi, D.; Bedidi, A.; Despan, D.; Rudant, J.P.; Bachelier, E.; Borderies, P. Phase shift and decorrelation of radar signal related to soil moisture changes. In *Retrieval of Bio- and Geo-Physical Parameters from SAR Data for Land Applications Workshop* ESTEC, Noordwijk, The Netherlands, October 21-23, ESA SP: 1998; pp. 423-430.
159. Luo, X.; Askne, J.; Smith, G.; Dammert, P. Coherence characteristics of radar signals from rough soil. *Progr. Electromagnet. Res. PIER* **2001**, *31*, 69-88.
160. Srivastava, S.K.; Jayaraman, V. Relating interferometric signature of repeat pass ERS-1 SAR signals to dynamic land cover changes. *Acta Astronaut.* **2001**, *48*, 37-44.
161. Hajnsek, I.; Papathanassiou, K.P.; Moreira, A.; Cloude, S.R. Surface parameter estimation using interferometric and polarimetric SAR. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '02)* Toronto, ON, Canada, 2002; Vol. 1, pp. 420-422.
162. Hajnsek, I.; Alvarez-Perez, J.L.; Papathanassiou, K.P.; Moreira, A.; Cloude, S.R. Surface parameter estimation using interferometric coherences at different polarisations. In *POLinSAR Workshop on Applications of SAR Polarimetry and Polarimetric Interferometry*, ESA-ESRIN, Frascati, Italy, January 14-16, 2003.
163. Gabriel, A.K.; Goldstein, R.; Zebker, H.A. Mapping small elevation changes over large areas. *J. Geophys. Res.* **1989**, *94*, 9183-9191.
164. Nolan, M.; Fatland, D.R. Penetration depth as a DInSAR observable and proxy for soil moisture. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 532-537.
165. Nolan, M.; Fatland, D.R.; Hinzman, L. DInSAR measurement of soil moisture. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 2802-2813.
166. Hajnsek, I.; Prats, P. Soil moisture estimation in time with D-InSAR. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS'08)* Boston, MA, USA, 2008; pp. 546-549.
167. Souyris, J.C.; Imbo, P.; Fjortoft, R.; Mingot, S.; Lee, J.S. Compact polarimetry based on symmetry properties of geophysical media: The p/4 mode. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 634-646.
168. Raney, R.K. Hybrid-polarity sar architecture. *IEEE Trans. Geosci. Remote Sens.* **2007**, *45*, 3397-3404.

169. Dubois-Fernandez, P.C.; Souyris, J.C.; Angelliaume, S.; Garestier, F. The compact polarimetry alternative for spaceborne sar at low frequency. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 3208-3222.
170. Nord, M.E.; Ainsworth, T.L.; Jong-Sen, L.; Stacy, N.J.S. Comparison of compact polarimetric synthetic aperture radar modes. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 174-188.
171. Ulaby, F.T.; Elachi, C. *Radar Polarimetry for Geoscience Applications*. Artech House: Norwood, MA, USA, 1990.
172. Cloude, S.R.; Pottier, E. An entropy based classification scheme for land applications of polarimetric SAR. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 68-78.
173. Hajnsek, I. *Inversion of Surface Parameters from Polarimetric SAR data*. PhD Thesis, Friedrich Schiller University of Jena (FSU): Jena, Germany, 2001.
174. Cloude, S.R.; Pottier, E. A review of target decomposition theorems in radar polarimetry. *IEEE Trans. Geosci. Remote Sens.* **1996**, *34*, 498-518.
175. Lee, J.S.; Boerner, W.M.; Schuler, D.L.; Ainsworth, T.L.; Hajnsek, I.; Papathanassiou, K.P.; Lüneburg, E. A review of polarimetric SAR algorithms and their applications. *J. Photogramm. Remote Sens.* **2004**, *9*, 31-80.
176. Freeman, A.; Durden, S.L. A three-component scattering model for polarimetric SAR data. *IEEE Trans. Geosci. Remote Sens.* **1998**, *36*, 963-973.
177. Cloude, S.R.; Pottier, E. An entropy based classification scheme for land applications of polarimetric SAR. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 68-78.
178. Hajnsek, I.; Pottier, E.; Cloude, S.R. Inversion of surface parameters from polarimetric SAR. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 727-744.
179. Hajnsek, I.; Jagdhuber, T.; Schon, H.; Papathanassiou, K.P. Potential of estimating soil moisture under vegetation cover by means of PolSAR. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 442-454.
180. Cloude, S.R.; Papathanassiou, K.; Hajnsek, I. An eigenvector method for the extraction of surface parameters in polarimetric SAR. In *Proceedings of the CEOS SAR Workshop*, European Space Agency: Toulouse, France, 2000; pp. 693-698.
181. Allain, S.; Ferro-Famil, L.; Pottier, E. Surface parameter retrieval from polarimetric and multi-frequency SAR data. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '03)*, Toulouse, France, 2003; Vol. 2, pp. 1417-1419.
182. Cloude, S.R. The Dual Polarisation entropy/alpha decomposition: A PALSAR case study. In *POLinSAR'07: the 3rd International Workshop on Science and Applications of SAR Polarimetry and Polarimetric Interferometry*, Frascati, Italy, January 22-26, 2007.
183. Williams, M.L. Potential for surface parameter estimation using compact polarimetric SAR. *IEEE Geosci. Remote Sens. Lett.* **2008**, *5*, 471-473.
184. Mattia, F.; Le Toan, T.; Souyris, J.C.; De Carolis, C.; Floury, N.; Posa, F.; Pasquariello, N. G. The effect of surface roughness on multifrequency polarimetric SAR data. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 954-966.
185. Schuler, D.L.; Jong-Sen, L.; Kasilingam, D.; Nesti, G. Surface roughness and slope measurements using polarimetric SAR data. *IEEE Trans. Geosci. Remote Sens.* **2002**, *40*, 687-698.

186. Malhotra, S.; Kasilingam, D.; Schuler, D. The dependence of polarimetric coherence on surface roughness for very rough surfaces. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '03)*, Toulouse, France, 2003; pp. 1654-1656.
187. Cloude, S.R.; Corr, D.G. A new parameter for soil moisture estimation. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '02)*, Toronto, ON, Canada, 2002; Vol. 1, 641-643.
188. Ulaby, F.T. SAR biophysical retrievals: lessons learned and challenges to overcome. In *Proceedings of the 2nd International Workshop on Retrieval of Bio- and Geo-physical Parameters from SAR Data for Land applications*, Noordwijk, The Netherlands, 1998; pp. 19-26.
189. Pathe, C.; Wagner, W.; Sabel, D.; Doubkova, M.; Basara, J. B. Using ENVISAT ASAR global mode data for surface soil moisture retrieval over oklahoma, USA. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 468-480.
190. Oldak, A.; Jackson, T.; Starks, P.; Elliott, R. Mapping near-surface soil moisture on regional scale using ERS-2 SAR data. *Int. J. Remote Sens.* **2003**, *24*, 4579-4598.
191. Wagner, W.; Pathe, C. Has SAR failed in soil moisture retrieval. In *Proceedings ENVISAT & ERS Symposium*, Salzburg, Austria, ESA SP-572: 2005; pp. 6-10.
192. Wagner, W.; Blöschl, G.; Pampaloni, P.; Calvet, J. Operational readiness of microwave remote sensing of soil moisture for hydrologic applications. *Hydrol. Res.* **2007**, *38*, 1-20.
193. Engman, E. Progress in microwave remote sensing of soil moisture. *Can. J. Remote Sens.* **1990**, *16*, 6-14.
194. Fung, A.K. *Microwave scattering and emission models and their applications*. Artech House: Boston, MA, 1994.
195. Hajnsek, I.; Papathanassiou, K.P.; Cloude, S.R. L- and P-band for surface parameter estimation. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS '01)*, Sydney, NSW, Australia, 2001; pp. 2775-2777.
196. Moran, M.S.; Vidal, A.; Troufleur, D.; Inoue, Y.; Mitchell, T.A. Ku- and C-band SAR for discriminating agricultural crop and soil conditions. *IEEE Trans. Geosci. Remote Sens.* **1998**, *36*, 265-272.
197. Karam, M.A.; Fung, A.K.; Lang, R.H.; Chauhan, N.S. A microwave scattering model for layered vegetation. *IEEE Trans. Geosci. Remote Sens.* **1992**, *30*, 767-784.