Microwave Remote Sensing of Land

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Abstract

Considering the rapid growth of population, its impact on the environment, and limited available resources on our planet, the need for monitoring the environmental processes and managing our resources is unequivocal. Microwave remote sensing provides a unique capability towards achieving this goal. Over the past decade, significant progress has been made in microwave remote sensing of land processes through development of advanced airborne and space-borne microwave sensors, and the tools – such as physics-based models and advanced inversion algorithms – needed for analyzing the data. These activities have sharply increased in recent years since the launch of the ERS-1/2, JERS-1, and RADARSAT satellites, and with the availability of radiometric data from SSM/I. A new era has begun with the recent space missions ESA-ENVISAT, NASA-AQUA, and NASDA-ADEOSII, and the upcoming PALSAR and RADARSAT2 missions, which open new horizons for a wide range of operational microwave remote-sensing applications. This paper highlights major activities and important results achieved in this area over the past years.

1. Introduction

The application of microwaves for remote sensing of terrestrial targets is motivated by the all-weather, day/night, and target-penetrating attributes of such systems. Though traditional optical and multi-spectral imaging systems can be used effectively in principle, issues related to the atmospheric effects often render such systems less desirable. In the past decade, several satellite-borne synthetic-aperture radars (SAR) were launched for the remote sensing of the environment.

The successful application of SAR technology to address a wide range of remote-sensing problems helped the advancement of SAR systems to include polarization diversity and operation in interferometric mode. The first remote-sensing space-borne polarimetric SAR system, and the first single-pass interferometric SAR, were flown aboard the Space Shuttle in 1994 [1] and 2000 [2], respectively. was given in [3]. A very good review of radar polarimetry techniques and interferometric SAR systems and applications can be found in [4] and [5].

The most significant event in recent years was the launch, performed by the European Space Agency, of the ENVISAT satellite, carrying onboard a set of innovative sensors, including the Advanced Synthetic Aperture Radar (ASAR) [6]. This C-band radar is a significant improvement over the ERS-1/2 SAR, in that it makes observations at different incidence angles and polarizations possible, and allows for scanSAR operations. The satellite was launched on March 1, 2002, but data were made available to the scientific community in the fall of 2002, only after the commissioning phase. Thus, most of the work performed so far with satellite radar still involves the use of data from the currently in-orbit ERS-2 and RADARSAT, or from archives of ERS-1 (C band) and JERS (L band).

The combined active microwave instrument (AMI), operating at C band (5.3 GHz) and with vertical polarization, is aboard the European remote-sensing satellite ERS-2. AMI is composed of a SAR and a scatterometer (SCAT), operating in an interleaved mode. In SAR wave mode, 10 km × 5 km images are acquired at a nominal incidence angle of 23°, with a spatial resolution of about 30 m. The ERS-1/2 scatterometer continuously illuminates a 500 km-wide swath with a resolution of 45 km [7]. A first interferogram, using radar data from the ERS-2's SAR instrument and Envisat's ASAR instrument, has already been produced by scientists from the German Aerospace Centre (DLR). They analyzed images taken in 1999 (ERS-2) and 2002 (Envisat) over the town of Las Vegas in the US [6]. Producing an interferogram with data from these two

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satellites was not initially considered to be feasible, since the SARs on ERS-2 and Envisat operate at slightly different frequencies, and this was enough to complicate the joint processing of data from the ERS and Envisat sensors. However, generation of interferograms using ERS and ENVISAT by the application of permanent scatterers with very stable scattering phase centers was proposed in [8, 9].

RADARSAT-1 was launched in November, 1995, circling the Earth in a sun-synchronous polar orbit [10]. RADARSAT-1 operates at C band, and offers users a wide variety of beam selections. The satellite's SAR has the unique ability to shape and steer its beam from an incidence angle of 10° to 60°, in swaths from 45 to 500 km in width, with resolutions ranging from eight to 100 m.

As far as passive systems are concerned, two space-borne microwave radiometers, called the Advanced Microwave Scanning Radiometer, were launched in 2002 to provide new observational data. One sensor is the AMSR-E, aboard the Earth Observing System (EOS) Aqua of the US National Aeronautics and Space Administration (NASA) [11]. The other is the AMSR [12], aboard the Advanced Earth Observing Satellite-II (ADEOS-II) of the National Space Development Agency of Japan (NASDA). AMSR and AMSR-E are almost identical sensors, and have lower frequencies of 6 GHz and 10 GHz, and much better ground resolution compared to previous sensors. Indeed, the ground resolution ranges from 43×75 km^2 at the lower frequency, to 3.5×5.9 km^2 at the highest frequency. We expect to retrieve soil moisture and vegetation biomass on a global scale with reasonable accuracy from the lower-frequency channels of these sensors. Geophysical products are currently being validated by means of several methods, such as the use of existing in-situ data, and by comparing data with data from other sensors [13].

Among the near-future space-borne radar remote-sensing systems, the Japanese fully polarimetric Phased Array type L-band Synthetic Aperture Radar (PALSAR), operating at 1.27 GHz, and RADARSAT-2, operating at C band, can be mentioned. In high-resolution mode (~10 m) the system can be used in fully polarimetric mode over a swath width of 70 km. PALSAR offers another attractive observational mode, called the ScanSAR mode. By sacrificing spatial resolution (~100 m), PALSAR can provide a swath width of the order of about 250-350 km, most appropriate for monitoring targets of large extent, such as sea ice and rain forests [14]. Scheduled for launch in 2004, RADARSAT-2 will provide data continuity to RADARSAT-1 users and offer data for new applications. The RADARSAT-2 Synthetic Aperture Radar (SAR) is fully polarimetric, and will be able to acquire data at all or any of HH, VV, and HV/VH polarizations over a range of resolutions from 3 m to 100 m [15].

Apart from the contributions made in the preparation of these missions, the microwave remote-sensing community has been deeply involved in improving the knowledge in the field by analyzing experimental data collected from satellite, airborne, and ground-based sensors, and is engaged in developing more advanced forward models and inversion algorithms. To this end, studies have also been performed by using data from sensors not specifically designed for land, use such as SSM/T, AMSU [16], and TRMM [17].

The literature concerning microwave remote-sensing terrestrial targets and Earth processes is rather extensive, and cannot be entirely covered here. This article attempts to highlight major activities and important results in this area over the past decade.

2. Retrieval of Land Parameters

The availability of a considerable amount of Synthetic Aperture Radar (SAR) and multi-frequency radiometric data, obtained in recent years from airborne and space-borne systems, has stimulated significant research in interpreting data and investigating their potential in various applications. For environmental studies, the focus of research on microwave remote-sensing of land processes can be categorized into: 1) land classification, 2) soil-moisture retrieval, 3) forest and crop biomass estimation, and 4) ice- and snow-pack parameter estimation.

2.1 Image Processing and Land Classification

The first step in most retrieval algorithms is image classification, where the domain of the imaged scene is divided into different general categories, which, in turn may each be subdivided into statistically homogeneous domains. Several different types of microwave image classifiers are now routinely in use. The classification techniques implemented so far can be categorized into statistical-based approaches, such as the maximum-likelihood classifier [18], unsupervised and knowledge-based classifiers [19, 20], and neural-network classifiers, which use a non-parametric classification technique [21-23]. A methodology known as the "decision tree" classification technique has also been used successfully for a wide range of classification problems, but it has not been tested in detail by the remote-sensing community [24]. Algorithms for edge and change detection, using polarimetric and/or multi-frequency SAR data, have been developed, and were reported in [25, 26].

Microwave land-coverage studies have been performed at high resolution with airborne sensors, such as JPL AirSAR [27] and CCRS C/X SAR [28]; satellite SAR; and at global scale, mainly with the ERS-1/2 Wind scatterometer and the SSM/I. The potential of multi-frequency polarimetric SAR data for separating agricultural fields from other types of surfaces, and in discriminating among classes of agricultural species, has been demonstrated by various authors [e.g., 28]. Lee et al. [30] exploited the land-use classification capabilities of fully polarimetric synthetic-aperture radar (SAR) versus dual-polarization and single-polarization SAR for P-, L-, and C-band frequencies. A variety of polarization combinations was investigated for application to crop and tree-age classification. The authors found that L-band fully polarimetric SAR data are best for crop classification, but that P band is best for forest-age classification. This is because longer-wavelength electromagnetic waves provide higher penetration. Moreover, the HH and VV phase difference is important for crop classification, but less important for tree-age classification

Recent research addressed to urban areas by using multi-temporal analysis of SAR data has demonstrated that the coarse resolution of ERS images does not prevent the possibility of characterizing these areas [31, 32]. Tupin et al. [33] established the usefulness of multiple SAR views in road detection.

Significant efforts have also been devoted to addressing land-cover characterization on a global scale by using ERS scatterometer data. These studies showed that the radar backscattering, σ°, was able to describe the vegetation cycle in a semi-arid region and in boreal forests [34, 35]. A few significant studies for distinguishing land surfaces and estimating quantitative parameters with the use of space-borne microwave radiometers were conducted using data from the Scanning Multi-channel Microwave Radiometer (SMMR) and the Special Sensor Microwave Imager (SSM/I). This research led to establishing empirical or semi-empirical rules for land-surface classification [e.g., 36, 37]. The 19-37 GHz spectral gradient and the 37 GHz brightness temperature, *Tb*, were effective for freeze/thaw classification in the northern prairies and for characterizing the land surface in Greenland [38, 39]. Convenient indices, derived by the observed backscattering and brightness temperature from the ERS scatterometer and the SSM/I, made possible the monitoring of seasonal variations in various types of land surfaces [40, 41].

2.2 Soil Moisture

Soil moisture, and its temporal and spatial variations, are influential parameters in both climatic and hydrologic models. The measurement of soil-moisture content (SMC) is one of the most important targets of remote sensing, and significant amounts of experimental and theoretical studies have been carried out since the late 1970s. The soil dielectric constant at microwave frequencies exhibits a strong dependence on the soil's moisture content. For example, at L band, the real part of the dielectric constant ranges from 3 for dry soil to about 25 for saturated soil. This variation can result in a change on the order of 10 dB in the magnitude of the radar-backscatter coefficient [42], and of 100 K in the magnitude of the brightness temperature. An important component required in the soil-moisture inverse problem is the knowledge of the relationship between the soil dielectric constant and its moisture content. Accurate empirical models and measurements for soil dielectric constant were given in [43-45].

As mentioned earlier, the radar backscatter and thermal emission at low microwave frequencies are both sensitive to soil-moisture content. Vegetation cover is one major difficulty encountered in practice, which masks the soil surface and reduces the radiometric and radar sensitivities to soil-moisture content. Controversial opinions have been expressed regarding the superiority of the radiometric technique over radar, or vice-versa. Du et al. [46] investigated the question by using radiative-transfer models for three types of canopies, all at 1.5 GHz, and this led to the conclusion that as far as vegetation effects are concerned, neither sensor can claim superiority over the other. From an experimental point of view, a certain conclusion on this point has not yet been reached. Surface roughness is the other disturbing factor that may significantly affect the measurement of soil moisture. This quantity has also been the subject of many investigations. In general, it has been stated that backscatter is more sensitive to this factor than emission.

2.2.1 Passive Systems

Soil-moisture-content research with microwave radiometers has been active since the late 1970s, and has recently been revitalized by new missions: the already-in-orbit AMSR-E and AMSR, and the planned SMOS, selected by the European Space Agency (ESA) in the framework of the Earth Explorer Opportunity Missions; and AQUARIUS, selected by NASA as part of the Earth System Science Pathfinder small-satellite program. The SMOS mission [47] is based on a dual-polarized L-band radiometer that uses aperture synthesis to achieve a ground resolution of 50 km. AQUARIUS [48], based on a combination of L-band active and passive conical-scanning instruments, will have similar performance, and will use radar data to correct for surface roughness.

Most experimental research on soil moisture with passive systems has been carried out in the US at GSFC in Greenbelt (Maryland), USDA in Beltsville (Maryland), JPL in Pasadena (California), MIT in Cambridge (Massachusetts), the University of Michigan (Michigan), and Princeton University (New Jersey); and in Europe at INRA in Avignon (France), the University of Amsterdam (The Netherlands), and the CNR in Florence (Italy). An excellent summary of recent research can be found in the special issue on "Large Scale Passive Microwave Remote Sensing of Soil Moisture" of the *IEEE Transactions on Geoscience and Remote Sensing*, published in August, 2001. Large airborne experiments, called the Southern Great Plains Hydrology Experiments, were conducted in the US in 1997 (SGP97) and 1999 (SGP99) to address significant gaps in the knowledge, and to validate retrieval algorithms designed for the AMSR and the AMSR-E. In 1997, the L-band Electronically Scanned Thinned Array

Radiometer (ESTAR) was used for daily mapping of soil-moisture content over an area greater than 10000 km^2 for a one-month period. Results showed the consistency of both the retrieval algorithm and the instrument. Error levels were on the order of 3% [49, 50]. In the SGP99, the Passive and Active L- and S-band airborne sensor (PALS) [51, 52] was used together with the C-band Polarimetric Scanning Radiometer (PSR/C). The acquired data provided information on the sensitivities of multi-channel low-frequency measurements to soil-moisture content for various vegetation conditions with water contents in the 0-2.5 kg m^2 range. The 1.41 GHz horizontal-polarization channel showed the greatest sensitivity, with a retrieval accuracy of 2.3%. PSR/C images showed spatial and temporal patterns consistent with meteorological and soil conditions, and indicated that the AMSR instrument can provide useful soil-moisture information.

As a part of the same SGP experiment, an observing-system simulation experiment (OSSE) was carried out to assess the impact of land-surface heterogeneity on the large-scale retrieval and validation of soil-moisture products, using the 6.925 GHz channel on the AMSR-E sensor. To do this, a high-resolution hydrologic model, a land-surface microwave-emission model (LSMEM), and an explicit simulation of the orbital and scanning characteristics for the AMSR-E were used. Results within the 575000 km^2 Red-Arkansas River basin showed that for surfaces with vegetation water content below 0.75 kg/m^2, two scale effects induced rms errors of 1.7% into daily 60 km AMSR-E soil moisture products, and rms differences of 3.0% into 60 km comparisons of AMSR-E soil-moisture products and in-situ field-scale measurements sampled on a fixed 25 km grid [53].

In the same area of SGP99, SSM/I and TMI satellite data were acquired over a two-week period under excellent meteorological conditions [10]. The analysis of the resulting maps showed that consistent satellite-based SMC retrieval is possible, and that data provided by the 6.9 GHz AMSR channel should offer significant improvements.

The problem of the effective temperature of the emitting surface at 6.6 GHz was investigated in [54], in which the magnitude of the long-term mean difference between actual and effective temperature was estimated by using data from the Scanning Microwave Multi-channel Radiometer (SMMR).

Various approaches have been considered for retrieving SMC from multi-frequency radiometric data, and, in particular, from the AMSR-E measurements [55]. These approaches differ primarily in the methods used to correct for the effects of soil texture, roughness, vegetation, and surface temperature. A common assumption is that over most land areas at the AMSR-E footprint scale, the effects of variability in soil texture and roughness on the observed brightness temperature are small compared with the effect of variability in soil—moisture content. This has been demonstrated in a number of model sensitivity studies [e.g., 56]. These parameters may therefore be approximated as non-variable. The vegetation-opacity coefficient can also be approximated as non-time-varying. However, it exhibits some dependence on crop type at the field scale, and the assumption of spatial uniformity must be considered a potential source of error. Soil-moisture-content retrieval approaches that have been investigated in previous studies include:

- Single-channel retrieval with sequential corrections using ancillary data [57, 58];
- Iterative forward model corrections using multi-channel brightness temperatures [56];
- Correction using multi-frequency polarization indices [59];
- Variations or combinations of the above methods [60, 61].

Other methods, based on Bayesian iterative inversion of a forward model [62] or neural networks [63, 64], have also been investigated.

The algorithm implemented for AMSR-E [56] was based on a radiative-transfer (RT) model; it used an iterative, least-squares algorithm, based on six radiometric channels. The primary rationale for this choice was that of minimizing the dependence on external ancillary data. The retrieval model assumes that temperature and moisture are uniform over the sensing depths of the frequencies used, and that the frequency dependence of the vegetation attenuation factor can be adequately characterized. The first factor is aided by using nighttime (1:30 a.m., descending-pass) measurements when the temperature and moisture profiles are reasonably uniform. Analysis of SMMR data taken over deserts and forests was used to obtain pre-launch estimates for AMSR-E.

Another algorithm, developed within the framework of the AMSR project, has been proposed in [59]. This algorithm is based on the sensitivity to moisture of both the brightness temperature, *Tb*, and the polarization index, *PI*, at C band, and uses the polarization index at X band to correct for the effect of vegetation by means of a semi-empirical model. Comparing the values of SMC retrieved from airborne measurements with those measured on the ground, the authors found a correlation coefficient of 0.78 with the standard error of estimate SE = 4.31. The algorithm was further validated by using data from the SMMR and the SSM/I. Another approach, based on polarization difference, which used a radiative-transfer model to solve for soil-moisture content and vegetation optical depth simultaneously, was tested with SMMR observations over several test sites in Illinois. Results compared well with field observations of soil-moisture content and vegetation-index data from satellite optical sensors [60].

Due to the coarse ground resolution of space-borne microwave measurements, the resolution cell may include a non-homogeneous surface. The effects of within-pixel variability were exploited by several authors, who found that errors in the retrieved soil-moisture content were generally negligible for a heterogeneous bare soil, and less than 3% of the actual soil moisture for a pixel that was heterogeneous in vegetation and soil moisture [65-71].

The thickness of the soil layer through which moisture can be directly estimated by means of a microwave radiometer has been investigated by many experimental studies. Most researchers have come to the conclusion that at L band this layer is about 5-10 cm. This result matches well with the requirements of those processes such as infiltration and evapotranspiration that take place within this first layer of the soil medium. In other applications, where soil-moisture profiles down to several decimeters are necessary, microwave must be coupled to appropriate hydrological models. The effectiveness of the Kalman filter for retrieving such a quantity was demonstrated in [72] by using field observations and a simulation study. The usefulness of assimilating remotely sensed measurements into land-surface models was discussed in [73-75]. Burke et al. [70] explored the potential for using low-resolution passive microwave in a two-dimensional Land Data Assimilation System (LDAS) for estimating deep-soil moisture from surface-soil moisture. Houser et al. [73] investigated four-dimensional (4-D) soil-moisture assimilation using in-situ and remote-sensing observations. A refined four-dimensional algorithm that accounts for model errors and fully incorporates process dynamics into the estimates was developed in [75].

Simultaneously with experimental research, theoretical investigations were performed to interpret experimental data and to provide tools for the retrieval of land parameters. The classical approach to computing the brightness temperature of soils is the radiative-transfer theory, which can treat multiple scattering in a medium consisting of random discrete scatterers. However, the theory assumes independent scattering, and then disregards coherent effects. If the temperature of the medium is constant and energy conservation holds, the emissivity can be expressed as one minus the reflectivity, and the problem of computing the brightness temperature is brought back to the computation of the bistatic scattering coefficients. Most of the models developed for soil and vegetation are based on this method. The problem of computing the brightness temperature of land surfaces has been extensively treated in the three volumes of the recent book by Tsang and Kong and their collaborators [76-78]

An evaluation of classical methods (Physical Optics, small perturbations, and integral equations) to compute the emissivity of rough soils from the bistatic scattering coefficient was performed by comparing model simulations with experimental data obtained at C and X bands on an artificial dielectric surface with the same statistical properties used in the model [79]. The results showed that on relatively smooth surfaces (height standard deviation HStD = 0.4 cm), all the models fitted the vertical component of emissivity quite well, and underestimated the horizontal component of emissivity. On rougher surfaces (HStD = 2.5 cm), the IEM model slightly underestimated the horizontal component and overestimated the vertical component.

Li et al. [80] have recently proposed a rigorous solution of the problem of computing emissivity from a two-dimensional (2D) wet soil with a random rough surface by applying a physics-based two-grid method, combined with a sparse-matrix canonical-grid method. The advantage of this approach is that unlike analytic approximations, such as the Kirchhoff method and the Small Perturbation Method, this method solves the three-dimensional Maxwell's equations numerically. The use of the fast numerical method presented in the paper shows that numerical simulations of emissivities can be calculated with modest CPU resources. Thus, the results of extensive numerical simulations can be directly applied to passive microwave remote sensing of soil moisture.

2.2.2 Active Systems

This possibility of monitoring soil-moisture changes using SAR data has stimulated a large number of studies focused on establishing a relationship between the observed SAR response and surface soil-moisture content. For a homogeneous soil with a perfectly smooth surface, the scattering of electromagnetic waves is totally forward, and depends on permittivity of the medium. For a rough surface, radiation is scattered in various directions, and also generates backscattering. Thus, two basic properties determine the backscatter response observed by the SAR system: the permittivity of the medium and the roughness characteristics of the surface. Both parameters are, in turn, related to different geophysical parameters of the soil. With the advent of the polarimetric SAR, radar remote sensing of soil moisture has attained significant prominence in the past two decades. Initially, extensive experimental studies using polarimetric scatterometers were carried to establish a relationship between radar response and the surface roughness and soil moisture [81]. Extensive field experiments have also been conducted to examine retrieval algorithms ranging from simple analytical to regression/ empirical models [82-84]. For example, the already mentioned SGP97 was conducted using a variety of active and passive remote-sensing tools on different platforms (truck, aircraft, and satellite) [85, 86].

Careful experiments under laboratory conditions or large field experiments all indicate that in order to retrieve soil-moisture content, more than a single backscatter observation is needed to separate the effects of surface-roughness parameters from the moisture content. Often times, only the surface rms height – and, in some cases, the surface correlation length – are sought for the surface-roughness parameters. In reality, the surface power spectral density is the quantity that affects the radar response;

however, retrieving surface parameters other than the rms height and correlation coefficient seems to be beyond the realm of possibility for radar remote-sensing tools. This implies that the experimental regressions between backscattering coefficient and soil-moisture content presented in the literature are both time and site dependent, and, thus, difficult to generalize.

SIR-C/X-SAR data pointed out that in the scale of surface roughness typical of agricultural areas, a co-polar L-band sensor provided the highest information content for estimating soil-moisture content and surface roughness. The sensitivity to soil-moisture content and surface roughness for individual fields was rather low, since both parameters affected the radar signal. However, in considering data averaged over a relatively wide area that included several fields, the correlation with the temporal variation of soil-moisture content was significant, since the effects of spatial roughness variations were smoothed [87]. On the other hand, the sensitivity to surface roughness was better manifested at a spatial scale, integrating in time to reduce the effects of moisture variation [87]. The retrieval of both soil moisture and surface roughness from multi-frequency polarimetric data was performed with good results by means of semi-empirical models [88, 89], or by inverting the IEM model [90].

The current limits of soil-moisture retrieval from ERS-SAR data were analyzed in [89] by using synthetic datasets, as well as a large pan-European database of ground and ERS-1 and ERS-2 measurements. The results from this study indicated that no more than two soil-moisture classes could be reliably distinguished using the ERS configuration, even for the limited roughness range considered.

In hydrological modeling of runoff and water balance, various input data – such as land use, soil moisture, and digital elevation terrain models (DEM) –can be acquired or estimated by the use of remote-sensing techniques. A good example of ERS SAR data assimilation in an integrated flood-forecasting model to translate rainfall into runoff was given in [91]. In the model, digital elevation terrain models derived from interferometric SAR data are used for a static description of a watershed, and dynamic model variables are obtained from the surface soil-moisture distribution estimated from SAR backscattering data.

Several scientists investigated the retrieval of soil-moisture content on a large scale by using ERS Wind Scatterometer data [e.g. 92, 93]. The results illustrated the applicability of these data for measuring land parameters, and offered the potential for deriving a physically-based alternative to empirical indices for estimating regionally-variable parameters.

As mentioned earlier, apart from surface-roughness parameters, the existence of short vegetation on the surface makes the retrieval of soil-moisture content very complicated. Vegetation cover and its temporal variations are believed to be the major stumbling blocks in monitoring soil-moisture-content variations using microwave. A very complicated coherent-scattering model, which accounts for scattering from rough surfaces, vegetation cover, and their near-field interaction, was demonstrated in [94]. The inverse of this model was then used to demonstrate its ability for estimating the physical parameters of a soybean field, including soil moisture from a polarimetric set of AIRSAR images.

2.3 Snow

Snow cover constitutes the largest component of any of the cryosphere, and plays a significant role in the global climate and climate response to global changes. It can be viewed as a sensitive indicator of variations in the climate system. Remote-sensing instruments have been shown to be the most appropriate tools for monitoring snow parameters over large extended areas. In addition to global-climate studies, remote sensing of snow packs is of great importance in forecasting the snow-water runoff. The currently available snow products are based on single sensors; thus, the temporal and spatial limitations are given by the sensor characteristics. For users to be able to utilize remote-sensing data in operational monitoring and management of snow, the data must fulfill the temporal and spatial resolution and accuracy requirements. The availability of data from new satellite sensors, such as ENVISAT, AQUA, and ADEOSII, should provide the scientific community with important tools for developing and bringing into operational use remote-sensing systems, for both regional and global mapping.

From the electromagnetic point of view, a snow medium can be considered to be a dense, heterogeneous medium, composed of an amorphous interconnected matrix of ice particles, air voids, a thin film of water on ice surfaces, and pockets of water among ice particles. Existing theoretical-modeling techniques for the snow medium can be categorized into two major groups: 1) field-based techniques (Maxwell's equations), and 2) techniques based on the law of conservation of power (radiative transfer). Field-based techniques are formulated either based on single scattering or dielectric fluctuations, and then the distorted Born approximation (DBA) is used to find the solution [77]. Although obtaining the solution for the distorted Born approximation is straightforward, some particular material characteristics, such as the dielectric correlation function, are exceedingly difficult to obtain. Measurement techniques for characterizing this correlation function involve a very arduous process [77]. It has been shown [95] that the correlation function must be known with high accuracy, including its tail region, to obtain an accurate prediction of scattering. At higher frequencies (X band and up), formulations based on the single-scattering theory fail because the size of the particles forming a snow medium becomes a considerable fraction of the wavelength, and they occupy an appreciable volume fraction ($>10\%$).

In this case, an appropriate approach is the radiative-transfer technique. Dense Medium Radiative Transfer Theory (DMRT), under the quasi-crystalline approximation with a coherent potential, and Strong Fluctuation Theory (SFT) are the most rigorous approaches to modeling microwave emission and scattering from snow packs at high frequencies [77, 96-98]. These approaches take into account the coherence of the scattering from random scatterers, and satisfy the energy-conservation constraint. An exhaustive description of the two theories can be found in [76-78]. Recent measurements, performed in the Italian Alps using multi-frequency passive sensors, demonstrated the capability of the DMRT to represent experimental data [99].

An approach to computing the effective permittivity of wet snow by using strong fluctuation theory was shown in [100]. In this work, snow was treated as a two-phase mixture where the water was considered to be inclusions embedded in dry snow. The shape of the scatterers was taken into account by using an anisotropic azimuthally symmetric correlation function. Model results were found to be in good agreement with experimental data. Although the DMRT method is quite rigorous, accurate determination of fundamental quantities of this formulation, such as extinction matrix and phase matrices, is not straightforward. Recently, numerical approaches for the determination of these quantities have been developed [101, 102]. In addition to numerical methods, quantities such as the extinction matrix can be measured experimentally, as shown in [103]. Apart from the theoretical approaches addressed above, purely empirical approaches may be considered [104]; these, however, have the obvious limitation that the entire parameter space of the target cannot be sufficiently well known to allow estimation of more-specific target properties. To circumvent the difficulties associated with the above-mentioned techniques and to offer some means by which realistic modeling of dense media might be accomplished, a new hybrid experimental /theoretical modeling scheme was introduced in [105]

2.3.1 Passive Systems

The capability of microwave radiometers to monitor snow parameters and seasonal variations in snow cover has been the subject of several experimental activities carried out since the late 1970s, using ground-based, airborne, and satellite systems [e.g., 106-111]. Measurements carried out between 3 GHz and 90 GHz pointed out the sensitivity of microwave emission to snow type and to snow-water equivalent (SWE). At the lower frequencies of the microwave band, emission from a layer of dry snow is mostly influenced by the soil conditions below the snow pack and by snow layering. However, at the higher frequencies the role played by volume scattering increases, and emissivity appears sensitive to snow-water equivalent. If snow melts, the presence of liquid water in the surface layer causes a strong increase in emissivity, especially at high frequencies [106, 108]. The average spectra of the brightness temperature show that the brightness temperature, *Tb*, of dry and refrozen snow decreases with frequency, whereas the *Tb* of wet snow increases [99, 106].

In general, microwave radiometers tend to underestimate the snow area compared with estimates from visible-infrared maps [109]. In addition, the errors in estimates of snow volume tend to be large, with standard errors of 20 mm snow-water equivalent or more [110]. For proper water-resource management and climate modeling, greater accuracy in a local scale and on a daily basis is required. Unfortunately, the spatial resolution of the SMMR and SSM/I instruments tends to limit their effective use to global-scale studies. Furthermore, currently available SSM/I data are acquired twice daily only at high latitudes, with a more restrictive coverage at lower latitudes. The AMSR and AMSR-E will help to overcome some of these drawbacks.

In general, high-frequency microwave emission from dry snow increases as snow depth (SD) increases. However, *Tb* measured by the SSM/I within the former Soviet Union during the 1987-1988 winter period showed dramatic deviations from this pattern. Indeed, in the middle of winter, *Tb* approached a minimum and then began to increase, despite the fact that the snow depth remained constant or continued to grow [111]. Model results suggested that the increase in *Tb* was due to a decrease in the single-scattering albedo as the snow pack aged. This decrease in the albedo was related to changes in the snow's crystalline structure, due to metamorphism. The midwinter minimum of *Tb* caused ambiguity in the relationship between snow-water equivalent and snow depth on *Tb* at high frequencies, and substantial nonlinearity of this dependence at intermediate frequencies. This midwinter minimum of *Tb* prevents the use of a simple, regression-type algorithm to derive the snow depth and snow-water equivalent from *Tb* measurements.

Several approaches have been proposed for retrieving snow parameters by means of empirical algorithms, such as the Spectral Polarization Difference (SPD), linear regressions, or iterative inversion of forward models [110, 112-114]. The inversion technique based on the HUT snow microwave emission model, developed in [115] and tested with SSM/I data, showed snow-water equivalent retrieval accuracies higher than those obtained with empirical approaches.

Since microwave radiation is sensitive to both snow depth and density, estimating snow depth alone requires that assumptions be made about the snow density. For average seasonal and global snow-depth estimation, "static" algorithms, which assume temporally constant grain size and density, have worked reasonably well [116]. However, in the cases of rapid changes in internal snow pack properties, estimates have been subject to errors. Dynamic algorithms, based on DMRT combined with density and grain-radius evolution models, have demonstrated their superiority, in that they tend to underestimate the snow depth less than do the static algorithms [117, 118].

Other studies were addressed to the combined use of electromagnetic and hydrological models [119, 120]. A three-component retrieval algorithm, developed in [120], included a DMRT model, a physically-based snow hydrology model (SHM) that incorporated meteorological and topographical data, and a neural network (NN). The DMRT model related physical snow parameters to *Tb*. The snow hydrology model simulated the mass and heat balance, and provided initial guesses for the neural network; the neural network was used to speed up the inversion of parameters. Inversion results obtained by applying the algorithm to measurements at 19 GHz and 37 GHz V and H polarizations compared favorably with ground-truth observations.

2.3.2 Active Systems

A great deal of experimental and theoretical work has been carried out pertaining to the radar response of snow. Similar to the soil-moisture problem, very careful experimentation with snow using radar systems over a wide range of radar attributes and snow conditions have been carried out initially to examine the feasibility, sensitivity, and accuracy of radar snow-parameter retrievals [121-124]. In addition, substantial efforts have been devoted to characterizing and measuring the very complex dielectric-constant behavior of snow with varying snow wetness [125-127].

Snow-parameter retrieval is mainly confounded by the complexity and dynamics of its structure and dielectric properties. To elaborate on this, consider a typical target of snow-covered ground. Target parameters that influence the radar response and that must be potentially considered include: 1) rough-surface parameters associated with the top surface of the snow; 2) the snow volume itself, i.e., density and particle-size distribution, and vertical distributions of these properties within the snow pack; 3) snow wetness, when present, may well be a very complex function of time and depth; and, finally, 4) the parameters of the ground beneath, such as dielectric constant, roughness parameters, and local slope.

Controlled experiments have concluded that microwave frequencies offer the highest potential for the retrieval of gross snow properties, such as depth or water equivalence, parameters that are especially important for hydrological applications. More specifically, a combination of L- and Ku-band radars – with the lower-frequency system measuring the parameters of the underlying ground surface and the higher-frequency radar monitoring the snow volume – was found the be an optimal configuration [122].

To examine the potential of active systems in mapping the extent of wet snow, experiments have been carried out by using both airborne and satellite SAR systems. For example, significant seasonal changes of Radarsat and ERS SAR backscatter from snow-covered surfaces in the Austrian Alps have been observed. These were mainly caused by variations of the snow liquid-water content and of the surface roughness [128]. A comparison of snow maps from SAR and Landsat-5 Thematic Mapper images showed good agreement in areas of continuous snow cover, whereas near the snow line, the SAR data slightly underestimated the snow extent.

Algorithms have been implemented for deriving the snow-covered areas (SCA) using change detection [128-130]. These studied showed that contrary to wet snow, the effect of dry snow in Alpine regions on C-band backscattering is too small to detect snow cover, and that a higher frequency would be necessary for snow retrievals [129]. However, the snow-water equivalent of dry snow was successfully retrieved on relatively smooth surfaces from the difference between the signal of the snow-free surfaces and the signal of the soil below the snow cover, which depends on the depth of the frozen soil layer. The latter is, in turn, related to the mass of snow [130]. Simulations obtained on a global scale with a model developed on the basis of data obtained from the Topex Poseidon Altimeter showed that Ku band provided more accurate snow-depth determinations than did C band [131], as predicated earlier by the controlled experiments.

The analysis of multi-frequency polarimetric SIR-C/X-SAR data showed that the frequency and polarization behavior of the radar-backscattering coefficients of a snow pack are very important for characterizing the physical state of snow and ice, and for separating the accumulation and ablation areas on glaciers [132]. The same data pointed out that the relationship between snow-water equivalent and backscattering coefficients at C and X band can be either positive or negative [133, 134]. Therefore, development of a simple empirical relationship between radar and snow parameters is unrealistic. Instead, snow depth and particle size were estimated from a physics-based first-order backscattering model, through the analysis of the importance of each scattering term and its sensitivity to snow properties.

In addition to the conventional backscattering analysis, recent work demonstrated the potential of the interferometric SAR techniques (InSAR) for separating bare soil from wet snow, and wet snow from dry snow. A new approach to retrieve information on the changes in snow-water equivalent from the phase difference in InSAR data was introduced in [135]. In the case of dry snow, the backscattering was from the snow-ground interface. However, the refraction of a radar wave in dry snow results in an interferometric phase difference, which is related to changes in snow depth and density. InSAR was also found to be a useful tool for monitoring the motion of glaciers [136, 137]. When this approach was limited by phase noise, intensity tracking, based on patch-intensity cross-correlation optimization, and coherence tracking, based on patch-coherence optimization, were successfully employed [138]

The utility of SAR data in estimating snow-cover area under wet-snow conditions is important for river-flow prediction, especially in applications such as hydro-power production and flood prevention.

Global observations with active systems were carried out by using scatterometric and altimetric data from satellites. The potential of a space-borne Ku-band scatterometer for monitoring global snow cover was demonstrated by using data from the National Aeronautics and Space Administration (NASA) scatterometer (NSCAT), operated on the Advanced Earth Observing Satellite (ADEOS) from September, 1996, to June, 1997 [140]. Sensitivity of Ku-band backscatter to snow conditions was illustrated with the dramatic change over the US northern plains and the Canadian prairie region corresponding to the snow event leading to the 1997 "Flood of the Century."

2.4 Forest Stands

A large portion of the Earth's surface is covered with vegetation of many different species and canopy configurations. Vegetation cover on the Earth's surface is an important factor in the study of global change. The total vegetation biomass is the most influential input to models for terrestrial ecosystems and atmospheric chemistry. The ability to monitor canopy parameters – such as total vegetation biomass, total leaf area index, and soil moisture content – is of vital importance to the study of the carbon cycle and global warming. Microwave remote-sensing techniques offer a unique opportunity to probe vegetation canopies at various depths by operating at different frequencies.

2.4.1 Passive Systems

Theoretical investigations have shown that passive microwave remote sensing can contribute significantly to the global study of soil and vegetation parameters in forests [141, 142]. However, microwave radiometers on satellites are hampered by the coarse ground resolution. On the other hand, airborne sensors provide much better resolution, and can be useful for detailed analyses of some particular areas and surveillance of forests subject to fires or other sudden changes. Moreover, the next-generation sensors (SMOS, AMSR, AMSR-E) will be able to attain a much more enhanced resolution. At present, only some experimental data are available. These data have been collected mostly in northern Europe on boreal coniferous forests using satellite [143, 144] and airborne data [145]. Recently, L-band radiometer measurements of coniferous forests were performed by flying the ESTAR radiometer over loblolly pine stands in eastern Virginia. The images of the area showed a strong correlation between forest biomass and the measured brightness temperature, *Tb* [146].

Airborne radiometric measurements in a frequency range from L to Ka band were carried out over six broad-leaved forests and one coniferous forest in Italy [147]. Ground-truth data of the major tree parameters were available for the same tree stands. The analysis of the collected data indicated that the use of microwave emission at the highest frequencies made it possible to identify some forest types, whereas L-band emission was more closely related to tree biomass. Other relationships were found between emission and leaf-area index, basal area, woody volume, and crown transparency. The significant relationship between L-band emission and woody volume was further analyzed by means of a discrete-element radiative-transfer model. The analysis showed that the main contribution to the total emission was due to the elements in tree crowns and, in particular, to primary and medium branches, while double reflection from soil was negligible. Simulations performed at L band by using a model validated with experimental data at C band confirmed these results, and pointed out an appreciable sensitivity to soil moisture, even under developed forests [148].

2.4.2 Active Systems

The use of polarimetric, interferometric, and polarimetric-interferometric SARs to survey forested areas has become increasingly important in recent years [149-153]. Experimental studies conducted since the early 1990s with space-borne and airborne SAR systems led to the conclusion that the radar-backscatter results from scattering and/or attenuation of leaves, branches, and trunks, leading to an indirect relationship between the radar measurements and the biomass parameters. The greater temporal stability of forest compared with many other types of land cover presented a means of mapping forest areas using multi-temporal data [154, 155]. However, the comparison of results obtained over different forest sites is difficult, due to differences in stand characteristics, validation procedures, parameters used as evaluation criteria, selection of stands, etc. Stand size seems to explain most of the variability of the results, and although an attempt has been made to suggest procedures to convert results from one stand size to another, there still are open issues to be addressed [156].

It has been shown that the radar measurements are no longer sensitive to biomass variation after a certain amount of biomass value, which depends on the electromagnetic frequency. This limit was estimated to be about 30-50 tons/ha at C and L band (5 GHz and 1.2 GHz), and about 150-200 tons/ha at P band (0.4 GHz), for both evergreen and coniferous forests [151, 157-159]. In general, the use of P-band channels can provide better estimates of stem biomass, while L-band channels can estimate the crown biomass more accurately [29, 153]. However, the most appropriate approach for estimating forest biomass is the use of lower-frequency systems, such as the VHF (20-90 MHz) airborne imaging radar CARABAS. Using this radar, signal saturation was not observed up to 900 m^3 ha. However, the sensitivity to the volume was high in the range of 0-500 m^3 ha (e.g., 1 dB to 1.5 dB for 50 m^3 ha), whereas it was reduced beyond 500 m^3 ha [160]. The accuracy of the estimated stem volume retrieved using these data and a new textural method based on the variations of the standard deviation of the backscattering coefficient was comparable to that of the ground truth [161]. The other forest parameters could not be estimated with such good accuracy, but this was partly due to using the dominant values instead of averages. Also, it was found that in the case of storms, the backscattering for a given stem volume was considerably higher for wind-thrown forests than for unaffected forests. This indicates that VHF SAR imagery has potential for mapping wind-thrown forests [162].

A key component in the study of microwave remote sensing of vegetation is the understanding of the spectral behavior of the dielectric constant of vegetation. Through careful experimentation and examination of the dielectric properties of water, bound water, and dry vegetation, an approximate empirical formulation for the dielectric constant of vegetation as a function of moisture content and temperature was reported in [163]. The validity of this model was examined by independent measurement techniques, and its accuracy was found to be with 10% of the measured quantities [164]. Extensive measurements of complex permittivity for various parts of a conifer were reported in [165].

In the early forest-scattering models, the forest structure was simplified in terms of a homogeneous random medium, and the single-scattering theory was applied to account for scattering and propagation in the random medium [166-168]. For example, in [166] and [167], vector radiative transfer was used to calculate the bistatic scattering from a forest stand, represented by a two-layer random medium. In a medium where particle size – such as tree trunks and large branches – is comparable to the extent of the medium, a radiative transfer model may not produce satisfactory results. Furthermore, an important feature of a high-fidelity scattering model is to preserve the structure of vegetation, as different species of vegetation have their own unique structures, and this has been shown to have considerable effect at P and L band. An important effect of the vegetation structure is the coherence effect, caused by the relative position of the vegetation particles, which produce certain interference patterns. To preserve the coherence effects and the nonuniform attenuation and scattering profile, a Monte Carlo coherent-scattering model for forest canopies was also presented in [169]. In this model, realistic-looking tree structures were constructed using a stochastic fractal algorithm, and the distorted Born approximation was used for scattered-field calculations. Common in all forest scattering and emission models are scattering formulations for broad leaves, needles, twigs, branches, and tree trunks [170 -175].

Recent advancements in the field of radar interferometry have opened a new door to the radar remote sensing of vegetation. In addition to the backscattering coefficient, radar interferometers measure two additional quantities that contain target information [176]. These quantities are the correlation coefficient and the interferogram phase. The premise of this investigation with regard to retrieving vegetation parameters from INSAR data stems from the fact that the location of the scattering phase center of a target is a strong function of the target's structure. For example, the scattering phase centers of non-vegetated terrain are located at or slightly below the surface, whereas for vegetated terrain, these scattering phase centers lie at or above the surface, depending upon the wavelength of the SAR and the attributes of the vegetation. In recent years, some experimental and theoretical studies have been carried out to demonstrate the potential of InSAR in retrieving forest parameters. For example in [177-180], experimental data using ERS-1 SAR repeat-pass and DO-SAR single-pass were employed to show the applications of SAR interferometry for classification of forest types and retrieval of tree heights. The accuracy achieved in separating forest/non-forest areas by using a single pair of repeat-pass SAR interferometry was on the order of 80%-85%. Similar or slightly better classification accuracies were reported with multi-temporal backscattering coefficients using C-band ERS data [154].

Simplified theoretical models have also been developed to establish relationships between the interferogram phase and coefficient of correlation with the physical parameters of vegetation and the underlying soil surface [181, 182]. A far more accurate model for estimation of scatter phase-center location, based on the Monte Carlo simulation of fractal trees, was developed later [183]. This model accounted for the exact structure, shape, size, number density, and orientation distributions of vegetation in desired forest stands, and its accuracy was tested against JPL TOPSAR [184] data.

Whereas radar polarimetry provides an enhanced capability in recovering target-structure anisotropy (preferred orientation), and SAR interferometry reveals the target's penetrability and vertical extent, a polarization-agile interferometric SAR has this combined capability, and can provide the target-structure parameters far more conveniently than can the individual sensors. Polarimetric target decomposition techniques have also been suggested and successfully demonstrated using polarimetric/interferometric SARs [185, 186]. More sophisticated techniques, using interferometric SARs – such as multi-baseline INSAR – have also been tried, and showed significant potential for retrieving vegetation parameters [187, 188].

The retrieval of target parameters in an imaged scene is possible through the use of multi-frequency observations, polarization diversity of imaging polarimetry, estimation of the scattering phase-center height, and textural information.

The study of the inversion problems has been of great importance from the onset of remote-sensing science [189, 190]. To make the inverse-scattering problem tractable, overly simplistic forward models were initially used [191]. With the availability of significant SAR and accurate ground-truth data, statistical and regression inversion methods have been investigated [192]. Like most empirical models, the success of these techniques is somewhat limited to the range of system and measured target-parameter space. Other systematic inversion algorithms, such as neural-network approaches [193] and genetic algorithms [194], using more sophisticated forward models, have been developed.

2.5 Short Vegetation Crops

As mentioned in the previous section, vegetation biomass plays a very important role in the Earth's climate dynamics and the atmosphere's carbon cycle. However, another vegetation class that must not be overlooked is the category of herbaceous vegetation, both natural and cultural. At approximately 30 million square kilometers, this vegetation type covers 20% of the Earth's dry surface, accounting for more than 30 billion metric tons of total biomass. An understanding on a global scale of the biophysical parameters that describe this vegetation is thus highly desirable.

Although the sensitivity of microwave emission to crop type and biomass has been demonstrated in several investigations, the ground resolution of passive systems is inadequate for operational systems, and recent research has mostly been addressed to the study of SAR data.

The large amount of SAR data collected at different times made it possible to evaluate the potential of multi-temporal analysis in timing critical phases of the crop-growth cycle, and in separating broad-leaf crops from cereals (small leaf) [29, 195, 196]. The radar response of these two types of crops to biomass showed that for crops characterized by small-plant constituents, such as wheat (narrow-leaf crops), $\sigma°$ decreased as the biomass increased, whereas the trend was quite the opposite in plants with bigger leaves and stems, such as sunflowers (broad-leaf crops) [197]. Model simulations confirmed the trends of the experimental data, and made it possible to evaluate the contribution of single-plant constituents to total backscattering. In "broad-leaf" crops, $\sigma°$ from stalks dominated at L band, while at C band, leaves made a significant contribution to scattering and attenuated the contribution of stems. In "narrow-leaf" crops, the contributions of leaves and stalks were comparable and close to total backscattering. The analysis of the contributions of each scattering mechanism showed that in general, double scattering was the most important contribution for stalks, direct scattering prevailed for leaves, and soil contribution was appreciable even for well-developed crops [198].

On the other hand multi-frequency observations pointed out that for remote sensing of crops, low microwave frequencies ($<$ 5 GHz) are recommended, and therefore one must carefully account for the coherence effects. The model developed in [199] may be among the first to address the coherence effects caused by the vegetation structure. A very careful coherent model for grass-type vegetation, such as a wheat field, and measurements over the entire growing season are reported in [200-202]. Simulations performed with a coherent model confirmed the experimental relations found between backscattering and the biomass of broad- and narrow-leaf crops, and demonstrated the contribution of the InSAR observation in crop discrimination [203].

A model based on the Method of Moments and Monte Carlo simulation for similar crops showed the importance of near-field scattering and coherence to the target radar response [204]. In [205], an analytical polarimetric coherent scattering model for short branching vegetation – such as a soybean crop – was developed that accounted for the second-order near-field interaction among particles, as well as the underlying rough surface and particles. In this paper, retrieval of soil moisture and vegetation parameters was demonstrated, using data obtained from JPL AIRSAR.

A number of studies have been carried out aimed at using remote-sensing data to improve the accuracy of crop-functioning models in predicting the yield and the evolution of canopy variables through the crop cycle. Two main approaches have been used and reported in [206]. In the first approach, some crop variables were retrieved by inverting the radiative-transfer models, and used to force or to recalibrate some well-identified parameters of the crop-functioning model. In the second approach, a crop model was coupled with a radiative transfer model to simulate the whole process from canopy functioning to remote-sensing data, by fitting simulated results to observed results. The assimilation of optical and radar data in a coupled crop-plus-radiative-transfer model was tested by [207], using data acquired over wheat fields. The study showed that assimilating optical and radar data into a crop model is feasible. However, in this case, the introduction of radar data did not improve the accuracy of the results.

3. Final Remarks

In this article, we tried to provide the reader with a comprehensive overview of the recent techniques and approaches in microwave remote sensing of land. Both analytical and experimental remote-sensing methods for active and passive systems were surveyed. It is important to mention here that the wealth of knowledge in this area is overwhelming, and it quickly became obvious to us that we could not possibly include all the significant contributions reported in the literature in the limited space of this article. This fact also indicates the great progress made in the science and technology of microwave remote sensing over the past decade, such as that related to the operational applications of SAR interferometry. Despite this significant progress, there are still considerable challenging problems for which the existing remote-sensing tools and methodologies do not provide solutions with desirable accuracies, as requested by the users. It is on these problems – such as land classification and the measurement of land hydrological parameters on a routine basis – that further research need to be focused. It is believed that further investments in advanced space-based remote-sensing instrumentations, with new functionalities and modalities – such as low-frequency active and passive systems aboard satellites with short revisit time – will provide the scientific community with sufficiently large, precise, and frequent databases to allow for accurate and consistent retrieval of target parameters.

4. References

1. http://southport.jpl.nasa.gov/desc/SIRCdesc.html.

2. http://www.jpl.nasa.gov/srtm.

3. F. M. Anderson and A. J. Lewis, *Manual of Remote Sensing, Principles and Applications of Imaging Radar*, New York, John Wiley & Sons, third Edition, 1998.

4. S. R. Cloude and E. Pottier, **"A Review of Target Decomposition Theorems in Radar Polarimetry**," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-34**, 2, March 1996, pp. 498-518.

5. P. A. Rosen, S. Hensley, I. R. Joughin, F. K. Li, S. N. Madsen, E. Rodriguez, and R. M. Goldstein, "**Synthetic Aperture Radar Interferometry**," *Proceedings of the IEEE*, **88**, 3, March 2000, pp. 333-382.

6. http://envisat.esa.int/

7. A. Bentamy, Y. Quilfen, and P. Queuffeulou, "Calibration of the ERS-1 Scatterometer C-Band Model," Technical. Rep., IFREMER DRO/OS, Institute Francaise de Recherche pour l'Exploitation de la Mer, France, January 1994.

8. A. Ferretti, C. Prati, F. Rocca, "Permanent Scatterers in SAR Interferometry," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 1, January 2001, pp. 8-20.

9. C. Colesanti, A. Ferretti, C. Prati, F. Rocca, "Full Exploitation of the ERS Archive: Multi Data Set Permanent Scatterers Analysis," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 7, July 2003, pp. 1685-1701.

10. http://www.space.gc.ca/csa_sectors/earth_environment/radarsat/default.asp

11. T. Kawanishi, T. Seyai, Y. Ito, K. Imaoka, T. Takeshima, Y. Ishido, A. Shibata, M. Miura, H. Inahata, and R. W. Spencer, "The Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), NASDA's Contribution to the EOS for Global Energy and Water Cycle Studies," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 2, February 2003, pp. 184-194.

12. A. Shibata, "AMSR/AMSR-E Algorithm Development and Data Distribution," *Proceedings of the IEEE 2000 International Geoscience and Remote Sensing Symposium (IGARSS 2000)*, Honolulu, Hawaii, 24-28 July 2000.

13. http://sharaku.eorc.nasda.go.jp/AMSR/index_e.htm.

14. http://alos.nasda.go.jp/2/palsar-e.html.

15. http://www.ccrs.nrcan.gc.ca/ccrs/data/satsens/radarsat/rsat2/radnews_e.html.

16. C. Prigent, J.-P. Wigneron, W. B. Rossow, and J. R. Pardo-Carrion, "Frequency and Angular Variations of Land Surface Microwave Emissivities: Can We Estimate SSM/T and AMSU Emissivities from SSM/I Emissivities?," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 5, September 2000, pp. 2373-2386.

17. T. J. Jackson and A. Y. Hsu, "Soil Moisture and TRMM Microwave Imager Relationships in the Southern Great Plains 1999 (SGP99) Experiment," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1632-1642.

18. Y. Jhung and P. H. Swain, "Bayesian Contextual Classification Based on Modified M-Estimates and Markov Random Fields," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-34**, 1, January 1996, pp. 68-75.

19. L. E. Pierce, F. T. Ulaby, K. Sarabandi, and M. C. Dobson," Knowledge-Based Classification of Polarimetric SAR Images," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-32**, 5, September 1994, pp. 1081-1086.

20. J. J. van Zyl, "Unsupervised Classification of Scattering Behavior Using Radar Polarimetry Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-27**, 1, January 1989, pp. 36-45.

21. J. A. Benediction, P. H. Swain, and O. K. Erase, "Neural Network Approaches Versus Statistical Methods in Classification of Multisource Remote Sensing Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-28**, 4, July 1990, pp. 540-551.

22. L. E. Pierce, K. Sarabandi, and F. T. Ulaby, "Application of an Artificial Neural Network in a Canopy Scattering Model Inversion," *International Journal of Remote Sensing*, **15**, 16, 1994, pp. 3263-3270.

23. P. M. Atkinson and A. R. L. Tatnall, "Neural Networks in Remote Sensing," *International Journal of Remote Sensing*, **18**, 4, 1997, pp. 699-709.

24. R. S. Safavian and D. Landgrebe, "A Survey of Decision Tree Classifier Methodology," *IEEE Transactions of Systems, Man, and Cybernetics*, **21**, 1991, pp. 660-675.

25. J. Schou, H. Skriver, A. A Nielsen, and K. Conradsen, "CFAR Edge Detector for Polarimetric SAR Images," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 1, January 2003, pp. 20-32.

26. K. Conradsen, A. A Nielsen, J. Schou, and H. Skriver, "A Test Statistics in the Complex Wishart Distribution and its Applications to Change Detection in Polarimetric SAR Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 1, January 2003, pp. 4-19.

27.http://airsar.jpl.nasa.gov/data/.

28.http://www.ccrs.nrcan.gc.ca/ccrs/data/satsens/airborne/sarbro/sbmain_e.html

29.P. Ferrazzoli, S. Paloscia, P. Pampaloni, G. Schiavon, S. Sigismondi, and D. Solimini, "The Potential of Multifrequency Polarimetric SAR in Assessing Agricultural and Arboreous Biomass," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 1, January 1997, pp. 5-17.

30.J. S. Lee, M. R. Grunes and Eric Pottier, "Quantitative Comparison of Classification Capability: Fully Polarimetric Versus Dual and Single-Polarization SAR," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 11, November 2001, pp. 2343-2351.

31.F. Dell'Acqua and P. Gamba, "Texture-Based Characterization of Urban Environments on Satellite SAR Images," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 1, January 2003, pp. 153-159.

32.G. Franceschetti, A. Iodice, D. Riccio, "**A Canonical Problem in Electromagnetic Backscattering from Buildings,**" *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 8, August 2002, pp 1787-1801.

33.F. Tupin, B. Houshmand, and M. Dactu, "Road Detection in Dense Urban Areas Using SAR Imagery and the Usefulness of Multiple Views," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 11, November 2002, pp. 2405-2414.

34.P. L. Frison and E. Mougin, "Monitoring Seasonal Vegetation Dynamics in the Sahel with ERS Wind Scatterometer Data, ESA SP-414," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 1997, pp. 163-168.

35.C. Schmullius, "Monitoring Siberian Forests and Agriculture with the ERS-1 Windscatterometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 5, September 1997, pp. 1363-1366.

36.C. M. U. Neale, M. J. McFarland, and K. Chang, "Land-Surface-Type Classification Using Microwave Brightness Temperatures from the Special Sensor Microwave/Imager," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-28**, 5, September 1990, pp. 829-838.

37.J. V. Fiore and N. C. Grody, "Classification of Snow Cover and Precipitation Using SSM/I Measurements: Case Studies," *International Journal of Remote Sensing*, **13**, 1992, pp. 3349-3361.

38.J. Judge, J. F. Galantowicz, A. W. England, and P. Dahl, "Freeze/Thaw Classification for Prairie Soils Using SSM/I Radiobrightnesses," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 4, July 1997, pp. 827-832.

39.N. C. Grody and Alan N. Basist, "Interpretation of SSM/I Measurements over Greenland," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 2, March 1997, pp. 360-366.

40.P.-L. Frison, E. Mougin, L. Jarlan, M. A. Karam, and P. Hiernaux, "Comparison of ERS Wind-Scatterometer and SSM/I Data for Sahelian Vegetation Monitoring," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 4, July 2000, pp. 1794-1803.

41.G. Macelloni, S. Paloscia, P. Pampaloni, and E. Santi, "Global Scale Monitoring of Soil and Vegetation Using Active and Passive Sensors," *International Journal Remote Sensing*, 2003, pp. 2409-2425.

42.Y. Oh, K. Sarabandi, and F. T. Ulaby, "An Empirical Model and an Inversion Technique for Radar Scattering from Bare Soil Surfaces," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 2, March 1992, pp. 370-381.

43.M. C. Dobson, F. T. Ulaby, M. T. Hallikainen, and M. A. El-Rayes, "Microwave Dielectric Behavior of Wet Soil – Part II – Dielectric Mixing Models," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-23**, 1, January 1985, pp. 35-46.

44.N. R. Peplinski, F. T. Ulaby, and M. C. Dobson, 1995, "Dielectric Properties of Soil in the 0.3 - 1.3 GHz Range," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 3, May 1995, pp. 803-806.

45.K. Sarabandi and E. S. Li, "A Microstrip Ring Resonator for Non-Invasive Dielectric Measurements," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 5, September 1997, pp. 1223-1231.

46.G. Du, F. T. Ulaby, and M. C. Dobson, "Sensitivity to Soil Moisture by Active and Passive Microwave Sensors," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 105-114.

47.Y. H. Kerr, Ph. Waldteufel, J.-P. Wigneron, J.-M. Martinuzzi, J. Font, and M. Berger, "Soil Moisture Retrieval from Space: The Soil Moisture and Ocean Salinity (SMOS) Mission," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1729-1735.

48.D. Le Vine, C. Koblinsky, and F. Pellerano, "The Measurement of Salinity from Space: Sensor Concept," IEEE International Geoscience and Remote Sensing Symposium, Sidney, Australia, July 9-13, 2001.

49.T. J. Jackson, D. M. Le Vine, A. Y. Hsu, A. Oldak, P. J. Starks, C. T. Swift, J. D. Isham, and M. Haken, "Soil Moisture Mapping at Regional Scales Using Microwave Radiometry: The Southern Great Plains Hydrology Experiment," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 5, September 1999, pp. 2136-2452.

50.R. Bindlish, W. P. Kustas, A. N. French, G. R. Diak, and J. R. Mecikalski, "Influence of Near-Surface Soil Moisture on Regional Scale Heat Fluxes: Model Results Using Microwave Remote Sensing Data from SGP97," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1719-1728.

51.E. G. Njoku, W. J. Wilson, S. H. Yueh, St. J. Dinardo, F. K. Li, T. J. Jackson, V. Lakshmi, and J. Bolten, "Observations of Soil Moisture Using a Passive and Active Low-Frequency Microwave Airborne Sensor During SGP99," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 12, December 2002, pp. 2659-2673.

52.T. J. Jackson, A.. J. Gasiewski, A. Oldak, M. Klein, E. G. Njoku, A. Yevgrafov, S. Christiani, and R. Bindlish, "Soil Moisture Retrieval Using the C-Band Polarimetric Scanning Radiometer During the Southern Great Plains 1999 Experiment," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 10, October 2002, pp. 2151-2161.

53.W. T. Crow, M. Drusch, and E. F. Wood, "An Observation System Simulation Experiment for the Impact of Land Surface Heterogeneity on AMSR-E Soil Moisture Retrieval," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1622-1631.

54. A. Van de Griend, "The Effective Thermodynamic Temperature of the Emitting Surface at 6.6 GHz and Consequences for Soil Moisture Monitoring from Space," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1673-1679.

55. E. G. Njoku, T. J. Jackson, V. Lakshmi, T. K. Chan, and S.V. Nghiem, "Soil Moisture Retrieval from AMSR-E," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 2, February 2003, pp. 215-229.

56. E. G. Njoku and Li Li, "Retrieval of Land Surface Parameters Using Passive Microwave Measurements at 6-18 GHz," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 1, January 1999, pp. 79-93.

57. T. J. Jackson, D. M. Le Vine, A. J. Griffis, D. C. Goodrich, T. J. Schmugge, C. T. Swift, and P. E. O'Neill, "Soil Moisture and Rainfall Estimation Over a Semiarid Environment with the ESTAR Microwave Radiometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-31**, 4, July 1993, pp. 836-841.

58. K. Vinnikov, A. Robock, S. Qiu, J. Entin, M. Owe, B. Choudhury, S. Hollinger, and E. Njoku, "Satellite Remote Sensing of Soil Moisture in Illinois, USA," *Journal Geophysical Research*, **GRS-104**, 1999, pp. 4145-4168.

59. S. Paloscia, G. Macelloni, E. Santi, and T. Koike, "A Multifrequency Algorithm for the Retrieval of Soil Moisture on a Large Scale Using Microwave Data from SMMR and SSM/I Satellites," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1655-1661.

60. M. Owe, R. de Jeu, and J. Walker, "A Methodology for Surface Soil Moisture and Vegetation Optical Depth Retrieval Using the Microwave Polarization Difference Index," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1643-1654.

61. T. J. Jackson and A. Y. Hsu, "Soil Moisture and TRMM Microwave Imager Relationships in the Southern Great Plains 1999 (SGP99) Experiment," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1632-1642.

62. D. T. Davis, Z. Chen, J.-N. Hwang, L. Tsang, and E. G. Njoku, "Solving Inverse Problems by Bayesian Iterative Inversion of a Forward Model with Applications to Parameter Mapping Using SMMR Remote Sensing Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 5, September 1995, pp. 1182-1193.

63. Y. Liou, S. Liu, and W. Wang, "Retrieving Soil Moisture from Simulated Brightness Temperatures by a Neural Network," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1662-1672.

64. S. Liu, Y. Liou, W. Wang, J.-P. Wigneron, and J.-B. Lee, "Retrieval of Crop Biomass and Soil Moisture From Measured 1.4 and 10.65 GHz Brightness Temperatures," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 6, June 2002, pp. 1260-1268.

65. J. F. Galantowicz, D. Entekhabi, and E. G. Njoku, " Estimation of Soil-Type Heterogeneity Effects in the Retrieval of Soil Moisture from Radiobrightness," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 312-315.

66. Y. A. Liou, J. Kim, and A. W. England, "Radiobrightness of Prairie Soil and Grassland During Dry-Down Simulations," *Radio Science*, **33**, 1998, pp. 259-265.

67. M. Drusch, E. F. Wood, and C. Simmer, "Up-scaling Effects in Passive Microwave Remote Sensing: ESTAR 1.4 GHz Measurements during SGP '97," *Geophysical Research Letters*, **26**, 2001, pp. 879-882.

68. W. T. Crow, M. Drusch, and E. F. Wood, "An Observation System Simulation Experiment for the Impact of Land Surface Heterogeneity on AMSR-E Soil Moisture," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 2001, pp. 1622-1631.

69. A. Guha and V. Lakshmi, "Sensitivity, Spatial Heterogeneity, and Scaling of C-Band Microwave Brightness Temperatures for Land Hydrology Studies," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 12, December 2002, pp. 2626-2635.

70. E. J. Burke and L. P. Simmonds, "Effects of Sub-Pixel Heterogeneity on the Retrieval of Soil Moisture from Passive Microwave Radiometry," *International Journal of Remote Sensing*, **24**, 10, May 2003, pp. 2085-2104.

71. E. J. Burke, R. J. Gurney, L. P. Simmonds, and T. J. Jackson, "Calibrating a Soil Water and Energy budget Model with Remotely Sensed Data to Obtain Quantitative Information about the Soil," *Water Resources Research*, **33**, 1997, pp. 1689-1697.

72. J. F. Galantowicz, D. Entekhabi, and E. G. Njoku, "Tests of Sequential Data Assimilation for Retrieving Profile Soil Moisture and Temperature from Observed L-Band Radiobrightness," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 4, July 1999, pp. 1860-1870.

73. P. R. Houser, W. J. Shuttleworth, J. S. Famiglietti, H. V. Gupta, K. H. Syed, and D. C. Goodrich, "Integration of Soil Moisture Remote Sensing and Hydrological Modeling Using Data Assimilation," *Water Resources Res.*, **34**, 1998, pp. 3405-3420

74. E. J. Burke, W. J. Shuttleworth, K. Lee, and L. A. Bastidas, "Using Area-Average Remotely Sensed Surface Soil Moisture in Multipatch Land Data Assimilation Systems," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 10, October 2001, pp. 2091-2100.

75. R. H. Reichle, D. B. McLaughlin, and D. Entekhabi, "Variational Data Assimilation of Microwave Radiobrightness Observations for Land Surface Hydrology Applications," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1708-1718.

76. L. Tsang, J. A. Kong, and K.-H. Ding, *Scattering of Electromagnetic Waves*, *Vol. I: Theories and Applications*, New York, John Wiley & Sons, 2000.

77. L. Tsang, J. A. Kong, K.-H. Ding, and C. O. Ao, *Scattering of Electromagnetic Waves*, *Vol. II*: *Numerical Simulations*, New York, John Wiley & Sons, 2001.

78. L. Tsang and J. A. Kong, *Scattering of Electromagnetic Waves*, *Vol. III: Advanced Topics*, New York, John Wiley & Sons, 2001.

79. G. Macelloni, G. Nesti, P. Pampaloni, S. Sigismondi, D. Tarchi, and S. Lolli, "Experimental Validation of Surface Scattering and Emission Models," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 459-469.

80. Q. Li, L. Tsang, J. Shi, and C. H. Chan, "Application of Physics-Based Two-Grid Method and Sparse Matrix Canonical Grid Method for Numerical Simulations of Emissivities of

Soils With Rough Surfaces at Microwave Frequencies," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 4, July 2000, pp. 1635-1643.

81. K. Sarabandi, Y. Oh, and F. T. Ulaby, "Measurement and Calibration of Differential Mueller Matrix of Distributed Targets," *IEEE Transactions on Antennas and Propagation*, **AP-40**, 12, December 1992, pp. 1524-1532.

82. Y. Oh, K. Sarabandi, and F. T. Ulaby, "An Empirical Model and an Inversion Technique for Radar Scattering from Bare Soil Surfaces," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 2, March 1992, pp. 370-381.

83. P. C. Dubois, J. van Zyl, and T. Engman, "Measuring Soil Moisture with Imaging Radars," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 4, July 1995, pp. 915-926.

84. Y. Kim and J.J. van Zyl, "On the Relationship Between Polarimetric Parameters and Soil Moisture," *Proceedings of the IEEE 2002 International Geoscience and Remote Sensing Symposium (IGARSS 2002)*, Toronto, June 2002.

85. A. J. Wickel and T. J. Jackson, "Multitemporal Monitoring of Soil Moisture with RADARSAT SAR during the 1997 Southern Great Plains Hydrology Experiment," *International Journal of Remote Sensing*, **22**, 8, 2001, pp. 1571-1583.

86. http://hydrolab.arsusda.gov/sgp97/gsm.html

87. G. Macelloni, S. Paloscia, P. Pampaloni, S. Sigismondi, P. De Matthaeis, P. Ferrazzoli, G. Schiavon and D. Solimini, "The SIR-C/X-SAR Experiment on Montespertoli Supersite: The Sensitivity to Hydrological Parameters," *International Journal of Remote Sensing*, **13**, 1999, pp. 2597-2612.

88. R. Bindlish and A. P. Barros, "Multifrequency Soil Moisture Inversion from SAR Measurements with the Use of IEM," *Remote Sensing of Environment*, **71**, 1, January 2000, pp. 67-88.

89. G. Satalino, F. Mattia, M. W. J. Davidson, T. Le Toan, G. Pasquariello, and M. Borgeaud, "On Current Limits of Soil Moisture Retrieval from ERS-SAR Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 11, November 2002, pp. 2438-2447.

90. L. Jarlan, P. Mazzega, and E. Mougin, "Retrieval of Land Surface Parameters in the Sahel From ERS Wind Scatterometer Data: A "Brute Force" Method," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 9, September 2002, pp. 2056-2062.

91. H. Bach and W. Mauser, "Methods and Examples for Remote Sensing Data Assimilation in Land Surface Process Modeling," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 7, July 2003, pp. 1629-1637.

92. I. H. Woodhouse and D. H. Hoekman, "Determining Land-Surface Parameters from the ERS Wind Scatterometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 126-140.

93. W. Wagner and K. Scipal, "Large-Scale Soil Moisture Mapping in Western Africa Using the ERS Scatterometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 4, July 2000, pp. 1777-1782.

94. T. C. Chiu and K. Sarabandi, "Electromagnetic Scattering from Short Branching Vegetation," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 911-925.

95. P. Siqueira, K. Sarabandi, and F. T. Ulaby, "Numerical Simulation of Scatterer Positions in a Very Dense Medium with an Application to the Two-dimensional Born Approximation," *Radio Science*, **30**, 5, 1995, pp. 1325-1339.

96. R. West, L. Tsang, and D. P. Winebrenner "Dense Medium Radiative Transfer Theory for Two Scattering Layers with a Rayleigh Distribution of Particle Sizes," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-31**, 2, March 1993, pp. 426-437.

97. L. Tsang, L. and J. A. Kong, "Scattering of Electromagnetic Waves from a Dense Medium Consisting of Correlated Mie Scatterers with Size Distributions and Applications to Dry Snow," *Journal of Electromagnetic Waves and Applications*, **6**, 3, 1992, pp. 265-296.

98. A. N. Arslan, H. Wang, J. Pulliainen, and M. Hallikainen, "Effective Permittivity of Wet Sow Using Strong Fluctuation Theory," *Progress In Electromagnetic Research, PIERS 31*, 2001, pp. 273-290.

99. G. Macelloni, S. Paloscia, P. Pampaloni, and M. Tedesco, "Microwave Emission from Dry Snow: A Comparison of Experimental and Model Result," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 12, December 2001, pp. 2649-2656.

100. K. Sarabandi and P. Siqueira, "Numerical Scattering Analysis for Two Dimensional Dense Random Media: Characterization of Effective Permittivity," *IEEE Transactions on Antennas and Propagation*, **AP-45**, 5, May 1997.

101. P. Siqueira and K. Sarabandi, "T-Matrix Determination of Effective Permittivity for Three-dimensional Dense Random Media," *IEEE Transactions on Antennas and Propagation*, **AP-48**, 2, February 2000, pp. 317-327.

102. A. Nashashibi A. and K. Sarabandi, "Experimental Characterization of the Effective Propagation Constant of Dense Random Media," *IEEE Transactions on Antennas and Propagation*, **AP-47**, 9, September 1999, pp. 1454-1462.

103. F. T. Ulaby, P. R. Siqueira, A. Nashashibi, and K. Sarabandi, "Semi-Empirical Model for Radar Backscatter from Snow at 35 and 95 GHz," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-34**, 5, September 1996, pp. 1059-1065.

104. F. T. Ulaby, R. K. Moore and A. K. Fung, *Microwave Remote Sensing: Active and Passive*, *Vol. III: Surface Scattering and Emission Theory*, Norwood, MA, Artech House, 1986.

105. J. R. Kendra and K. Sarabandi, "A Hybrid Experimental/Theoretical Scattering Model for Dense Random Media," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 1, January 1999, pp. 21-35.

106. E. Schanda, C. Mätzler and K. Künzi, "Microwave Remote Sensing of Snow Cover," *International Journal of Remote Sensing*, **4**, 1983, pp. 149-158.

107. H. Rott, K. Strum, and H. Miller. "Active and Passive Microwave Signatures of Antarctic Firn by Means of Field Measurements and Satellite Data." *Annals of Glaciology*, **17**, 1993, pp. 337-342.

108. P. Pampaloni, G. Macelloni, S. Paloscia, M. Tedesco, R. Ranzi, M. Tomirotti, A. Cagnati, A. Crepaz, "The Microwave

Alpine Snow Melting Experiment (MASMEx 2002): A Contribution to the ENVISNOW Project," *Proceedings of the IEEE 2003 International Geoscience and Remote Sensing Symposium IGARSS 2003*, Toulouse, France, 2003.

109. L. Armstrong and M. J. Brodzik, "Recent Northern Hemisphere Snow Extent: a Comparison of Data Derived from Visible and Microwave Satellite Sensors," *Geophysical Research Letters*, **28**, 2001, pp. 3673-3676.

110. J. Pulliainen and M. Hallikainen, "Retrieval of Regional Snow Water Equivalent from Space/borne Passive Microwave observations," *Remote Sensing of Environment*, **75**, 2001, pp. 76-85.

111. S. Rosenfeld and N. C. Grody, "Metamorphic Signature of Snow Revealed in SSM/I Measurements," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 53-63.

112. D. T. Davis, Z. Chen, L. Tsang, J. N. Hwang, and A. T. C. Chang, "Retrieval of Snow Parameters by Iterative Inversion of a Neural Network," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-31**, 4, July 1993, pp. 842-851.

113. M. Hallikainen, P. Jolma, "Comparison of Algorithms for Retrieval of Snow Water Equivalent from Nimbus-7 SMMR Data in Finland, " *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 1, January 1992, pp. 124-131.

114. P. R. Singh and T. Y. Gan, "Retrieval of Snow Water Equivalent Using Passive Microwave Brightness Temperature Data," *Remote Sensing of Environment*, **74**, 2, November 2000, pp. 275-286.

115. J. T. Pulliainen, J. Grandell, and M. Hallikainen, "HUT Snow Emission Model and its Applicability to Snow Water Equivalent Retrieval," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 3, May 1999, pp. 1378-1390.

116. J. L. Foster, A. T. C. Chang, and D. K. Hall, "Comparison of Snow Mass Estimates from a Prototype Passive Microwave Snow Algorithm, a Revised Algorithm and Snow Depth Climatology," *Remote Sensing of Environment*, **62**, 1997, pp. 132-142.

117. R. E. Kelly, A. T. Chang, L. Tsang and J. L. Foster, "A Prototype AMSR-E Global Snow Area and Snow Depth Algorithm," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 2, February 2003, pp. 230-242.

118. J. Guo, L. Tsang, E. G. Josberger, A. W. Wood, J. N. Hwang, and D. P. Lettenmaier, "Mapping the Spatial Distribution and Time Evolution of Snow Water Equivalent With Passive Microwave Measurements," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-41**, 3, March 2003, pp. 612-621.

119. L. L. Wilson, L. Tsang, J.-N. Hwang, and C.-T. Chen, "Mapping Snow Water Equivalent by Combining a Spatially Distributed Snow Hydrology Model with Passive Microwave Remote-Sensing Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 2, March 1999, pp. 690-704.

120. C. T. Chen, B. Nijssen, J. Guo, L. Tsang, A. W. Wood, J.-N. Hwang, and D. P. Lettenmaier, "Passive Microwave Remote Sensing of Snow Constrained by Hydrological Simulations," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 8, August 2001, pp. 1744-1756.

121. W. H. Stiles and F. T. Ulaby, "The Active and Passive Microwave Response to Snow Parameters 1. & 2. Wetness," *Journal Geophysical Research*, **85**, C2, 1980.

122. C. Maetzler, E. Schanda, and W. Good, "Towards the Definition of Optimum Sensor Specifications for Microwave Remote Sensing of Snow," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-20**, 1, January 1982, pp. 57-66.

123. A. T. C. Chang, J. L. Foster, M. Owe, and D. K. Hall, "Passive and Active Microwave Studies of Wet Snowpack Properties," *Nordic Hydrology*, **16**, 1985, pp. 57-66.

124. J. R. Kendra, K. Sarabandi, and F. T. Ulaby, "Radar Measurements of Snow: Experiment and Analysis," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-36**, 3, May 1998, pp. 864-879.

125. M. Hallikainen, F. T. Ulaby, and M. Abdelrazik, "Dielectric Properties of Snow in the 3 to 37 GHz Range," *IEEE Transactions on Antennas and Propagation*, **AP-34**, 1986, pp. 1329-1339.

126. M. E. Tiuri, A. H. Sihvola, E. G. Nyfors, and M. T. Hallikainen, "The Complex Dielectric Constant of Snow at Microwave Frequencies," *IEEE Journal of Oceanic Engineering*, **9**, 1984, pp. 377-382.

127. J. R. Kendra, F. T. Ulaby, and K. Sarabandi, "Snow Probe for *in situ* Determination of Wetness and Density," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-32**, 6, November 1994, pp. 1152-1159.

128. T. H. Nagler, H. Rott, and G. Glendinning, "Snowmelt Runoff Modelling by Means of Radarsat and ERS SAR," *Canadian Journal of Remote Sensing*, **26**, 6, 2000, pp. 512-520.

129. T. Nagler and H. Rott, "Retrieval of Wet Snow by Means of Multitemporal SAR Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 754-765.

130. M. Bernier, J-P. Fortin, Y. Gauthier, R. Gauthier, R. Roy, and P. Vincent, "Determination of Snow Water Equivalent Using Radarsat SAR data in Eastern Canada," *Hydrological Processes*, **13**, 18, 1999, pp. 3041-3051.

131. F. Papa, B. Legresy, N. M. Mognard, E. G. Josberger, and F. Remy, "Estimating Terrestrial Snow Depth With the Topex-Poseidon Altimeter and Radiometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 10, October 2002, pp. 2162-2169.

132. D. Floricioiu and H. Rott, "Seasonal and Short-Term Variability of Multifrequency, Polarimetric Radar Backscatter of Alpine Terrain from SIR-C/X-SAR and AIRSAR Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 12, December 2001, pp. 2634-2648.

133. J. Shi and J. Dozier, "Estimation of Snow Water Equivalence Using SIR-C/X-SAR, Part I: Inferring Snow Density and Subsurface," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 6, November 2000, pp. 2465-2474.

134. J. Shi and J. Dozier, "Estimation of Snow Water Equivalence Using SIR-C/X-SAR, Part II: Inferring Snow Depth and Particle Size," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 6, November 2000, pp. 2475-2488.

135. T. Guneriussen, K. A. Høgda, H. Johnsen, and I. Lauknes, " InSAR for Estimation of Changes in Snow Water Equivalent of Dry Snow," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 10, October 2001, pp. 2101-2108.

136. R. Goldstein, R. Engelhard, B. Kamb, and R. Frolich, "Satellite Radar Interferometry for Monitoring Ice Sheet Motion:

Application to an Antarctic Ice Stream," *Science*, **262**, December 1993, pp. 1525-1530.

137. J. J. Mohr, N. Reeh, and S. Madsen, "Three-Dimensional Glacial Flow and Surface Elevation Measured with Radar Interferometry," *Nature*, **391**, January 1998, pp. 273-276.

138. T. Strozzi, A. Luckman, T. Murray, U. Wegmüller and C. L. Werner, "Glacier Motion Estimation Using SAR Offset-Tracking Procedures," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 11, November 2002.

139. J.-P. Kärnä, J. Pulliainen, M. Huttunen and J. Koskinen, "Assimilation of SAR data to operational hydrological runoff and snow melt forecasting model," *Proceedings of the IEEE 2002 International Geoscience and Remote Sensing Symposium (IGARSS 2002)*, 2002.

140. S. V. Nghiem and W.-Y. Tsai, "Global Snow Cover Monitoring With Spaceborne Ku-band Scatterometer," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 10, October 2001, pp. 2118-2134.

141. P. Ferrazzoli and L. Guerriero, "Passive Microwave Remote Sensing of Forests: A Model Investigation," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-34**, 2, March 1996, pp. 433-443.

142. M. A. Karam, "A Physical Model for Microwave Radiometry of Vegetation," *IEEE Transactions on Geoscience and Remote Sensing* **GRS-35**, 4, 1997, pp. 1045-1058.

143. M. T. Hallikainen, P. A. Jolma, and J. M. Hyyppa, "Satellite Microwave Radiometry of Forest and Surface Types in Finland," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-26**, 5, September 1988, pp. 622-628.

144. L. Kurvonen, J. Pulliainen, and M. Hallikainen, "Monitoring of Boreal Forests with Multitemporal Special Sensor Microwave Imager," *Radio Science*, **33**, 1998, pp. 731-744.

145. N. Kruopis, J. Praks, A. N. Arslan, H. M. Alasalmi, J. Koskinen, and M. T. Hallikainen, "Passive Microwave Measurements of Snow-Covered Forest Areas in EMAC'95," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 6, November 1999, pp. 2699-2705.

146. R. H. Lang, P. de Matthaeis, D. M. Le Vine, S. Bidwell, M. Haken, and N. Chauhan, "L-Band Radiometer Measurements of Conifer Forests," *Proceedings of the IEEE 2000 International Geoscience and Remote Sensing Symposium (IGARSS 2000)*, Honolulu, Hawaii, July 2000, pp. 1930-1932.

147. G. Macelloni, S. Paloscia, P. Pampaloni, and R. Ruisi, "Airborne Multi-Frequency L- to Ka - Band Radiometric Measurements over Forests," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 11, November 2001, pp. 2507-2513.

148. P. Ferrazzoli, L. Guerriero, J. P. Wigneron, "Simulating L-band Emission of Forests in View of Future Satellite Applications," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 12, December 2002, pp. 2700-2708.

149. S. J. Durden, J. J. van Zyle, and H. A. Zebker, "Modeling and Observation of the Radar Polarization Signature of Forested Areas," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-27**, 3, May 1989, pp. 290-301.

150. M. C. Dobson, F. T. Ulaby, T. Le Toan, A. Beaudoin, and E. S. Kasischke, "Dependence of Radar Backscatter on Conifer Forest Biomass," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 2, March 1992, pp. 402-415.

151. M. L. Imhoff, "A Theoretical Analysis of the Effect of Forest Structure on SAR Backscatter and the Remote Sensing of Biomass", *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 2, 1995, pp. 341-352.

152. M. C. Dobson, F. T. Ulaby, L. E. Pirece, T. L. Sharik, K. M. Bergen, J. Kellndorfer, J. R. Kendra, E. Li, Y. C. Lin, A. Nashashibi, K. Sarabandi, and P. Siqueira, "Estimation of Forest Biomass," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 4, July 1995, pp. 887-895.

153. S. S. Saatchi and M. Moghaddam, "Estimation of Crown and Stem Water Content and Biomass of Boreal Forest Using Polarimetric SAR Imagery," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2000, pp. 697-708.

154. S. Quegan, T. Le Toan, J. J. Yu, F. Ribbes, and N. Floury, "Multitemporal ERS SAR Analysis Applied to Forest Mapping," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 741-753.

155. J. T. Pulliainen, L. Kurvonen, and M. T. Hallikainen, "Multitemporal Behavior of L- and C-Band SAR Observations of Boreal Forests," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 2, March 1999, pp. 927-937.

156. H. J. Hyyppä and J. M. Hyyppä, "Effects of Stand Size on the Accuracy of Remote Sensing-Based Forest Inventory," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 12, December 2001, pp. 2613-2621.

157. T. Le Toan, A. Beaudoin, J. Riom, and D. Guyon, "Relating Forest Biomass to SAR Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, March 1992, pp. 403-411.

158. M. C. Dobson, F. T. Ulaby, T. Le Toan, A. Beaudoin, E. Kasischke, and N. L. Christensen, "Dependence of radar backscatter on coniferous biomass," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 2, March 1992, pp. 412-415.

159. A. Beaudoin, T. Le Toan, S. Goze, E. Nezry, A. Lopes, E. Mougin, C. C. Hsu, H. C. Han, J. A. Kong, and R. T. Shin, "Retrieval of Forest Biomass from SAR Data," *International Journal of Remote Sensing*, **15**, March 1994, pp. 2777-2796.

160. P. Melon, J. M. Martinez, T. Le Toan, L. M. H. Ulander, and A. Beaudoin, "On the Retrieving of Forest Stem Volume From VHF SAR Data: Observation and Modeling," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 11, November 2001, pp. 2364-2372.

161. A. T. Manninen and L. M. H. Ulander, "Forestry Parameter Retrieval From Texture in CARABAS VHF-Band SAR Images," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 12, December 2001, pp. 2622-2633.

162. J. E. S. Fransson, F. Walter, K. Blennow, A. Gustavsson, and L. M. H. Ulander, "Detection of Storm-Damaged Forested Areas Using Airborne CARABAS-II VHF SAR Image Data," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 10, October 2002, 2170-2175.

163. F. T. Ulaby and M. A. El-Rayes, "Microwave Dielectric Spectrum of Vegetation, Part II: Dual-Dispersion Model," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-25**, 5, September 1987, pp. 550-557.

164.K. Sarabandi, “A Technique for Dielectric Measurement of Cylindrical Objects in a Rectangular Waveguide,” *IEEE Transactions on Instrumentation Measurements*, **43**, 6, December 1994, pp. 793-798.

165.A. Franchois, Y. Piñeiro and R. H. Lang Microwave Permittivity Measurements of Two Conifers *IEEE Transactions on Geoscience and Remote Sensing* **GRS- 36**, 5, 1998, pp. 1384-1394.

166.F. T. Ulaby, K. Sarabandi, K. MacDonald, M. Whitt, and M. C. Dobson, “Michigan Microwave Canopy Scattering Model,” *International Journal of Remote Sensing*, **11**, 7, 1990, pp. 1223-1253.

167.M. A. Karam and A. K. Fung, “Electromagnetic Scattering from a Layer of Finite Length, Randomly Oriented, Dielectric Circular Cylinders over a Rough Interface with Application to Vegetation,” *International Journal of Remote Sensing*, **9**, 1988, pp. 1109-1134.

168.R. H. Lang and J. S. Sidhu, “Electromagnetic Backscattering from a Layer of Vegetation: a Discrete Approach,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-21**, 1, January 1983, pp. 62-71.

169.Y. C. Lin and K. Sarabandi, “A Monte Carlo Coherent Scattering Model For Forest Canopies Using Fractal-Generated Trees,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 1, January 1999, pp. 440-451.

170.R. Schiffer and K. O. Thielheim, “Light Scattering by Dielectric Needles and Disks,’“ *Journal of Applied Physics*, **50**, 4, April 1979.

171.K. Sarabandi and T. B. A. Senior, “Low-frequency Scattering from Cylindrical Structures at Oblique Incidence,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-28**, 5, September 1990, pp. 879-885.

172.S. S. Seker and A. Schneider, “Electromagnetic Scattering from a Dielectric Cylinder of Finite Length,” *IEEE Transactions on Antennas and Propagation*, **AP-36**, 2, February 1988, pp. 303-307.

173.K. Sarabandi, T. B. A. Senior, and F. T. Ulaby, “Effect of Curvature on the Backscattering from a Leaf,” *Journal of Electromagnetic Waves and Applications*, **2**, 1988, pp. 653-670.

174.T. B. A. Senior, K. Sarabandi, and F.T. Ulaby, “Measuring and Modeling the Backscattering Cross Section of a Leaf,” *Radio Science*, **22**, 1987, pp. 1109-1116.

175.Y. C. Lin, and K. Sarabandi, “Electromagnetic Scattering Model for a Tree Trunk above a Ground Plane,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 4, July 1995, pp. 1063-1070.

176.E. Rodriguez and J. M. Martin, “Theory and Design of Interferometric Synthetic Aperture Radars,” *Proceedings of the IEEE*, **F139**, 2, 1992, pp. 147-159.

177.J. O. Hagberg, L. M. H. Ulander, and J. Askne, “Repeat-pass SAR Interferometry over forested terrain,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 2, March 1995, pp. 331-340.

178.U. Wegmueller and C. L. Werner, “SAR Interferometry Signature of Forest,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 5, September 1995, pp. 1153-1161.

179.T. Strozzi, P. B. G. Dammert, U. Wegmüller, J.-M. Martinez, J. I. H. Askne, A. Beaudoin, and M. T. Hallikainen, “Land Use Mapping with ERS SAR Interferometry,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 766 -775.

180.N. P. Faller and E. H. Meier, “First Results with the Airborne Single-Pass DO-SAR Interferometer,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-33**, 5, September 1995, pp. 1230-1237.

181.K. Sarabandi, “D*K*-Radar Equivalent of Interferometric SARs: A Theoretical Study for Determination of Vegetation Height,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-35**, 5, September 1997, pp. 1267-1276.

182.R. N. Treuhaft, S. N. Madsen, M. Moghaddam, and J. J. van Zyl, “Vegetation Characteristics and Underlying Topography from Interferometric Radar,” *Radio Science*, **31**, 6, 1996, pp. 1449-1485.

183.K. Sarabandi and Y. C. Lin, “Simulation of Interferometric SAR Response for Characterization of Scattering Phase Center Statistics of Forest Canopies,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 115-125.

184.H. A. Zebker, S. N. Madsen, J. Martin, K. B. Wheeler, T. Miller, Y. Lou, G. Alberti, S. Vetrella, and A. Cucci, “The TOPSAR Interferometric Radar Topographic Mapping Instrument,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 5, September 1992, pp. 933-940.

185.S. R. Cloude and K.P. Pathanassiou, “Polarimetric SAR interferometry,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-34**, 2, March 1996, pp. 498-518.

186.R. Cloude, K. P. Papathanassiou, I. Woodhouse, J. Hope, J. C. Suarez Minguez, P. Osborne, and G. Wright, “The Glen-Affric Project: Forest Mapping using Polarimetric Radar Interferometry,” *Proceedings of the IEEE 2001 International Geoscience and Remote Sensing Symposium (IGARSS 2001)*, Sydney, Australia, 9-13, July, 2001.

187.R. Treuhaft, M. Moghaddam, J. van Zyl, and K. Sarabandi, “Estimating Vegetation and Surface Topographic Parameters from Multibaseline Radar Interferometry,” *Proceedings of the IEEE 1996 International Geoscience and Remote Sensing Symposium (IGARSS 1996)*, Lincoln, Nebraska, May 1996.

188.A. Reigber and A. Moreira, “First Demonstration of Airborne SAR Tomography Using Multibaseline L-Band Data,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 5, September 2000, pp. 2142-2152.

189.V. Dimri, *Deconvolution and Inverse Theory: Application to Geophysical Problems*, New York, Elsevier, 1992.

190.M. K. Sen, *Global Optimization Methods in Geophysical Inversion*, New York, Elsevier, 1995.

191.E. P. W. Attema and F. T. Ulaby, “Vegetation Modeled as a Water Cloud,” *Radio Science*, **13**, 1978, pp. 357-364.

192.S. Quegan, T. Le Toan, J. J. Yu, F. Ribbes and N. Floury “Multitemporal ERS SAR Analysis Applied to Forest Mapping,” *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 741-753.

193.L. Pierce, K. Sarabandi, and F. Ulaby, “Application of an Artificial Neural Network in Canopy scattering inversion,” *International Journal of Remote Sensing*, **15**, 1994, pp. 3263-3270.

194. Y. C. Lin and K. Sarabandi, "Retrieval of Forest Parameters Using a Fractal-based Coherent Scattering Model and a Genetic Algorithm," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 3, May 1999, pp. 1415-1424.

195. H. Skriver, M. T. Svendsen, and A. G Thomsen, "Multitemporal C- and L-Band Polarimetric Signatures of Crops," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 5, September 1999, pp. 2413.

196. P. Saich and M. Borgeaud, "Interpreting ERS SAR Signatures of Agricultural Crops in Flevoland, 1993-1996," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, 2000, pp. 651-657.

197. G. Macelloni, S. Paloscia, P. Pampaloni, and S. Sigismondi, "The Potential of *C*-and *L*-Band SAR in Estimating Vegetation Biomass: The ERS-1 And JERS-1 Experiments," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-37**, 4, July 1999, pp. 2107-2110G.

198. Macelloni, S. Paloscia, P. Pampaloni, F. Marliani, and M. Gai, "The Relationship between the Backscattering Coefficient and the Biomass of Narrow and Broad Laf Crops," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-39**, 4, April 2001, pp. 873-884.

199. S. H. Yueh, J. A. Kong, J. K. Jao, R. T. Shin, and T. L. Toan, "Branching Model for Vegetation," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-30**, 2, March 1992, pp. 390-402.

200. J. M. Stiles and K. Sarabandi, "A Scattering Model for Thin Dielectric Cylinders of Arbitrary Cross-Section and Electrical Length," *IEEE Transactions on Antennas and Propagation*, **AP-44**, 2, February 1996, pp. 260-266.

201. J. M. Stiles, K. Sarabandi, and F.T. Ulaby, "Electromagnetic Scattering from Grassland: Part II, Measurement and Modeling Results," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 349-356.

202. J. M. Stiles and K. Sarabandi, "Electromagnetic Scattering from Grassland: Part I, A Fully Coherent Scattering Model," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 1, January 2000, pp. 339-348.

203. F. Marliani, S. Paloscia, P. Pampaloni and J. A. Kong, "Simulating coherent backscattering from crops during the growing cycle," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 1, January 2002, pp. 162-177.

204. Y. Oh, Y. Jang, and K. Sarabandi, "Full-Wave Analysis of Microwave Scattering from Short Vegetation: An Investigation on the Effect of Multiple Scattering," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-40**, 11, November 2002, pp. 2522-2526.

205. T. C. Chiu and K. Sarabandi, "Electromagnetic Scattering from Short Branching Vegetation," *IEEE Transactions on Geoscience and Remote Sensing*, **GRS-38**, 2, March 2000, pp. 911-925.

206. M. Guérif and C. Duke, "Calibration of the SUCROS Emergence and Early Growth Module for Sugar Beet Using Optical Remote Sensing Data Assimilation," *European Journal of Agronomy*, **9**, 1998, pp. 127-136.

207. L. Prévot, F. Baret, and A. Chanzy, "Assimilation of Multi-Sensor and Multi-Temporal Remote Sensing Data to Monitor Vegetation and Soil: The Alpilles-ReSeDA Project," *Proceedings of the International Geoscience and Remote Sensing Symposium IGARSS'98*, Seattle, WA, July 6-10, 1998.