Doctoral Thesis

Multiscale soil moisture retrievals from microwave remote sensing observations

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Cover image and design: Daniel Nuñez.
A mis padres y a mi hermano

A todas las personas con las que he compartido estos años de tesis
Abstract

Soil moisture is a key state variable of the terrestrial water cycle. It is the main variable that links the Earth’s water, energy and carbon cycles, and soil moisture variations affect the evolution of weather and climate over continental regions. Accurate observations of the Earth’s changing soil moisture are needed to achieve sustainable land and water management, to enhance weather and climate forecasting skill, and to develop improved flood and drought monitoring capability. This Ph.D. Thesis focuses on the measurement of the Earth’s surface soil moisture from space at a global and regional scale.

Theoretical and experimental studies have proven that L-band passive remote sensing is optimal for soil moisture sensing due to its all-weather capabilities and the direct relationship between soil emissivity and soil water content under most vegetation covers. However, achieving a temporal and spatial resolution that could satisfy land applications has been a challenge to passive microwave remote sensing in the last decades, since a real aperture radiometer would need a large rotating antenna, which is difficult to implement on a spacecraft. Currently, there are three main approaches to solving this problem: (i) the use of an L-band synthetic aperture radiometer, which is the solution implemented in the ESA Soil Moisture and Ocean Salinity (SMOS) mission, launched on November the 2nd 2009; (ii) the use of a large lightweight radiometer and a high-resolution radar operating at L-band, which is the solution adopted by the NASA Soil Moisture Active Passive (SMAP) mission, scheduled for launch in 2014; (iii) the development of pixel disaggregation techniques using higher resolution data, which could apply to both SMOS and SMAP.

Estimation of soil moisture from passive L-band measurements is complex since there are other soil and vegetation parameters affecting the land emission that must be carefully accounted for in the retrieval process. The first part of this work focuses on the analysis of the SMOS soil moisture inversion algorithm, which is crucial to retrieve accurate soil moisture estimations from the radiometric measurements. Different retrieval configurations are examined using simulated SMOS data, considering the option of adding a priori information from parameters dominating the land emission at L-band –soil moisture, soil roughness, soil temperature, vegetation albedo and vegetation opacity– with different associated uncertainties. Results illustrate the effect of adding or not auxiliary information on the precision of soil moisture retrievals and an optimal retrieval configuration for SMOS is devised.

The spatial resolution of SMOS and SMAP radiometers (40-50 km) is adequate for many global applications, but is a limiting factor to its application in regional scale studies, where a resolution of 1-10 km is needed. The second part of this Thesis contains three novel approaches for the improvement of the spatial resolution of SMOS and SMAP observations:

- A deconvolution scheme for the improvement of the spatial resolution of SMOS radiometric observations has been developed. Results using simulated SMOS observations and airborne field experimental data show that with this approach it is feasible to improve the product of spatial resolution and radiometric sensitivity of SMOS observations in a 49% over land pixels and in a 30% over sea pixels.

- A downscaling algorithm for improving the spatial resolution of SMOS-derived soil moisture estimates using higher-resolution visible/infrared data from MODIS has been
developed. Results of its application to airborne field experimental data and to the first SMOS images acquired during the commissioning phase provide a first evidence of its capabilities. SMOS-derived soil moisture maps at 64, 32, 16 and 8 km have been obtained; the soil moisture variability is nicely captured at the different spatial scales, but further research is needed to validate the accuracy of the retrievals at every spatial resolution and establish a downscaling limit.

- A change detection approach for combining SMAP radar and radiometer observations into a 10 km soil moisture product has been developed and validated using airborne field experimental data and SMAP-like observations.

This work has been developed within the preparatory activities of SMOS and SMAP, the two first-ever satellites dedicated to monitoring the temporal and spatial variation on the Earth's soil moisture fields. The retrieval studies and downscaling algorithms presented will timely contribute to get the most out of these vital observations, that will further our understanding of the Earth’s water cycle, will help improve weather and climate models, and will lead to a better water resource management.
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Every so often, I like to go to the window, look up, and smile for a satellite picture

Stephen Wright (1955-)

1

Introduction

Two space missions have been proposed to provide the first dedicated global measurements of the Earth’s surface soil moisture: the European Space Agency (ESA) launched the SMOS mission in November 2009 and the US National Aeronautics and Space Administration (NASA) plans to launch the SMAP mission in 2014. This thesis has been performed within the preparatory activities of these missions, involving the analysis of the retrieval techniques, which have an impact on the accuracy of the estimations, and the development of downscaling algorithms to enhance the spatial resolution of the observations. As it will be presented along this document, the spatial resolution of SMOS and SMAP measurements can be improved from \( \sim 50 \text{ to } 60 \text{ km} \) down to \( \sim 10 \text{ km} \), without a significant degradation of the Root Mean Square Error (RMSE).

This Chapter describes the motivation of this work and the context in which it has been developed. It contains background information related to SMOS and SMAP space-borne projects, reviews the the state-of-the-art of the soil moisture downscaling algorithms, and presents the Thesis outline.

1.1 Motivation

Although soil only holds a small percentage of the total global water budget, soil moisture plays an important role in the Earth’s water cycle; it is a key variable in the water and energy exchanges that occur at the land-surface/atmosphere interface and conditions the evolution of weather and climate over continental regions. Global observations of the Earth’s changing soil moisture are needed to enhance climate prediction skills and weather forecasting, which will benefit climate-sensitive socio-economic activities, including water management, agricultural productivity estimation, flood prediction and drought monitoring [Entekhabi et al., 1999; Krajewski et al., 2006; Wagner et al., 2007].

Experimental and theoretical studies have shown that passive L-band microwave remote sensing is the most promising technique for global monitoring of soil moisture due to its all weather capability and the direct relationship of soil emissivity with soil water content [Shutko and Rautov, 1982; Schmugge et al., 1986; Njoku et al., 2002]. Microwave remote sensing encompasses both active and passive forms, depending on the sensor and its mode of operation [Ulaby et al., 1981]. Active sensors (radars) are capable of remotely sensing soil moisture at high spatial resolution (\( \sim 1 \text{ km} \) or even higher with SAR), but radar backscatter
is highly influenced by surface roughness, topography, vegetation canopy structure and water content [Dubois et al., 1995; Shi et al., 1997]. In contrast, passive sensors (radiometers) have a reduced sensitivity to land surface roughness and vegetation cover, but their spatial resolution is typically low (≈ 40-50 km) [Jackson et al., 1996; Njoku and Entekhabi, 1996]. The limited-duration SkyLab mission in the 1970s was the earliest demonstration of soil moisture retrieval from passive L-band observations on orbit [Jackson et al., 2004]. In the near future, two space missions will measure soil moisture at global scale using L-band microwave radiometers: the ESA launched the Soil Moisture and Ocean Salinity (SMOS) mission in November 2009 [Kerr et al., 2001], and the NASA will launch the Soil Moisture Active Passive (SMAP) mission in 2014 [National Research Council, 2007]. These two missions will provide unprecedented decade-long global mapping of the Earth’s surface soil moisture fields with high accuracy and a ground resolution between 40-50 km. SMAP has a high-resolution radar to enhance the spatial resolution of the retrievals up to 10 km.

Estimation of soil moisture from radiometric measurements is not simple since there are many soil and vegetation parameters affecting the land emission. An analysis of the algorithms to retrieve bio/geophysical variables from brightness temperature measurements and the assessment of the impact of each of the parameters involved is crucial for obtaining accurate soil moisture estimations. Due to technological limitations, the spatial resolution of SMOS and SMAP radiometers is limited to 40-50 km. This resolution, while adequate for many global applications, is a limiting factor to its application in regional scale studies, where a resolution of 1-10 km is needed [Entekhabi et al., 1999; Crow et al., 2005a]. This Ph.D. Thesis focuses on the measurement of the Earth’s surface soil moisture from space – both on a global level, through the analysis of retrieval algorithms that impact the accuracy of the observations, and on a local level, through the development of downscaling techniques that could enhance the spatial resolution of the observations.

The research described on this Thesis has been carried out at the UPC Remote Sensing Laboratory, which has been involved in the SMOS instrument concept and science applications since 1993, and where more than 15 Ph.D. Thesis have been pursued covering different aspects of the mission and potential improvements. This working context has provided a unique opportunity for participating in both the engineering and the scientific sides of the SMOS mission. Also, a 4-month stay at MIT with professor D. Entekhabi made possible the work conducted in the frame of the SMAP mission.

1.2 Importance of soil moisture estimations

Soil moisture, as the state variable of the water cycle over land, controls water fluxes between the atmosphere, the surface, and the subsurface (See Fig. 1.1). Because a large amount of heat is exchanged when water changes phase, the water cycle is fundamental to the dynamics of the Earth’s energy cycle. Also, since water is the ultimate solvent in the Earth system, biogeochemical cycles such as carbon, nitrogen and methane are embedded in the water cycle. Through these dynamics, soil moisture conditions the evolution of weather and climate over continental regions. Hence, global measurements of soil moisture are needed to improve our understanding of water cycle processes, ecosystem productivity, and the linkages between the Earth’s water, energy, and carbon cycles.

Global soil moisture information will be transformational for the Earth’s system science; it will help characterize the relationship between soil moisture, its freeze/thaw state, and the associated environmental constraints to ecosystem processes including land-atmosphere
1.2. Importance of soil moisture estimations

carbon, water and energy exchange, and vegetation productivity. At the same time, global soil moisture information will enable societal benefit applications such as better water resource assessment, improved weather forecasts, natural hazards mitigation, predictions of agricultural productivity, and enhanced climate prediction, human health and defense services. The prospective use of remotely-sensed soil moisture data on these applications is briefly described in the following sections. More information can be found in SMOS and SMAP home pages, which are www.esa.int and smap.jpl.nasa.gov, respectively.

Figure 1.1 Precipitation, evaporation, evapotranspiration and runoff are the processes that move water through the water cycle. Values in the diagram show the volume of water that moves along each path in a year (www.unep.org)

Weather forecast applications

The quality of weather forecasts is significantly dependent on the availability of accurate initial states for key atmospheric variables, due to the chaotic nature of the atmosphere. To date, significant effort has been concentrated on measuring the initial states of temperature, air density, winds, and water vapor to improve weather forecasts; however, it is now recognized that the next significant advances in the quality of weather forecasts will come from constraining the systems coupled to the atmosphere such as soil moisture over land. Numerous studies show that the initialization of global weather forecast models with accurate soil moisture information will enhance their prediction skills and extend their forecast lead-times. While the spatial resolution of SMOS and SMAP radiometers (~ 40-50 km) is adequate for global applications, downscaling techniques must be developed to extend the use of the data to regional scale studies, where a resolution of 1-10 km is needed [Entekhabi et al., 1999].

Temporal sampling requirements for surface soil moisture follow from the time scales of surface wetting and drying. Capturing the impacts of storm/interstorm sequences, combined
Chapter 1. Introduction

with the inertia of surface storage, requires a revisit of \( \sim 3 \) days \cite{Calvet1998, Walker2004}. The baseline SMOS and SMAP implementation meets this measurement requirement, though improved latency might increase operational use.

**Hydrological hazards mitigation: drought, flood, and landslides**

Prediction of droughts, floods and flash-floods requires not only precipitation information, but also soil moisture and freeze/thaw state information. Also, soil moisture in mountainous areas is one of the most important factors of landslides. To date, there is no global in situ or current satellite capability to monitor and map soil moisture, and estimations are produced from models, with a high degree of uncertainty \cite{Crow2005}. The assimilation of accurate soil moisture observations at the scale of severe weather phenomena over land (1-10 km) on model predictions will therefore help to improve both drought and flood forecasts, enabling more effective hazards monitoring and mitigation efforts (see Fig. 1.2).

![Figure 1.2 Soil moisture initialization of Numerical Weather Prediction models leading to an improved precipitation forecasts (adapted from Chen et al., 2001)](image)

**Agricultural productivity**

Ecosystem services require direct monitoring of soil moisture availability to plants (natural and cropped) to assess productivity. Hence, the use of realistic soil moisture data on the models will allow significant improvements in agricultural productivity forecasting and operational crop productivity and water stress information systems.

**Climate prediction applications**

Soil moisture data will help improve seasonal climate predictions, which will benefit climate-sensitive socio-economic activities, including water management, agriculture, and fire, flood, and drought hazards monitoring \cite{Douville2004}. Also, projections of the terrestrial water cycle and fresh-water supplies under global change are critically dependent on how models link the water cycle to the energy cycle. How the water cycle responds to an increased radiative forcing due to accumulation of greenhouse gases in the atmosphere depends on how the models parameterize surface energy flux rate dependencies on soil moisture. Thus, global observations of soil moisture provide a clear opportunity to improve our understanding of global change impacts.

**Human health services**

Soil moisture mapping will allow monitoring and prediction of factors that impact human health. For instance, soil moisture information at high resolution might contribute to a
better water resource assessment, and will allow monitoring of soil moisture anomalies, which could be linked to human diseases [Shaman and Day, 2005]. Also, soil moisture information will indirectly benefit human health applications, e.g. better weather forecasts, leading to predictions of virus spreading rates and heat stress; better flood forecasting, leading to improved disaster preparation and response, and improved seasonal soil moisture forecasts, leading to improved famine early warning systems.

**Defense applications**

High resolution soil moisture data would be very helpful for terrain trafficability assessment, which is a major element on land autonomous deployments and has a significant tactical value [Flores et al., 2009]. Also, soil moisture estimates are required to initialize aviation weather forecast models, and will enable improved forecasts of density altitude, fog formation, and dust generation.

### 1.3 Earth observation for global mapping of soil moisture

Currently, there are two space missions dedicated to monitoring the temporal and spatial variation of the Earth’s soil moisture: the ESA Soil Moisture and Ocean Salinity (SMOS) mission, launched in November 2009, and the NASA Soil Moisture Active Passive (SMAP) mission, that will be launched in 2014. These two missions will provide unprecedented global mapping of the Earth’s surface soil moisture fields, and are expected to satisfy the science and applications needs on Section 1.2.

Both SMOS and SMAP use microwave radiometry at L-band (1.400-1.427 GHz) to make soil moisture measurements. Theoretical and experimental studies have shown that L-band radiometry is optimal for soil moisture sensing due to the direct relationship of soil emissivity with soil water content [Wang and Choudhury, 1981; Schmugge et al., 1986; Jackson et al., 2004]. Also, the atmosphere at microwave frequencies may be considered transparent, and vegetation is semi-transparent (up to $\sim 5$ kg/m$^2$), which allows observations of the underlying layers [Jackson et al., 1982; Jackson and Schmugge, 1991; Njoku and Entekhabi, 1996]. SMOS and SMAP radiometers are expected to provide highly accurate soil moisture estimations with a ground resolution of about 40-50 km. SMAP also has a high-resolution radar to enhance the spatial resolution of the retrievals up to 10 km.

Alternatives to L-band radiometry for soil moisture sensing include the use of higher frequency radiometers, the use of radars operating at L-band, or the use of visible/infrared sensors. However, they suffer from major drawbacks that limit their applicability, as will be discussed hereafter.

Higher frequency microwave radiometers such as those at C-band or X-band (i.e. AMSR-E, WindSat, TMI) are sensitive to soil moisture, but present the disadvantage of being highly attenuated by vegetation. Therefore, its applicability is limited to areas with moderate vegetation ($< 3$ kg/m$^2$). In contrast, L-band radiometric observations are sensitive to soil moisture through vegetation of up to $\sim 5$ kg/m$^2$, which corresponds to about 70% of the non-frozen land regions on Earth, excluding dense forests. Also, at higher frequencies the atmosphere is less opaque –its effects need to be corrected– and the soil penetration depth is lower ($\sim 1$ cm vs. the $\sim 5$ cm at L-band). Note that greater penetration depths are desirable to characterize the soil moisture below the skin layer of the emitting surface.
Radars operating at L-band (i.e. JERS, PALSAR), in turn, are capable of sensing soil moisture and provide higher spatial resolution than radiometers (< 1 km). However, they typically operate with narrow swaths, meaning that they do not meet the temporal requirements of global land hydrology applications (~ 3 days). Also, radar measurements are highly affected by soil surface roughness and vegetation scattering, which leads to a high uncertainty in the soil moisture retrieval algorithms [Dubois et al., 1995; Shi et al., 1997].

Visible/infrared sensors are also capable of providing high spatial resolution (< 1 km), and controlled experiments have shown their potential to sense soil moisture [Idso et al., 1975; Price, 1977; Adegoke and Carleton, 2002; Wang et al., 2007]. However, they are equally sensitive to soil types, and it is difficult to decouple the two signatures. Hence, visible/infrared sensors are commonly used to provide an indirect measurement of soil moisture, but not to retrieve it. Also note that observations in the optical domain are totally masked in the presence of cloud cover.

All things considered, it is generally recognised that passive microwave is the most promising remote sensing method for soil moisture measurement [Njoku et al., 2002]. However, achieving a spatial resolution that could satisfy land applications has been a challenge to passive microwave remote sensing in the last decades, and the reason why soil moisture estimation by satellite has not been planned until recently. The problem is that to achieve adequate coverage and spatial resolution at L-band, a real-aperture radiometer would require a large rotating antenna, which is difficult to implement on a spacecraft. There are three main approaches to solving this problem that are currently under investigation and that will be widely covered in this Thesis:

- The use of synthetic aperture radiometry, which is the solution adopted by SMOS.
- The use of large lightweight antennas, which is the solution adopted by SMAP.
- The development of pixel disaggregation techniques using higher resolution data, which could apply to both SMOS and SMAP.

### 1.3.1 The SMOS mission

The Soil Moisture and Ocean Salinity (SMOS) mission, launched on November the 2\textsuperscript{nd} 2009, is the first satellite ever attempted to globally measure the Earth’s soil moisture and ocean salinity by means of L-band microwave radiometry. Soil moisture is a critical state variable of the terrestrial water cycle and the factor that links the global water, energy and carbon cycles. Moreover, sea surface salinity, jointly with sea surface temperature, determines the water density and regulates the global ocean circulation currents that moderate the Earth’s climate system. The data acquired from this mission will contribute to furthering our knowledge of the Earth’s water cycle [Kerr et al., 2001; Barré et al., 2008].

SMOS is the second Earth Explorer Opportunity mission as part of the ESA’s Living Planet Programme. ESA’s Opportunity missions are intended to be small research missions that focus on specific aspects of the Earth’s environment and/or demonstrate new remote sensing technologies. The SMOS mission is a direct response to the current lack of global observations of soil moisture and ocean salinity, and was thought of as a cost-effective, demonstrator mission with a nominal (extended) lifetime of 3 (5) years. It has a Sun-synchronous, quasi-circular, dusk-dawn orbit, with a mean altitude of 758 km, and with 6 am/6 pm overpass times. The SMOS single payload is a completely new type of instrument: an L-band two dimensional synthetic aperture radiometer with multiangular and
Table 1.1 Main scientific requirements of the SMOS mission. See also Mission Objectives and Scientific Requirements of the SMOS mission [2003]

<table>
<thead>
<tr>
<th>Land: global Soil moisture and vegetation water content maps</th>
<th>0.04 m$^3$/m$^3$ (4%) every 3 days 0.2 kg/m$^2$ every 6 days &lt; 50 km spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ocean: global Sea Surface Salinity maps</td>
<td>0.1 psu every 30 days 200 km spatial resolution</td>
</tr>
<tr>
<td>Cryosphere (experimental):</td>
<td>Improved snow mantle monitoring and multilayer ice structure</td>
</tr>
</tbody>
</table>

dual-polarization/full-polarimetric capabilities, the Microwave Imaging Radiometer using Aperture Synthesis (MIRAS)(Fig. 1.4).

Figure 1.3 First uncalibrated data sent to Earth by the MIRAS instrument on ESA’s SMOS satellite (from www.esa.int, 20 November 2009)

SMOS is expected to provide global maps of soil moisture every 3 days –compatible with the temporal variability of the near surface soil moisture over continental surfaces–, with a ground resolution better than 50 km, and an accuracy of 0.04 m$^3$/m$^3$ volumetric humidity. This is comparable to being able to detect one teaspoonful of water mixed into a handful of dry soil. For ocean salinity, maps with an accuracy better than 0.1 practical salinity units (psu) and 200 km ground resolution will be acquired every 30 days, which is comparable to detecting 0.1 g of salt in a liter of water. As secondary objectives, SMOS is expected to provide vegetation water content maps with an accuracy of 0.2 kg/m$^2$ every 6 days, and will contribute to studies of the cryosphere [Mission Objectives and Scientific Requirements of the SMOS mission, 2003]. The SMOS mission requirements are summarized in Table 1.1.

L-band is a protected frequency band for radio-astronomy and remote sensing satellite services. However, it is bordered by radio location and communications services, and field experimental campaigns have provided an evidence that there is a potential risk for corruption due to out-of-band emission or Radio Frequency Interferences (RFIs). Indeed, first SMOS data (on Fig. 1.3) presented a clear RFI contamination (in red); as a consequence, the development of a RFI detection and mitigation approach has become a high priority activity during the SMOS commissioning phase.
Chapter 1. Introduction

The Microwave Imaging Radiometer by Aperture Synthesis

The SMOS single payload is MIRAS, a novel two-dimensional synthetic aperture radiometer with dual-polarization/full-polarimetric imaging capabilities that provides brightness temperature measurements of the Earth’s surface at different incidence angles.

![Figure 1.4](image1.png)

**Figure 1.4** SMOS-MIRAS undergoing testing in the Large Space Simulator at ESA-ESTEC (a), and SMOS-MIRAS artist’s view (b), from [www.esa.int](http://www.esa.int)

As said, in order to achieve adequate coverage and spatial resolution for observing soil moisture at L-band, a large rotating antenna is needed, which is a difficult and costly solution for a spacecraft. An elegant alternative was proposed by the SMOS mission by means of an innovative interferometric radiometer concept: the required antenna aperture is synthesized from 69 separate receivers, which are equally distributed over a Y-shaped antenna array—formed by three deployable arms of about 3.5 m length, and a central structure. The interferometric approach, inspired by the techniques used in radio astronomy over several decades, is based on measuring the cross-correlation of the observations from all possible combinations of receiver pairs in order to sample the signal that would have been received by a real aperture antenna.

![Figure 1.5](image2.png)

**Figure 1.5** SMOS observation geometry, from Camps et al. [2005]

A synthetic aperture interferometric radiometer forms a brightness temperature image in the director cosines domain $(\xi, \eta) = (\sin \theta \cos \phi, \sin \theta \sin \phi)$ by a Fourier synthesis technique.
of the cross-correlation of the signals collected by each pair of receiving elements [Campos et al., 2008]. In MIRAS, the receiving elements are distributed along three arms 120° apart, and they are spaced \( d = 0.875 \) wavelengths. This antenna spacing was selected to optimize the instrument’s angular resolution, while keeping a swath wide enough so as to meet the revisit time requirement [Waldteufel et al., 2003]. However, since the Nyquist criterion for hexagonal sampling (\( d = 1/\sqrt{3} = 0.577 \) wavelengths [Campos et al., 1997]) is not satisfied, the reconstructed 2-D brightness temperature images present aliasing. Figure 1.5 illustrates the SMOS observation geometry: the half space in front of the antenna array is mapped into the unit circle in (\( \xi, \eta \)) coordinates, and the Earth aliases overlap with the Earth image, determining the alias-free Field Of View (FOV), marked in yellow. Sophisticated image reconstruction algorithms are required to account for instrument imperfections and obtain brightness temperature maps in the antenna reference frame (Level 1b data) from the calibrated visibilities (Level 1a data). Note that the image reconstruction process induces radiometric accuracy and bias errors, in addition to the random noise errors induced by a conventional radiometer.

![Figure 1.5](image1.png)

**Figure 1.5** MIRAS observation geometry: the half space in front of the antenna array is mapped into the unit circle in (\( \xi, \eta \)) coordinates, and the Earth aliases overlap with the Earth image, determining the alias-free Field Of View (FOV), marked in yellow. Sophisticated image reconstruction algorithms are required to account for instrument imperfections and obtain brightness temperature maps in the antenna reference frame (Level 1b data) from the calibrated visibilities (Level 1a data). Note that the image reconstruction process induces radiometric accuracy and bias errors, in addition to the random noise errors induced by a conventional radiometer.

MIRAS takes a two-dimensional brightness temperature image every 1.2 seconds with a characteristic irregular curved hexagon-shaped field-of-view (FOV) of about 1000 km swath width (Fig. 1.6 (a)). The SMOS FOV in cross-track/along-track coordinates (Earth reference frame) is shown in Fig. 1.6 (b). As the satellite moves along its orbital path, each pixel is observed under different viewing angles (from 0° to 65°; dashed contours centered at nadir). SMOS observations are characterized for having a different pixel size, orientation, and noise level, depending on the pixel’s location within the instrument FOV. The spatial resolution varies from 30 km at nadir to 90 km at the upper borders; The radiometric sensitivity varies from 3.5 K at boresight to 5.8 K off-boresight. By registering a lot of independent information of each pixel, it is expected that soil and vegetation contributions could nicely be separated [Kerr et al., 2001].

The grid chosen for the delivery of SMOS data is the Icosahedral Snyder Equal Area (ISEA) 4H9, which provides a uniform inter-cell distance of \( \sim 15 \) km [Sahr et al., 2003]. This fine grid has been adopted in order to provide the correct sampling for the measurements at
the highest spatial resolution (30 km at nadir direction, Fig. 1.6(b)) since, according to the Nyquist sampling theorem, the sampling frequency must be greater than twice the highest frequency of the input signal in order to be able to reconstruct the original perfectly from the sampled version.

MIRAS can work in two operation modes: the dual-polarization and the full-polarimetric mode [Martín-Neira et al., 2002]. In the dual-polarization mode, MIRAS measures the brightness temperatures in horizontal and vertical polarization. In full-polarimetric mode, MIRAS measures the four Stokes parameters (see Section 2.1.6). Receivers need to be calibrated to ensure that the accuracy requirements of the mission can be met. On board calibration is performed by injecting stable noise signals into all the receivers several times per orbit. In addition, an external absolute calibration is performed every two weeks with celestial targets [McMullan et al., 2008]. Data is stored on-board and transmitted using an X-band down-link whenever a ground station is seen by the satellite.

SMOS mission products

The SMOS mission products are divided into four categories:

- **Level 0 products** consist of unprocessed SMOS data with added Earth Explorer headers. Level 0 products include, for instance, satellite data and calibration data from correlators.

- **Level 1 products** are divided into three subcategories:
  1. **Level 1a products** are calibrated visibilities (cross-correlations) grouped as snapshots.
  2. **Level 1b products** are snapshot maps of radiometrically corrected and calibrated brightness temperatures, referred to the antenna polarisation reference frame ($T_{xx}$, $T_{yy}$, and $T_{xy}$, as well in the full-polarimetric mode).
  3. **Level 1c products** are swath-based maps of brightness temperatures referred to a fixed grid on an Earth ellipsoid ($T_{hh}$, $T_{vv}$, and $T_I = T_{hh} + T_{vv} = T_{xx} + T_{yy}$). Level 1c products are generated separately for land and sea applications.

- **Level 2 products** are soil moisture or surface salinity swath-based maps which have been computed from Level 1c products. The conversion from Level 1c brightness temperatures to Level 2 maps includes a first step to mitigate the impact of Faraday rotation, Sun/Moon/galactic glint, atmospheric attenuation, etc. and it is done separately for soil moisture and ocean salinity.

- **Level 3 products** are based upon the spatio-temporal aggregation of Level 2 data.

- **Level 4 products** are improved Level 2/3 products through the use of auxiliary data from other sources.

Level 0 to Level 2 data products will be archived for 10 years after the end of the SMOS extended operational lifetime in orbit. Further information on these levels is given in Zundo et al. [2005].
1.3. Earth observation for global mapping of soil moisture

Simulation and processing tools

In this Ph.D. Thesis, the SMOS End-to-end Performance Simulator (SEPS) has been used to generate SMOS-like brightness temperatures, waiting for the true satellite measurements. In turn, a dedicated L2 Processor Simulator has been implemented to retrieve soil moisture from SEPS simulated data.

SEPS is a simulation tool that covers the complete simulation of the environmental conditions seen by the radiometer, the full MIRAS instrument modelling, the determination of the retrieved relevant data measured by the instrument, image reconstruction algorithms, and graphic outputs such as fully-polarimetric brightness temperature maps reconstructed on the Earth [Camps et al., 2003; SEPS Architectural Detailed Design Document, 2006]. Due to the unique characteristics of SMOS observations, the use of SEPS in this Ph.D. Thesis was essential and permits a better understanding of the problems that may arise at a later stage using real SMOS data. The L2 Processor Simulator is a dedicated software, originally developed for SMOS salinity retrieval studies by Talone et al. [2009]; Sabia et al. [2010], which was modified in the frame of this Ph.D. Thesis for soil moisture retrieval studies; it is a simplified version of the SMOS Level 2 Processor, which integrates the forward model and optimization algorithm described in Sections 2.2 and 2.3, incorporates the experience gained from experimental land emissivity studies [Monerris, 2009], and is designed to be used directly with SEPS output data. The L2 Processor Simulator has been entirely implemented during this research work and is key to devise an optimal soil moisture retrieval configuration for SMOS.

1.3.2 The SMAP mission

The Soil Moisture Active Passive (SMAP) space mission, scheduled for launch in 2014, has been recommended by the NRC Earth Science Decadal Survey Panel to provide global measurements of the Earth’s near-surface soil moisture, and to distinguish frozen from thawed land surfaces [National Research Council, 2007].

![Figure 1.7 SMAP measurement geometry](smap.jpl.nasa.gov)

In order to solve the size-mass issues of real aperture antennas working at L-band, SMAP incorporates a deployable light-weight mesh antenna with a 6 m diameter. SMAP is based on the NASA Hydros (Hydrosphere State) mission [Entekhabi et al., 2004] that progressed through Phase A development until it was put on hold in 2005 due to NASA budgetary constraints. The mission payload consists of an approximately 40 km footprint L-band microwave radiometer measuring the first three Stokes parameters $T_{vv}$, $T_{hh}$ and $T_{U}$, and a 3 km
footprint L-band synthetic aperture radar sensing backscattering coefficients at \( hh \), \( vv \) and \( hv \) polarizations. The SMAP radar and radiometer share a single feedhorn and parabolic mesh reflector to make coincident measurements of surface backscatter and emission. The reflector rotates about its nadir axis at 14.6 rpm, providing a conically scanning antenna beam with a surface incidence angle of approximately 40°; this angle maximizes the independent information obtainable from the vertical and horizontal polarized brightness temperatures. The SMAP measurement geometry is illustrated in Fig. 1.7.

Soil moisture retrieval over smooth bare soils is well established using microwave radar and radiometer sensors. However, roughness and vegetation effects are more difficult to decouple using radar, which leads to a higher uncertainty in radar only soil moisture retrieval algorithms. It is expected that the high resolution radar could serve to improve the spatial resolution of the accurate radiometer observations. Also, SMAP provides the option of exploring data fusion of passive and active microwave observations in soil moisture retrieval algorithms.

SMAP aims at providing global scale land surface soil moisture observations with a 3 day revisit time and its key derived products are:

- Soil moisture at 40 km for hydroclimatology, obtained from the radiometer measurements.
- Soil moisture at 10 km resolution for hydrometeorology, obtained by combining the high radar spatial resolution and the high radiometer accuracy in a joint retrieval algorithm.
- Freeze/thaw state at 3 km resolution from the radar measurements.

### 1.4 Soil moisture downscaling algorithms

The retrieval of surface soil moisture is optimal in the microwave domain, and has been demonstrated through a number of field experiments using ground-based or aircraft mounted radiometers (e.g. [Jackson et al., 1999; Narayan et al., 2004; Saleh et al., 2009; Monerris, 2009]). Therefore, global estimation of soil moisture from remote sensing observations holds great promise for many applications. However, the spatial resolution of the upcoming satellite-based microwave radiometers (\( \sim 40-50 \) km) is too coarse to serve regional scale applications, where a resolution of 1 to 10 km is needed [Entekhabi et al., 1999; Crow et al., 2000].

The combination of radiometric data at low spatial resolution with higher resolution data coming from other sensors offers a potential solution to decompose or disaggregate large pixels into smaller ones. Also, additional information on factors controlling soil moisture variability such as soil properties, vegetation characteristics, or meteorologic observations could be used, given that reasonable physical models or empirical relationships apply.

In this context, different approaches have been explored to disaggregate low-resolution passive microwave remote sensing data to the higher resolution required. Some of these methods are based on the use of topographic and surface properties. For example, [Pellenq et al. 2003] coupled a radiative transfer model with a hydrological model to spatially redistribute the soil water content as a function of topography and soil properties. Also, [Kim and Barros 2002] developed an algorithm to downscale a coarse resolution soil moisture pixel using empirical connections between the spatial and temporal variability of soil moisture and
1.4. Soil moisture downscaling algorithms

The behavior of auxiliary data such as topography, soil texture, vegetation water content, and rainfall.

The use of visible-near infrared, and thermal infrared remote sensing data for downscaling passive microwave observations has also been proposed. Most of these approaches are based on the so-called “triangle method” that relates land surface parameters to soil moisture [Carlson, 2007]; high resolution surface temperature and a vegetation index are aggregated to the scale of the microwave observation for the purpose of building a linking model that is then applied at fine scale to disaggregate the passive soil moisture observations into high-resolution soil moisture. Chauhan et al. [2003] demonstrated this strategy using 1-km Advanced Very High Resolution Radiometer (AVHRR) and 25 km Special Sensor Microwave/Imager (SSM/I) data; Merlin et al. [2008a] propose a variant of this method for SMOS using 1-km MODerate resolution Imaging Spectroradiometer (MODIS) data, soil dependant parameters, and wind speed data. As an alternative to these empirically-based approaches, a physically-based algorithm that includes a complex surface process model and high resolution multispectral data and surface variables involved in a land-surface-atmosphere model is presented in Merlin et al. [2005]. This method is simplified using an energy balance model in Merlin et al. [2008b]. However, the applicability of these algorithms to the upcoming space-borne observations is limited to the availability of the high resolution soil and vegetation parameters they need at global scale. Also, note that the use of optical data limits the use of these approaches to clear-sky conditions.

There is another approach to disaggregation that is central to the SMAP mission design. It is expected that a 10 km soil moisture product could result from the integration of passive and active technologies, based on different studies devoted to the combination of complementary radiometer and radar microwave observations. Njoku et al. [2002] found that radar and radiometer data from the Passive and Active L- and S-band airborne sensor (PALS) showed similar sensitivities to soil moisture spatial distributions when observed as temporal changes, and demonstrated the feasibility of a change detection approach to monitor the temporal evolution of soil moisture. A similar approach is used in Narayan et al. [2006] to downscale PALS data using AIRborne Synthetic Aperture Radar (AIRSAR) data, and vegetation water content measurements. A totally different strategy is followed in Zhan et al. [2006], where a Bayesian method is used to downscale radiometer observations using radar measurements in an Hydros-like simulated environment.

Other schemes for disaggregating passive microwave pixels include the work of Cardot et al. [2005], where a temporal interpolation method is proposed to couple high and low spatial resolution images of mixed pixels, and in the work of Tsegaye et al. [2003], where a neural network is proposed to downscale low-resolution satellite microwave remote sensing using a coupled hydrologic/radiative transfer model as input for its training.

It is likely that the minimum pixel size will be limited, with the main restrictions being: i) the spatial/temporal resolution that is technically achievable by the spaceborne remote sensing systems, ii) the noise amplification that the smaller pixels will exhibit, and iii) the strength of the physical link between soil water content and the dominant processes that control its variability at the two spatial scales used when disaggregating. With current technologies, it is expected that the downscaling limit will be on the range of tens of km. However, new passive technologies could lead the way to future missions with higher spatial resolutions, and innovative downscaling approaches could also be developed to eventually result in products < 1 km.

Spatial resolution is still a challenge for passive microwave remote sensing of land. The study and development of downscaling techniques for upcoming microwave remote sensors
is of great importance and will considerably increase its range of applications. The original contributions of this work in the field of soil moisture downscaling algorithms are fully contained in Chapters 5, 6, and 7.

1.5 Thesis outline

This Ph.D. Thesis is devoted to the retrieval of accurate and high-resolution soil moisture retrievals from microwave remote sensing observations, and is organized as follows:

Chapter 1 describes the motivation of this work and justifies its scientific and technological interest within the SMOS and the upcoming SMAP missions. The state-of-the-art of soil moisture downscaling algorithms is presented.

Chapter 2 reviews the basics of microwave radiometry, and presents the theoretical and experimental background to remote sensing of soil moisture using microwave radiometry. The state-of-the-art of soil moisture retrieval techniques is outlined.

Chapter 3 examines different SMOS retrieval configurations, depending on the ancillary information that is used in the retrievals and its associated uncertainty. The auxiliary data impact on soil moisture retrievals is thoroughly evaluated using SMOS simulated data and an optimal retrieval configuration is devised.

Chapter 4 analyzes the soil moisture inversion algorithm, both theoretically and in terms of performance. A sensitivity analysis of the SMOS soil moisture inversion algorithm illustrates the effect of adding or not a priori information on the precision of the retrievals. An analysis with simulated SMOS data gives a first feeling of the quantitative errors that should be expected from real upcoming measurements.

Chapter 5 introduces a deconvolution scheme to improve the spatial resolution of SMOS data. Different deconvolution techniques are presented that optimally perform noise regularization and include different levels of auxiliary information in the image reconstruction process. Results with simulated SMOS data and passive L-band airborne observations are shown in terms of both spatial resolution and radiometric sensitivity enhancement.

Chapter 6 explores the possibility of improving the spatial resolution of SMOS-derived soil moisture estimates using higher resolution visible/infrared satellite data. Preliminary results using passive L-band airborne data and the first SMOS brightness temperature images acquired during the commissioning phase are shown.

Chapter 7 presents a change detection algorithm to obtain high resolution soil moisture estimates from SMAP radar and radiometer observations. The downscaling approach is tested using simulated SMAP data and active/passive airborne observations.

Chapter 8 summarizes the main conclusions of this work, remarks its original contributions, and presents suggestions for follow-on research.
It remains completely unknown to us what the objects may be by themselves apart from the receptivity of our senses. We know nothing but our manner of perceiving them...

Immanuel Kant (1724-1804)

2

Review of passive microwave remote sensing of soil moisture

The emission of thermal microwave radiation from soils is strongly dependent on its soil moisture content. The theoretical basis for measuring soil moisture at microwave frequencies lies in the large contrast between the dielectric properties of liquid water and soil material. This chapter reviews the theoretical and experimental background to remote sensing of soil moisture using microwave radiometry. The state-of-the-art of the soil moisture retrieval techniques is also included.

2.1 Basic concepts on microwave radiometry

The Earth continuously receives electromagnetic radiation coming mainly from the Sun. Part of it is scattered and/or absorbed by the atmosphere, and the other part is transmitted to the Earth’s surface. At the Earth’s surface, part of this energy is absorbed, and part is scattered outwards. The energy absorbed is then transformed into thermal energy, which leads to a temperature increase until the thermodynamic equilibrium is reached. At this state, according to Thermodynamics, all media (gases, liquids, solids and plasma) radiate energy to keep the energy balance. Radiometry is the field of science that studies the thermal electromagnetic energy radiated by the bodies. Radiometers are instruments capable of measuring the power emitted by a body with high accuracy. The basic concepts of microwave radiometry are reviewed in this section.

2.1.1 Brightness and power collected by an antenna

The power emitted by a source in a solid angle $\Omega$ by unit surface is called radiance or brightness $B(\theta, \phi)$ [Wsr$^{-1}$m$^{-2}$],

$$B(\theta, \phi) = \frac{F_t(\theta, \phi)}{A_t},$$

and depends on the source’s normalized radiation pattern $F_t(\theta, \phi)$ and the total radiating area $A_t$.

Considering the case represented in Fig. 2.1, where an antenna with effective area $A_t$ and normalized radiation pattern $F_n(\theta, \phi)$ is receiving an incident brightness coming from
an extended source (such as the sky or the terrain), the total power received by the antenna is given by

\[ P = \frac{A r}{2} \int_{f}^{f+\Delta f} \int_{4\pi} B_f(\theta, \phi) F_n(\theta, \phi) d\Omega df, \tag{2.2} \]

where \( B_f(\theta, \phi) \) is the spectral brightness, defined as the brightness per unit bandwidth \( df \), \( d\Omega \) is the differential of soil angle, and \( \Delta f \) is the bandwidth of the receiving antenna. The factor 1/2 accounts for the fact that thermal radiation is randomly unpolarized, while antennas can only collect one polarization.

### 2.1.2 Blackbody radiation

All bodies at a non-zero absolute physical temperature radiate electromagnetic energy. The increase of radiated energy is proportional to the temperature increase. In 1901, Planck introduced the concept of a blackbody radiator in his quantum theory, which represents a reference, relative to which the radiant emittance of a material can be expressed.

A blackbody is defined as an idealized, perfectly opaque material that absorbs all the incident radiation at all frequencies, reflecting none. Also, a blackbody is a perfect emitter, since otherwise its temperature would indefinitely increase. Therefore, when a black-body reaches the thermodynamic equilibrium, it radiates all the absorbed energy omnidirectionally. The blackbody spectral brightness \( B_f \) is given by the Planck’s radiation law:

\[ B_f \simeq \frac{2hf^3}{c^2} \left( e^{\frac{hf}{kB}T} - 1 \right)^{-1}, \tag{2.3} \]

where \( f \) is the frequency in Hz, \( h = 6.63 \cdot 10^{-34} \) J·s is the Planck’s constant, \( k_B = 1.38 \cdot 10^{23} \) J/K is the Boltzmann’s constant, \( T \) is the physical temperature in K, and \( c = 3 \cdot 10^8 \) m/s is the speed of light.

At microwave frequencies, \( hf/k_BT \ll 1 \), and the Taylor’s approximation

\[ e^x - 1 \approx (1 + x + \frac{x^2}{2} + \cdots) - 1 \simeq x, \text{ for } x \ll 1 \tag{2.4} \]
can be used to simplify (2.3) to

\[ B_f = \frac{2f^2k_B T}{c^2} = \frac{2k_BT}{\lambda^2}, \quad (2.5) \]

where \( \lambda = c/f \) is the wavelength. This is the Rayleigh-Jeans law, a low-frequency approximation of the Planck’s radiation law. The Rayleigh-Jeans law is widely used in microwave radiometry since it is mathematically simpler than the Planck law and has a deviation error smaller than 1% for \( f < 117 \text{ GHz} \) and \( T=300 \text{ K} \). A graphical comparison of the Planck law and the Rayleigh-Jeans law is provided in Fig. 2.2 for \( T=300 \text{ K} \) (≈ the Earth’s temperature) and \( T=6000 \text{ K} \) (≈ the Sun’s temperature).

\[ \text{Figure 2.2} \quad \text{Comparison of Planck radiation law with its low-frequency approximation (Rayleigh-Jeans law) for } T=300 \text{ K and } T=6000 \text{ K.} \]

Hence, the brightness of a blackbody \( B_{bb} \) at a physical temperature \( T \) and a bandwidth \( \Delta f \) in the microwave region can be expressed as

\[ B_{bb} = B_f \cdot \Delta f = \frac{2k_BT}{\lambda^2} \Delta f. \quad (2.6) \]

The power collected by an antenna with normalized radiation pattern \( F_n(\theta, \phi) \) surrounded by a blackbody at a constant physical temperature \( T \) is given by (2.2) and (2.5), and can be expressed as

\[ P_{bb} = \frac{Ar}{2} \int_0^{f+\Delta f} \int_0^{2\pi} \frac{2k_BT}{\lambda^2} F_n(\theta, \phi) d\Omega df. \quad (2.7) \]

The antenna solid angle can be expressed as a function of its effective area

\[ \Omega_p = \int_0^{2\pi} \int_0^{\pi} F_n(\theta, \phi) d\Omega = \frac{\lambda^2}{Ar}. \quad (2.8) \]

Hence, assuming the system bandwidth \( \Delta f \) small enough so that \( B_f \) can be considered constant over the frequency range, (2.7) becomes

\[ P_{bb} = k_BT\Delta f. \quad (2.9) \]

This direct linear relationship between power and temperature is of fundamental importance in microwave remote sensing, where the power received by an antenna is commonly given in units of temperature (see Section 2.1.4).
2.1.3 Gray body radiation

A blackbody is a useful theoretical concept for describing radiation principles, but real materials or gray bodies do not behave like blackbodies: they do not absorb all the energy incident upon them and its emission is lower than that of perfect blackbodies. It is therefore convenient to define a microwave brightness temperature $T_B(\theta, \phi)$, so that the brightness of a gray body can be expressed, similarly to (2.6), as

$$B(\theta, \phi) = \frac{2k_B}{\lambda^2} T_B(\theta, \phi) \Delta f.$$  \hfill (2.10)

$T_B(\theta, \phi)$ is the temperature that a blackbody would have to produce the observed brightness $B(\theta, \phi)$; it is not the real temperature of the object, but an effective temperature. The brightness of gray bodies relative to that of blackbodies at the same physical temperature is called the emissivity $e(\theta, \phi)$,

$$e(\theta, \phi) = \frac{B(\theta, \phi)}{B_{bb}} = \frac{T_B(\theta, \phi)}{T}.$$  \hfill (2.11)

Note that, since real materials emit less than a blackbody, $B(\theta, \phi) \leq B_{bb}$, and therefore $0 \leq e(\theta, \phi) \leq 1$. The emissivity equals 0 in the case of a perfect reflector (e.g. a lossless metal), and 1 in the case of a perfect absorber, a blackbody. Thus, the brightness temperature $T_B(\theta, \phi)$ of a material is always smaller than, or equal to, its physical temperature $T$.

2.1.4 Power-temperature correspondence

In the microwave region, since the radiance emitted by an object is proportional to its physical temperature (from (2.5)), it is convenient to express the radiance in units of temperature. Hence, the brightness temperature $T_B(\theta, \phi)$ is used to characterize the radiation of an object (from (2.10)). Similarly, an apparent temperature $T_{AP}$ is defined to characterize the total brightness incident over a radiometer antenna $B_i(\theta, \phi)$, as

$$B_i(\theta, \phi) = \frac{2k_B}{\lambda^2} T_{AP}(\theta, \phi) \Delta f.$$  \hfill (2.12)

Therefore, the power collected by an antenna with normalized radiation pattern $F_n(\theta, \phi)$ receiving a non-blackbody incidence brightness is given by (2.2) and (2.12),

$$P = \frac{A_r}{2} \int_{f_{m}}^{f_{m}+\Delta f} \int_{4\pi} 2k_B T_{AP}(\theta, \phi) F_n(\theta, \phi) d\Omega df.$$  \hfill (2.13)

It is convenient to define an antenna temperature $T_A$ as the temperature equivalent of the power received with an antenna, so that (2.9) holds as $P = k_B T_A \Delta f$ for gray bodies. Hence, $T_A$ can be expressed as

$$T_A = \frac{A_r}{\lambda^2} \int_{4\pi} T_{AP}(\theta, \phi) F_n(\theta, \phi) d\Omega.$$  \hfill (2.14)

Note that $T_A$ includes contributions from the target being observed as well as from radiation emitted and scattered from other sources, but not from internal elements.
2.1. Basic concepts on microwave radiometry

![Figure 2.3](image)

Figure 2.3 Radiation incident upon an Earth-looking radiometer. Relationships between the antenna temperature $T_A$, apparent temperature $T_{AP}$, and brightness temperature $T_B$, from Ulaby et al. [1981]

The case of prime interest in passive remote sensing is that of an Earth-looking radiometer, as illustrated in Fig. 2.3. In this case, the radiation incident upon the antenna is a function of both the land surface and the atmosphere, and may be expressed as

$$T_{AP}(\theta, \phi) = T_{UP} + (T_B + T_{SC}) \frac{1}{L_a},$$

(2.15)

where $T_B$ is the brightness temperature of the observed scene, $T_{UP}$ is the atmospheric upward radiation, $T_{SC}$ is the downward atmospheric radiation scattered by the Earth’s surface in the direction of the antenna, and $L_a$ represents the attenuation of the atmosphere. At the lower microwave frequencies used in soil moisture sensing, the atmospheric effects are small and may be safely neglected in most cases.

2.1.5 Measuring brightness temperatures from space

Space-borne radiometers are very sensitive receivers capable of measuring the radiance emitted by the Earth’s surface with high accuracy. They are designed to transform the radiation collected by an antenna into mappable electric signals, and its performance is usually characterized by its radiometric resolution, accuracy, and spatial resolution [Randa et al., 2008]:

- The radiometric resolution (sometimes called sensitivity) is computed as the smallest change in input brightness temperature or radiance that can be detected in the system output.

- The radiometric accuracy represents the closeness of the agreement between the measured antenna temperature and its true value (systematic error). Because the true value cannot be determined exactly, the measured or calculated value of highest available accuracy is typically taken to be the true value.

- The spatial resolution is the ability of the sensor to separate two closely spaced identical point sources.
In a remote sensing mission, in addition to instrumental errors, other phenomena can degrade the radiometric resolution and must be corrected (compensated for). At L-band, the atmosphere is almost transparent, and the main error sources are the Faraday rotation and the space radiation, which are described hereafter.

**Faraday Rotation**

When propagating through the ionosphere, a linearly polarized wave undergoes a progressive rotation of its plane of polarization due to the presence of the geomagnetic field and the anisotropy of the plasma medium [ITU-R P.531-6, 2001]. This phenomena is known as Faraday rotation, which may be expressed as:

\[ \varphi = 2.36 \cdot 10^{-14} B_{av} N_T f^{-2}, \]  

(2.16)

where \( \varphi \) [rad] is the rotation angle, \( f \) [GHz] is the frequency, \( N_T \) [electrons/m\(^2\)] is the ionospheric total electron content (TEC), and \( B_{av} \) [Wb/m\(^2\)] is the average Earth’s magnetic field along the propagation path.

**Figure 2.4** Typical values of Faraday rotation angle as a function of TEC and frequency, from *ITU-R P.531-6* [2001].

Figure 2.4 shows typical values of the Faraday rotation angle as a function of TEC and frequency. TEC is significantly affected by the solar radiation, and shows significant temporal and latitudinal variations; assuming low latitudes, the Faraday rotation angle at L-band can be as low as 4° at night (TEC of \( 10^{16} \) electrons/m\(^2\)) and as high as 30° at noon (TEC of \( 10^{18} \) electrons/m\(^2\)). This rotation may result in errors on the brightness temperatures of 1-10 K, which is sufficient to cause errors in the retrieval of the surface parameters [Yueh, 2000]. As it will be seen, an effective way to avoid this problem is to use the first Stokes parameter \( T_I = T_{xx} + T_{yy} = T_{hh} + T_{vv} \), which is invariant to rotations (see Section 2.1.6). Fully polarimetric measurements are also useful here since the Faraday effect only rotates the polarization, rather than changing the nature of the polarization. Note that, although the Faraday rotation could be compensated for, the accuracy of the Faraday estimations may not be enough for the required parameter’s accuracy.
Space radiation

Microwave radiation from space reflects over the Earth’s surface and is also measured by the antenna. Three main space phenomena should be considered, and their contribution to the antenna temperature needs to be taken into account:

- **The cosmic radiation level**: It is fairly constant (≈ 2.7 K) and, therefore, it does not affect the quality of measurements.

- **The galactic noise**: It comes from the reflection over the Earth’s surface of the pole or the center of the galaxy, and varies from 0.8 K to 40 K at L-band [LeVine and Abraham, 2002]. It should be either avoided, by selecting a convenient orbit, or corrected through the use of existing galactic noise maps. However, the absolute accuracy of these maps is still questionable and the scattering models present errors.

- **Sun glint**: It is the most important noise source, the Sun brightness temperature value is higher than 100,000 K, and any reflection of Sun radiation collected by the antenna would seriously affect measurements. Hence, direct reflections should be avoided by pointing the instrument to the shadow zone of a polar sun-synchronous orbit.

### 2.1.6 The Stokes parameters

The polarization of an electromagnetic wave can be completely described by the four Stokes parameters $I$, $Q$, $U$, $V$. The first Stokes parameter ($I$) describes the total intensity of electromagnetic emission and the second Stokes parameter ($Q$) is the difference between the intensity in two orthogonal directions in a given polarization frame, i.e., vertical and horizontal polarizations. The third ($U$) and fourth ($V$) Stokes parameters, respectively, represent the real and imaginary parts of the cross-correlation between these orthogonal polarizations [Randa et al., 2008]:

\[
I = \frac{\langle |E_v|^2 \rangle + \langle |E_h|^2 \rangle}{\eta_o},
\]

\[
Q = \frac{\langle |E_v|^2 \rangle - \langle |E_h|^2 \rangle}{\eta_o},
\]

\[
U = 2 \cdot \text{Re} \langle E_v E_h^* \rangle \eta_o,
\]

\[
V = 2 \cdot \text{Im} \langle E_v E_h^* \rangle \eta_o,
\]

(2.17)

where $E_v$ and $E_h$ are the electric field components at vertical and horizontal polarizations, respectively, and $\eta_o$ is the electromagnetic wave impedance of the medium (120π Ω in vacuum).

In polarimetric remote sensing radiometry the Stokes parameters are conventionally expressed in terms of brightness temperature:

\[
T_I = T_{vv} + T_{hh} = \frac{\lambda^2}{k_B T_w} \cdot I,
\]

\[
T_Q = T_{vv} - T_{hh} = \frac{\lambda^2}{k_B T_w} \cdot Q,
\]

\[
T_U = T_{-45} + T_{45} = \frac{\lambda^2}{k_B T_w} \cdot U,
\]

\[
T_V = T_{lc} + T_{rc} = \frac{\lambda^2}{k_B T_w} \cdot V,
\]

(2.18)
where \( \lambda \) is the wavelength, and \( B_w \) is the noise-equivalent bandwidth. \( T_{vv} \) and \( T_{hh} \) are the vertical and horizontal brightness temperatures, \( T_{45} \) and \( T_{-45} \) represent orthogonal measurements skewed \( \pm 45^\circ \) with respect to normal, and \( T_{lc} \) and \( T_{rc} \) refer to left-hand and right-hand circular polarized quantities. Note that in previously published literature, \( I, Q, U, \) and \( V \) have also been used for the Stokes parameters in brightness temperature – instead of \( T_I, T_Q, T_U, T_V \), which was a source of confusion. This practice was agreed to be discouraged in Randa et al. [2008].

Generally, the energy emitted from the Earth’s surface is partly polarized, meaning that the vertical brightness temperature is different from the horizontal. Whereas conventional dual-polarization radiometers only measure vertical and horizontal polarized brightness temperatures, a polarimetric radiometer is capable of directly or indirectly measuring all four Stokes parameters, which provides a full characterization of the polarization properties of the emitted energy.

Note that the Faraday rotation \( \varphi \) mixes the polarization as follows

\[
E_{v}^{\text{Faraday}} = E_v \cos \varphi + E_h \sin \varphi, \\
E_{h}^{\text{Faraday}} = -E_v \sin \varphi + E_h \cos \varphi.
\]  

Hence, the first and fourth Stokes parameter are invariant to rotations, whereas the second and third Stokes parameter are not. In remote sensing, third and fourth Stokes parameters are primarily used for correcting polarization rotation [Yueh et al., 1995; Martín-Neira et al., 2002] or, in the case of the ocean for instance, to infer wind direction information [Brown et al., 2006].

### 2.2 L-band emission of land covers

The theory behind L-band microwave remote sensing is based on the large contrast between the dielectric constant of dry soil (\( \sim 4 \)) and water (\( \sim 80 \)). This contrast results in a broad range in the dielectric properties of soil-water mixtures (4-40), and is the primary influence on the natural microwave emission from the soil [Schmugge et al., 1986]. The large dielectric constant of water is the result of the water molecule’s alignment of its permanent dipole in response to an applied electromagnetic field. Therefore, when water is added to the soil, its dielectric constant is strongly increased [Behari, 2005]. The emissivity of land covers depends on the dielectric constant of the soil surface—which is governed by the moisture content and soil type—, but also on other surface characteristics such as soil temperature, soil roughness, and vegetation canopy. The effects of these parameters on the emitted radiation are presented hereafter.

#### 2.2.1 Thermal radiation and surface emissivity

The thermal radiation or brightness temperature emitted by the Earth’s surface (\( T_{Bp} \)) is determined by its physical temperature \( T \) and its emissivity \( e_p \) (see Section 2.1.3), according to:

\[
T_{Bp} = e_p \cdot T,
\]  

where the subscript \( p \) denotes either vertical (\( v \)) or horizontal (\( h \)) polarization. The emissivity may be further related to the reflectivity \( \Gamma_{s,p} \) of the surface:

\[
e_p = 1 - \Gamma_{s,p}.
\]
2.2. L-band emission of land covers

For a flat surface, and a medium of uniform dielectric constant, the expressions for reflectivity at vertical and horizontal polarizations are given by the power Fresnel reflection coefficients \((\Gamma_{s,p} \approx \Gamma_{o,p})\), as:

\[
\Gamma_{ov} = \frac{|\epsilon_s \cos \theta - \sqrt{\epsilon_s - \sin^2 \theta}|^2}{|\epsilon_s \cos \theta + \sqrt{\epsilon_s - \sin^2 \theta}|^2},
\]

\[
\Gamma_{oh} = \frac{|\cos \theta - \sqrt{\epsilon_s - \sin^2 \theta}|^2}{|\cos \theta + \sqrt{\epsilon_s - \sin^2 \theta}|^2},
\]

(2.22)

where \(\theta\) is the incidence angle and \(\epsilon_s\) is the complex dielectric constant of soils, which is in turn governed by the moisture content and the soil type.

2.2.2 Water in soils

Water in soils is commonly classified as bound and free water; bound water is the water absorbed by the surface of soil particles, while free water is the liquid water located in the pore spaces. The porosity of a soil determines the total volume occupied by pores per unit volume of soil. Soils with small pores (clayey soils) will hold more water per unit volume than soils with large pores (sandy soils). While pore spaces of dry soils are mostly filled with air, pore spaces of wet soils are filled with water. Processes such as infiltration, ground-water movement, and storage occur in these void spaces.

The soil moisture, or water in a soil, is expressed as a ratio, which can range from 0 (completely dry) to the value of the materials’ porosity at saturation (\(\sim 0.5\)). It is usually expressed in per cent, and can be determined in two ways:

1. Gravimetric soil moisture \(m_g\), which is defined as the mass of water per unit mass of dry soil, and can be calculated from the wet \(w_w\) and dry \(w_d\) weights of a soil sample, as:

\[
m_g = \frac{w_w - w_d}{w_d}.
\]

(2.23)

2. Volumetric soil moisture \(m_v\), defined as the volume of water per unit volume of soil, determined from the volume of water \(V_w\) and the total volume \(V_T\) (soil volume + water volume + void space), and related to \(m_g\) through the soil bulk density \(\rho_b\):

\[
m_v = \frac{V_w}{V_T} = m_g \rho_b = m_g \frac{w_d}{V_T}.
\]

(2.24)

Since precipitation, evapotranspiration and other water-related variables are commonly expressed in terms of flux, volumetric expressions for water content are often preferred in environmental studies. Furthermore, the in situ soil moisture measurements used to validate remote sensing observations are commonly acquired using dielectric probes, which directly provide volumetric measurements. Hence, soil moisture measurements are expressed in volumetric units throughout this work.

2.2.3 Dielectric properties of soils

Soil emission at microwave frequencies is related to the soil water content by the dielectric constant. The dielectric constant is a measure of the soil response to an electromagnetic
wave; it is defined as a complex number ($\epsilon_s = \epsilon'_s + j\epsilon''_s$), where the real part determines the propagation characteristics of the energy as it passes through the soil, and the imaginary part determines the energy losses. In a heterogeneous medium such as the soil, the complex dielectric constant is a combination of the individual constituent parts, including air, water, rock, etc. Other factors which influence the dielectric constant are soil texture, temperature, salinity, and wavelength. The dielectric constant is a difficult quantity to measure on a routine basis outside the laboratory, and values are generally derived from semi-empirical models that use an estimation of the ratio rock/water/air based on the given soil properties [Wang and Schmugge, 1980; Hallikainen et al., 1985; Dobson et al., 1985; Mironov et al., 2004]. Comprehensive information on the different dielectric constant models is reported, among others, in [Behari, 2005] and [Chukhlantsev, 2006].

![Figure 2.5](image)

**Figure 2.5** Measured dielectric constant at 1.4 GHz for five soils with different textural composition, from Hallikainen et al. [1985]

The relationship between the measured dielectric constant and the volumetric soil moisture content for a variety of soil types at a frequency of 1.4 GHz is shown in Fig. 2.5. The dependence on soil type is due to the different percentages of water bound to the particle surfaces in the different soils, which takes minimum values in sands (2-3%) and maximum values in clays (20-40%). Bound water exhibits molecular rotation less freely than free water, and contributes little to the dielectric constant of the soil water mixture. This is evident in clay soils, which hold greater percentages of bound water, and therefore have a lower dielectric constant than sandy or silty soils at the same moisture content. Also, Fig. 2.5 shows that the relationship between dielectric constant and volumetric soil moisture is almost linear, except at low moisture contents. This non-linearity at low moisture contents is due to the strong bonds developed between the surfaces of soil particles and the thin films of water that surround them, which impede the free rotation of the water molecules. As more water is added, the molecules are further from the particle surface and are able to rotate...
more freely, hence increasing the soil dielectric constant [de Jeu et al., 2008].

Soil moisture, through its relationship to the real and imaginary parts of the dielectric constant, has an impact on the soil penetration depth. The penetration depth $\gamma_D$ is defined as the soil depth from above which 63% ($1 - 1/e$) of the radiation emitted by the surface originates [Ulaby et al., 1981], and can be expressed as:

$$\gamma_D = \frac{\lambda \sqrt{\epsilon'_s}}{2\pi \epsilon_s},$$

(2.25)

The penetration depth of microwaves rapidly decreases with increasing soil wetness; for a wavelength $\lambda$ of 21 cm (L-band), $\gamma_D$ varies from approximately 75 cm for a normally dry soil ($\epsilon'_s = 5$ and $\epsilon''_s = 0.1$) to about 3.7 cm for a wet soil ($\epsilon'_s = 30$ and $\epsilon''_s = 5$). Knowledge of the penetration depth is important because it is an indicator of the thickness of the surface layer within which variations in moisture and temperature can significantly affect the emitted radiation.

The dielectric constant of dry soils is almost independent of temperature; for wet soils, the dielectric constant is only weakly dependent on temperature, and for the range of temperatures encountered in nature this dependence may be ignored. However, frozen soils have much lower dielectric constants than unfrozen soils, as the contained water is no longer in liquid phase. This feature has led to studies of microwave radiometry for detecting areas of permafrost and freeze-thaw boundaries in soils [England, 1990].

### 2.2.4 Surface roughness

The effect of surface roughness on the microwave emission from bare soils is illustrated in Fig. 2.6, which shows experimental data measured at 1.4 GHz for three fields with different surface roughness conditions [Newton and Rouse, 1980]. It shows that surface roughness increases the emissivity of natural surfaces—due to the increase in the soil area interacting with the atmosphere—and reduces the difference between the vertical and horizontal polarizations. Also, the sensitivity of emissivity to soil moisture variations decreases significantly as the surface roughness increases, since it reduces the range in measurable emissivity from dry to wet soil conditions [Wang, 1983].

The effect of soil surface roughness on the emissivity has been an issue widely addressed in the literature, and different approaches have been proposed to modify the reflectivity in (2.21) for rough surfaces. Peake [1959] developed an integral equation model to fully characterize the scattered radiation. A simpler, semi-empirical expression for rough surface reflectivity was reported in Choudhury et al. [1979]:

$$\Gamma_{sp} = \Gamma_{op} \exp(-h_s \cos^2(\theta)), \tag{2.26}$$

where $\Gamma_{op}$ is the reflectivity at $p$-polarization ($p=v$ or $h$) of a flat surface given by (2.22), $h_s = 4k^2\sigma^2_s$ is the soil roughness parameter, related to the electromagnetic wavenumber $k$ and the standard deviation of the surface height $\sigma_s$, and $\theta$ is the incidence angle. A more elaborated formulation was proposed in Wang and Choudhury [1981]:

$$\Gamma_{sp}(\theta) = [(1 - Q_s)\Gamma_{op}(\theta) + Q_s\Gamma_{op}(\theta)] \exp(-h_s \cos^n(\theta)), \tag{2.27}$$

where $Q_s$ models the effects of the polarization mixing and $n$ expresses the angular dependence of roughness.
A detailed analysis of the soil roughness effects performed by Wigneron et al. [2001] showed that both $Q_s$ and $n$ could be set equal to zero at L-band and that the roughness parameter $h_s$ could be semi-empirically estimated comprising most surface roughness conditions. Typical values for $h_s$ have been suggested, ranging from 0.2 for a smooth surface, to 1 for a rough ploughed field. This is consistent with L-band airborne and ground-based experiments, where soil roughness has generally found to be rather smooth over agricultural or natural areas [Jackson et al., 1999; Panciera et al., 2009; Saleh et al., 2009].

Also, recent studies have introduced an $h_s$ parametrization dependent on soil moisture [Wigneron et al., 2001; Schneebberger et al., 2004; Escorihuela et al., 2007]. However, these studies have been performed under very local conditions, and there is no evidence of the potential benefits that they may introduce at global scale. To date, the accuracy of the approaches linking $h_s$ and soil moisture is not well established for a variety of roughness conditions and the relationship between $h_s$, surface roughness characteristics such as $\sigma_s$ or correlation length, and soil moisture has not been fully understood.

### 2.2.5 Vegetation effects

When the soil is covered by vegetation, its emission is affected by the canopy layer: it absorbs and scatters the radiation emanating from the soil and also adds its own contribution. In areas of sufficiently dense canopy, the emitted soil radiation will become masked, and the observed emissivity will be due largely to the vegetation. The magnitude of the absorption by the canopy depends upon the wavelength and the vegetation water content.

A variety of models have been developed to account for the effects of vegetation on the observed microwave signal [Kirdiashev et al., 1979; Mo et al., 1982; Jackson et al., 1982;
2.2. L-band emission of land covers

Ulaby and Wilson, 1985; Wigneron et al., 1995; Meesters et al., 2005]. Altogether, the radiation from the land surface as observed from above the canopy is usually expressed as a simple radiative transfer equation known as the \( \tau - \omega \) model [Mo et al., 1982]:

\[
T_{Bp} = e_p T_s \gamma + (1 - \omega) T_v (1 - \gamma) + (1 - e_p)(1 - \omega) T_v (1 - \gamma) \gamma, \tag{2.28}
\]

where \( T_s \) and \( T_v \) are the effective temperatures of the soil and the vegetation respectively, \( \gamma \) is the transmissivity of the vegetation layer, and \( \omega \) is the single scattering albedo. The first term of the above equation defines the radiation from the soil as attenuated by the overlying vegetation. The second term accounts for the upward radiation directly from the vegetation, while the third term defines the downward radiation from the vegetation, reflected upward by the soil and again attenuated by the canopy.

The single scattering albedo \( \omega \) describes the scattering of the soil emissivity within the vegetation, and is a function of soil geometry. The transmissivity of the vegetation can be further defined in terms of the vegetation optical depth \( \tau \) and the incidence angle \( \theta \):

\[
\gamma = \exp(-\tau / \cos(\theta)). \tag{2.29}
\]

The optical depth is related to the vegetation density and frequency, and can be linearly related to the vegetation water content VWC [kg/m\(^2\)] at L-band through an empirical parameter, \( b \) [van de Griend and Wigneron, 2004]:

\[
\tau = b \cdot \text{VWC}. \tag{2.30}
\]

Alternatively, the vegetation optical depth could also be linearly related to the log of the Normal Difference Vegetation Index (NDVI) [Burke et al., 2001]:

\[
\tau = \alpha + \beta (1 - \log(\text{NDVI})). \tag{2.31}
\]

There is some experimental evidence indicating possible polarization and angle dependence of both \( \tau \) and \( \omega \). However, this dependence has been observed mainly during field experiments over vegetation that exhibits a predominant orientation, such as vertical stalks in tall grasses, grains and maize [Kirdiashev et al., 1979; Wigneron et al., 1995; Hornbuckle et al., 2003], whereas canopy and stem structure of most vegetation covers are randomly oriented. However, the effects of any systematic orientation of vegetation elements would most likely be minimized at satellite scales [Owe et al., 2001; Martínez-Vázquez et al., 2009].

Both SMOS and SMAP orbits were chosen with overpass times of 6 am/6 pm, so that temperature gradients within the soil and vegetation are minimized. Hence, (2.28) can be simplified assuming that the temperature of the vegetation canopy is in equilibrium with the soil temperature \( (T_s = T_v) \) [Hornbuckle and England, 2005]. Therefore, (2.28) may be rewritten as:

\[
T_{Bp} = [e_p \gamma + (1 - \omega)(1 - \gamma)(1 + (1 - e_p) \gamma)] T_s. \tag{2.32}
\]

Figure 2.7 shows the dependence of brightness temperature with incidence angle and polarization for six main surface conditions combining dry, moist and wet soils with bare and vegetation-covered surfaces, from (2.32). In the bare soil scenarios on Fig. 2.7 (a), it can be seen that V-pol increases with the incidence angle, whereas H-pol decreases with increasing incidence angle. Fig. 2.7 (b) shows that vegetation increases the soil emissivity, and decreases the difference between the vertically and horizontally polarized brightness temperatures, and between the dry and wet soil conditions. This indicates that correction for the vegetation effects is necessary to obtain accurate soil moisture estimates. Furthermore,
retrievals become increasingly unreliable as the opacity of the vegetation layer increases [Jackson and Schmugge, 1991]. Figure 2.7 also illustrates that the emissivity of dry soils is greater than the emissivity of wet soils, with a soil brightness temperature variation at nadir of $\sim 80$ K in the bare soil scenarios and of $\sim 40$ K in the vegetation-covered scenarios. In the two cases, this variation is much larger than the noise sensitivity threshold of a microwave radiometer (typically $< 1$ K), so that a large signal-to-noise ratio is obtained. This is a major advantage of the passive microwave technique for soil moisture remote sensing.

2.3 Soil moisture retrieval techniques

The brightness temperature of land covers is influenced by many variables, the most important being soil moisture $s_m$, soil roughness (parameterized by the soil roughness parameter $h_s$), soil temperature $T_s$, and vegetation characteristics such as albedo $\omega$ and opacity $\tau$. The challenge of retrieval or inversion techniques is to reconstruct the environmental parameters from the measured signal by using a minimum of auxiliary data. Within the SMOS and SMAP preparatory activities, different soil moisture retrieval algorithms have been developed and validated from microwave modeling and field experiments using ground-based, airborne, and space shuttle instruments.

The first retrieval techniques were based on deriving an empirical relationship between the geophysical variables and the radiative transfer equation through a regression technique (see the review by Wigneron et al. [2003]). However, these approaches have limited applicability, since the regression is often valid only for the test sites where they were obtained.

Another approach to soil moisture retrieval is based on the use of neural networks. These algorithms have been used with satisfactory results in the retrieval of agricultural parameters from radiometric data [Frate et al., 2003], but need a training phase that is not always feasible.

A third type of algorithms are based on the inversion of geophysical model functions. This is the most widely-used retrieval technique; it is the one adopted by SMOS, and by
SMAP for the passive-only soil moisture product. The SMOS retrieval algorithm is designed so as to make full use of its multi-angular dual-polarization/full-polarimetric observations, whereas the SMAP algorithm is based in observations at a constant incidence angle $\theta = 40^\circ$.

In the case of SMAP, the high resolution radar will be additionally used to identify inland water bodies, topography, and vegetation characteristics within the 40 km radiometer resolution. The use of radar-derived information in the retrievals for the estimation of vegetation characteristics is also under consideration [Meesters et al., 2005; Kurum et al., 2009].

### 2.3. Soil moisture retrieval techniques

#### SMOS multi-angular retrieval algorithm approach

The SMOS soil moisture retrieval algorithm consists of inverting a geophysical model function by finding the set of input variables (mainly five: $s_m$, $T_s$, $h_s$, $\omega$ and $\tau$) which generate the brightness temperatures that best match the observed brightness temperatures. This inversion is performed by minimizing a cost function that accounts for the weighted squared differences between model and measured data, using the iterative Levenberg-Marquardt method [Marquardt, 1963]. The $\tau - \omega$ geophysical model function in (2.28) is the core of the forward model used to mimic the Earth’s emission at L-band (the L-MEB model [Wigneron et al., 2007]).

Assuming that the measurement errors are Gaussian, the fundamental least-squares cost function ($CF$) for observation-model misfits is:

$$CF = (F^{\text{meas}} - F^{\text{model}})^T C_{F}^{-1} (F^{\text{meas}} - F^{\text{model}}) + (p_i - p_{i0})^T C_p^{-1} (p_i - p_{i0}), \quad (2.33)$$

where $F^{\text{meas}}$ and $F^{\text{model}}$ are vectors of length $N$ containing the microwave radiometer observations at different incidence angles, measured by MIRAS and obtained using the forward model, respectively. $N$ is the number of observations of the same point at different incidence angles acquired in a satellite overpass; $C_F$ is the covariance matrix of the observations, which depends on the SMOS operation mode and the reference frame [Camps et al., 2005]; $p_i$ are the retrieved physical parameters that may influence the modeled $T_B$, including $s_m$, $T_s$, $h_s$, $\tau$ and $\omega$; $p_{i0}$ are prior estimates of parameters $p_i$ (obtained from other sources such as satellite measurements or model outputs, the auxiliary information); and $C_p$ is a diagonal matrix containing the variances of the prior estimates of parameters $\sigma^2_{p,0}$ [SMOS Algorithm Theoretical Bases Document, 2007].

If the model error is uncorrelated between different measurements, then $C_F$ is diagonal, and (2.33) can be expressed as:

$$CF = \sum_{n=1}^{N} \frac{||F_{n}^{\text{meas}} - F_{n}^{\text{model}}||^2}{\sigma^2_{F_n}} + \sum_{i=1}^{M} \frac{(p_i - p_{i0})^2}{\sigma^2_{p,0}}, \quad (2.34)$$

where $\sigma_{F_n}$ is the radiometric accuracy for the $n^{th}$ observation, and $M$ is the number of parameters $p_i$ to be retrieved. $\sigma_{p,0}$ represents the uncertainty on the $a \ priori$ parameter $p_{i0}$, and its value is used to parameterize the constraint on the parameter $p_i$ in the retrievals: $p_i$ can be set to be free ($\sigma_{p,0} = 100$, no $a \ priori$ information is used), it can be constrained to be more or less close to the reference value $p_{i0}$, or it can be constant ($\sigma_{p,0} < 10^{-3}$, assuming high accuracy on the $a \ priori$ information). Note that $p_{i0}$ are specified $a \ priori$, whereas $p_i$ values are adjusted during the minimization process.

The retrieval of the geophysical parameters can be formulated using the vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations separately ($F_n = [T_{vv}, T_{hh}]^T$ in the Earth reference frame and
Chapter 2. Review of passive microwave remote sensing of soil moisture

$F_n = [T_{xx}, T_{yy}]^T$ in the antenna frame), or using the first Stokes parameter ($F_n = [T_I]^T = [T_{xx} + T_{yy}] = [T_{hh} + T_{vv}]$) \cite{Camps2005}. These two approaches will be considered in this work. Note that, up to date, the formulation of the soil moisture retrieval problem on the Earth reference frame is the preferred option for SMOS \cite{Pard2004, Saleh2009}. Hence, the formulation of the problem in terms of the first Stokes parameter is presented as an alternative approach, since retrievals using $T_I$ could benefit of having less angular dependency than $(T_{vv}, T_{hh})$, therefore reducing the degrees of freedom during the inversion process, which could lead to better soil moisture retrievals. Also, retrievals using $T_I$ are unaffected by Faraday rotations, which is critical from an operational point of view.

The SMOS soil moisture retrieval algorithm is robust and has been demonstrated using both field campaign and synthetic model-generated data. However, radiometer observations must be combined with auxiliary data in the inversion process to achieve the required accuracy ($0.04 \text{ m}^3/\text{m}^3$) and the retrieval setup needs yet to be optimized. In this Thesis, key aspects for the retrieval of accurate soil moisture estimations from SMOS have been addressed: in Chapter 3, the auxiliary data impact on soil moisture retrievals is thoroughly evaluated and an optimal retrieval configuration is devised; in Chapter 4, the soil moisture inversion algorithm is analyzed both theoretically and in terms of performance with simulated SMOS data. After the successful launch of SMOS in November 2009, these studies will timely contribute to consolidate the operational soil moisture retrieval algorithm, which is essential to demonstrate the SMOS capabilities over land.
Auxiliary data impact on SMOS soil moisture retrievals

Previous studies have remarked the necessity of combining SMOS brightness temperatures with auxiliary data to retrieve soil moisture with an accuracy better than the 0.04 m$^3$/m$^3$ benchmark. However, the required auxiliary data and optimal soil moisture retrieval setup need yet to be optimized. This chapter examines the performance of the SMOS soil moisture retrieval algorithm for different retrieval configurations, depending on the ancillary information that is used in the retrievals and its associated uncertainty. Also, the impact of using vertical and horizontal brightness temperatures, or using the first Stokes parameter in the minimization process is analyzed. Results with simulated SMOS data show the accuracy obtained with the different retrieval setups for four main surface conditions combining wet and dry soils with bare and vegetation-covered surfaces, and an optimum soil moisture retrieval configuration is devised.

3.1 Introduction

The SMOS mission aims at providing the first global soil moisture measurements with an accuracy of 0.04 m$^3$/m$^3$ over 50 x 50 km$^2$ and a temporal resolution of 3 days. There is also a high interest in obtaining vegetation water content (VWC) maps with an accuracy of 0.2 kg/m$^2$ from SMOS observations [Mission Objectives and Scientific Requirements of the SMOS mission, 2003]. The retrieval of soil moisture from passive microwave remote sensing observations has been described in considerable detail in Chapter 2.

The bare soil emissivity depends mainly on its surface roughness (determined using the soil roughness parameter $h_s$), surface temperature $T_s$, and soil dielectric constant, which is in turn related to the soil moisture content $s_m$ and soil type. When the soil is covered by vegetation, its emission is affected by the canopy layer: it attenuates the soil emission and adds its own contribution. The vegetation optical depth $\tau$ (from which vegetation water content maps can be derived [van de Griend and Wigneron, 2004]) is used to account for the vegetation attenuation, and the vegetation albedo $\omega$ is used to describe the dispersion of the radiation within the vegetation (see Section 2.2). Several configurations have been proposed for de-coupling the contribution of each of these surface parameters in the L-band emission and hence retrieving soil moisture from SMOS observations. For instance, Wigneron et al.
[1995] presented the possibility of simultaneously retrieving $s_m$ and $\tau$ (the two parameter 2-P retrieval method) using experimental L-band observations over crop fields. The so-called 3-P retrieval method, in which $T_s$ is retrieved in addition to $s_m$ and $\tau$, is applied to a synthetic simulated dataset in Pellarin et al. [2003]. By extension, the N-P retrieval method, where N corresponds to the number of parameters that are retrieved, is analyzed in Pardé et al. [2004] and Camps et al. [2005]. In all these studies, the parameters are retrieved by minimizing a Cost Function (CF) which accounts for the weighted squared differences between measured and simulated brightness temperatures – using for the later the $\tau - \omega$ radiative model [Ulaby and Wilson, 1985; Mo et al., 1982] – and between the retrieved quantities and their estimated values, with weights reflecting a priori uncertainties on these variables (see Section 2.3).

Since different retrieval setups lead to different accuracy results, an in-depth study of the different cost function configurations for retrieving soil moisture estimates from SMOS observations is paramount. Although some retrieval issues regarding the parameters to be retrieved have been analyzed in the above-cited studies, the a priori information used in the retrievals and its required uncertainty are key aspects yet to be determined. Also, the optimum MIRAS operation mode (dual-polarization or full-polarimetric) is an open issue to be addressed during the commissioning phase activities. In this study, the ancillary data impact on soil moisture and vegetation optical depth retrievals is thoroughly evaluated using SMOS simulated data, the use of the vertical ($T_{vv}$) and horizontal ($T_{hh}$) brightness temperatures separately, and of the first Stokes parameter ($T_I$) on the minimization process is explored, and an optimal retrieval configuration is devised. The simulation strategy is described in Section 3.2, and simulation results are analyzed in Section 3.3. The main findings and contributions of this work are discussed in Section 3.4.

### 3.2 Simulation and retrieval strategy

The performance of different retrieval configurations, depending on the a priori information that is used in the retrievals and its associated uncertainty, is analyzed using SMOS-like brightness temperatures ($T_B$) generated by SEPS. The L2 Processor Simulator, in turn, is used to retrieve soil moisture from SEPS realistic $T_B$ (see Section 1.3.1). The L2 Processor integrates the forward model in Section 2.2 and the optimization algorithm in Section 2.3.

In the forward modeling, the effect of surface roughness on the microwave emission has been corrected using (2.27), where $Q_s$ and $n$ have been set equal to zero, according to Wigneron et al. [2001], and the roughness parameter $h_s$ has been retrieved as a free parameter, without using any interdependency on soil moisture or surface roughness characteristics (see Section 2.2.4). The vegetation contribution has been modeled using (2.32), where it is assumed that: (i) vegetation canopy is in equilibrium with soil temperature, (ii) $\tau$ and $\omega$ are polarization and angle independent (see Section 2.2.5). The dielectric mixing model in Wang and Schmugge [1980] has been used to relate soil moisture to soil emissivity, where soil texture has been assumed to be equal to the ECOCLIMAP’s mean global clay and sand fractions [Masson et al., 2003], which are 20.4% and 48.3%, respectively, and soil porosity has been set to 38%.

In the present study, the impact that the uncertainty of the ancillary data used in the minimization process has on the retrieval of soil moisture and vegetation optical depth from SMOS observations has been thoroughly evaluated. To do so, the five parameters dominating the microwave emission at L-band ($s_m$, $h_s$, $T_s$, $\omega$ and $\tau$) have been considered as possible a priori information to be used in the retrievals; the uncertainties of $s_m$ and $h_s$
3.2. Simulation and retrieval strategy

over the bare soils scenarios, and of $\tau$ and $\omega$ over the vegetation-covered scenarios have been progressively tuned in different L2 Processor simulations, starting from very large values (no prior information is added) to very restrictive conditions (high confidence on the a priori information). $T_s$ is set to its first-guess value during the retrieval process with an accuracy of 2 K, in agreement with results of previous studies [Pellarin et al., 2003; Pardé et al., 2004; Davenport et al., 2005]. Then, when all uncertainties are set to large values, all parameters are free and retrieved (i.e. an N-P approach). In contrast, when a high constraint is imposed on a parameter, it is set to a constant value and, therefore, it is not retrieved (i.e. 2-P is explored when a high constraint is imposed on $h_s$ and $\omega$, and $s_m$ and $\tau$ are free and retrieved).

Also, each simulation has been formulated using vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations separately and using the first Stokes parameter ($T_I$) so as to compare these two approaches. Note that, up to date, the formulation of the SMOS-derived soil moisture retrieval problem on the Earth reference frame (and therefore the use of the full-polarimetric mode) is the preferred one [Pardé et al., 2004; Saleh et al., 2009]. Hence, in this study the retrieval is formulated in terms of $T_I$ as an alternative approach, since retrievals using the first Stokes parameter could benefit of having less angular dependency than $T_{vv} - T_{hh}$, therefore reducing the degrees of freedom during the inversion process, which could lead to better soil moisture retrievals. Also, retrievals using $T_I$ are more robust to geometric and Faraday rotations, which is critical from an operational point of view.

Note that the use of $T_{vv} - T_{hh}$ or $T_I$ may be linked to the choice of the MIRAS full-polarimetric mode or the dual-polarization mode, respectively. If retrievals are formulated using the two polarizations separately, the Faraday rotation in the ionosphere should be corrected since at L-band it can be sufficient so as to cause errors in the retrieval of the surface parameters (see Section 2.1.5). Therefore, as third and/or fourth Stokes parameters could be highly useful for a precise Faraday correction, the $CF$ formulation in the Earth or antenna frame is usually linked to the use of the full-polarimetric mode. Also, large singularities are induced by the inversion of the geometric and Faraday rotations while passing the measured brightness temperatures from antenna to Earth frame in dual-polarization mode [Waldteufel and Caudal, 2002]. In contrast, $T_I$ is unaffected by Faraday rotation; retrievals using the first Stokes parameter can be calculated in the two operation modes, with the difference that when the dual-polarization mode is used the integration time is maximized and better radiometric sensitivity could be obtained [Camps et al., 2005].

It is important to outline that retrievals are performed under the following guidelines and assumptions:

- The geophysical models used in the L2 Processor Simulator are the same as in SEPS.
Then, the effect of the model used is not affecting the results.

- The performance of the cost function configuration is not dependent on $\sigma_{F_n}$, since the absolute accuracy of the radiometric measurements is available on the SEPS output and is used in the retrievals.

- The search limits of the retrieved variables in the $CF$ have been reduced within reasonable bounds, namely $0 \leq s_m \leq 0.5 $ m$^3$/m$^3$, $250 \leq T_s \leq 350$ K, $0 \leq h_s \leq 5$, $0 \leq \tau \leq 3$ Np, and $0 \leq \omega \leq 0.3$, to reduce the computational time.

- The reference values of the parameters used in the $CF$ are determined from a normal distribution with a standard deviation of 2 K for $T_s$, 0.05 for $h_s$, 0.1 for $\omega$, 0.1 Np for $\tau$, and 0.04 m$^3$/m$^3$ for $s_m$, added to the original values. Thus, since realistic initial values
are used on the minimization process, the study focuses on selecting the optimum level of a priori information to be used in the retrievals and its associated uncertainty.

These simplifications are needed to make an homogeneous and approachable intercomparison study of the different retrieval configurations. However, note that further studies will be required to assess the limitations imposed by heterogeneity of vegetation cover and soil characteristics within a satellite footprint.

Four master scenarios (bare dry soil, bare wet soil, vegetation-covered dry soil and vegetation-covered wet soil) have been created using SEPS with the aim of comparing the different retrieval configurations and addressing separately the contribution of the bare soil parameters \( s_m, T_s \) and \( h_s \), and of the vegetation descriptors \( \tau \) and \( \omega \), on a dry and on a wet soil. Constant input parameters have been used in the simulations to evidence the contribution of each parameter in the final result and facilitate the analysis. Soil moisture values of 0.02 m\(^3\)/m\(^3\) and 0.2 m\(^3\)/m\(^3\) have been defined to represent dry and wet soils, respectively, the \( h_s \) is set to 0.2 –representing rather smooth roughness conditions–, and nominal values are given to the vegetation parameters \( \tau = 0.24 \) Np and \( \omega = 0 \) [SMOS Algorithm Theoretical Bases Document, 2007]. These parameters have been summarized in Table 3.1.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( s_m ) [m(^3)/m(^3)]</th>
<th>( h_s )</th>
<th>( T_s ) [K]</th>
<th>( \tau ) [Np]</th>
<th>( \omega )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare dry soil</td>
<td>0.02</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bare wet soil</td>
<td>0.2</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dry soil + canopy</td>
<td>0.02</td>
<td>0.2</td>
<td>300</td>
<td>0.24</td>
<td>0</td>
</tr>
<tr>
<td>Wet soil + canopy</td>
<td>0.2</td>
<td>0.2</td>
<td>300</td>
<td>0.24</td>
<td>0</td>
</tr>
</tbody>
</table>

### 3.3 Simulation results

On a first stage, a bare soil scenario is simulated to retrieve \( s_m, T_s \) and \( h_s \). It is assumed that \( T_s \) is known by means of thermal infrared observations and/or meteorological models with an accuracy of 2 K, so \( \sigma_{T_s} \) is set to 2 K [Wan, 2008]. The entire range of variability of \( s_m \) and \( h_s \) on the CF is analyzed and results are shown for bare dry and wet soil on Fig. 3.1 (a) and (b), respectively, using \( T_{vv} - T_{hh} \) and on Fig. 3.2 (a) and (b), respectively, using \( T_I \). From these results, it can be inferred that it is important –although not critical– to add a restriction on the soil roughness parameter \( h_s \). An expected error of 0.05 on \( h_s \) is therefore suggested for the soil moisture retrieval scheme. With this constraint, SMOS scientific requirements are met in the case of using \( T_I \) (a \( s_m \) RMSE of 0.02 m\(^3\)/m\(^3\) is obtained over dry soils and of 0.04 m\(^3\)/m\(^3\) over wet soils). In the case of using \( T_{vv} - T_{hh} \), however, a \( s_m \) RMSE of \( \approx 0.08 - 0.09 \) m\(^3\)/m\(^3\) is obtained over both dry and wet soils.

After this initial study, a vegetation-covered scenario is simulated to retrieve \( s_m, T_s, \tau \) and \( \omega \). On these experiments \( h_s \) is set to 0.2 and will not be retrieved so as to de-couple the effect of soil roughness, and no restrictions are added on soil moisture (\( \sigma_{s_m} = 100 \) m\(^3\)/m\(^3\)). Therefore, the simulations over vegetation-covered scenes embrace the entire range of variability of the vegetation descriptors \( \tau \) and \( \omega \), keeping \( \sigma_{s_m} = 100 \) m\(^3\)/m\(^3\) and \( \sigma_{T_s} = 2 \)
3.3. Simulation results

K. Retrieved $s_m$ RMSE versus the uncertainty on $\tau$ is shown for dry and wet soils on Fig. 3.1 (c) and (d), respectively, using $T_{vv}-T_{hh}$ and on Fig. 3.2 (c) and (d) using $T_I$. From these figures, it can be noted that there is a strong decrease of the brightness temperatures sensitivity to $s_m$ in the presence of vegetation and that $s_m$ RMSE increases with $\sigma_\tau$. When $\sigma_\tau \rightarrow \infty$, $s_m$ RMSE converges nearly to the same values in the two formulations ($s_m$ RMSE $\approx 0.11 - 0.14 \; m^3/m^3$ for vegetation-covered dry soils and $s_m$ RMSE $\approx 0.10 - 0.11 \; m^3/m^3$ for vegetation-covered wet soils). Since there is also a high interest in deriving VWC maps from future SMOS observations, the optical depth RMSE obtained with the different simulations has also been analyzed and is plotted versus the uncertainty on $\tau$ on Fig. 3.1 (e) and (f) for vegetation-covered dry and wet soils, respectively, using $T_{vv}-T_{hh}$ and on Fig. 3.2 (e) and (f), respectively, using $T_I$. From these figures, it can be remarked that optical depth RMSE increases monotonically with $\sigma_\tau$ when using the two formulations. In the case of high uncertainty on the vegetation parameters ( $\sigma_\tau = 3, \sigma_\omega \rightarrow \infty$), $\tau$ RMSE converges to the same values for dry and wet soils: $\tau$ RMSE $\approx 0.8 - 0.9 \; Np$ using $T_{vv}-T_{hh}$ and $\tau$ RMSE $\approx 0.5 \; Np$ using $T_I$.

The most beneficial retrieval configuration will be the one providing the minimum $s_m$ and $\tau$ RMSE. The choice of $\sigma_\tau$ is clear: since $s_m$ and $\tau$ RMSE increase monotonically with $\sigma_\tau$, the ideal case would be to fix it ($\sigma_\tau = 0.001 \; Np$). Yet, although the study is theoretical and covers all the range of variability of the parameters, only realistic uncertainties in the ancillary data must be considered in selecting the optimum. Thus, considering the auxiliary sources available, an expected error of 0.1 $Np$ in vegetation optical depth is suggested in the $CF$ formulation.

Regarding the choice of $\sigma_\omega$, a clear improvement can be observed on $\tau$ RMSE when a high constraint is imposed on $\omega$ ($\sigma_\omega = 0.001$) and $\sigma_\tau > 0.3 \; Np$, whereas a lower constraint of 0.1 seems to have little or no effect (compared to the case of no restrictions on $\omega, \sigma_\omega \rightarrow \infty$); adding or not restrictions on $\omega$, though, does not cause $s_m$ RMSE to vary significantly. From these results, it can be inferred that no constraints on $\omega$ are needed under nominal vegetation conditions. Nonetheless, note that auxiliary information of $\omega$ could be needed in the case of heterogeneous areas and dense vegetation covers [Pardé et al., 2004; Davenport et al., 2005]. With these constraints ($\sigma_\tau = 0.1 \; Np, \sigma_\omega \rightarrow \infty$), a $s_m$ RMSE of 0.11 $m^3/m^3$ is obtained on vegetation-covered scenarios using $T_{vv}-T_{hh}$, and a $s_m$ RMSE of $\approx 0.06 - 0.07 \; m^3/m^3$ using $T_I$. These results indicate that the $s_m$ RMSE mission requirement of 0.04 $m^3/m^3$, which is also the accuracy of most soil moisture sensors [Delta-T Devices Ltd., 2007], could not be fully satisfied in the presence of vegetation.

Regarding $\tau$ retrievals, adding the suggested restrictions on the $CF$ of $\sigma_\tau = 0.1 \; Np$ and $\sigma_\omega = 0.1$ is notably improving the accuracy of the results (a $\tau$ RMSE of 0.2 $Np$ is obtained using $T_{vv}-T_{hh}$ and of 0.1 $Np$ using $T_I$).

From (2.30), the optical depth can be linearly related to the VWC using the so-called $b$ parameter, which depends mainly of crop type and frequency. At L-band, a value of $b = 0.15 \; m^2/kg$ was found to be representative of most agricultural crops at L-band, with the exception of grasses [van de Griend and Wigneron, 2004]. Using this value, VWC maps with an accuracy of $\approx 3.3 - 6 \; kg/m^2$ could be obtained in the case of complete uncertainty on the vegetation parameters ($\sigma_\tau = 3 \; Np, \sigma_\omega \rightarrow \infty$), and VWC maps with an accuracy of $\approx 0.6-1.3 \; kg/m^2$ could be obtained in the case of adding the suggested $\tau$ and $\omega$ restrictions. These calculations, although not precise, indicate that the use of vegetation optical depth data as auxiliary information in the minimization process is critical to derive VWC maps from SMOS at the required accuracy of 0.2 $kg/m^2$. 

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Figure 3.1 Graphical plots of retrievals formulated using vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations. Retrieved soil moisture RMSE over (a) bare dry soil, and (b) bare wet soil scenario, for different uncertainties on auxiliary soil moisture ($\sigma_{sm}$) and roughness parameter ($\sigma_{hs}$). Retrieved optical depth RMSE over (c) vegetation-covered dry soil, (d) vegetation-covered wet soil, (e) vegetation-covered dry soil, and (f) vegetation-covered wet soil scenario, for different uncertainties on auxiliary optical depth ($\sigma_{\tau}$) and albedo ($\sigma_{\omega}$).
3.3. Simulation results

Figure 3.2 Graphical plots of retrievals formulated using the first Stokes parameter ($T_I$). Retrieved soil moisture RMSE over a (a) bare dry soil, and (b) bare wet soil scenario, for different uncertainties on auxiliary soil moisture ($\sigma_{s_m}$) and roughness parameter ($\sigma_{h_s}$). Retrieved optical depth RMSE over a (c) vegetation-covered dry soil, (d) vegetation-covered wet soil, (e) vegetation-covered dry soil, and (f) vegetation-covered wet soil scenario, for different uncertainties on auxiliary optical depth ($\sigma_\tau$) and albedo ($\sigma_\omega$).
Chapter 3. Auxiliary data impact on SMOS soil moisture retrievals

3.4 Discussion and conclusions

This study has analyzed the impact in the soil moisture retrieval performance of adding ancillary data with different associated uncertainty, and of using vertical ($T_h$) and horizontal ($T_{hh}$) polarizations separately or the first Stokes parameter ($T_I$), which may be linked to the choice of the full-polarimetric or dual-polarization SMOS operation mode. The performance of the different methods has been analyzed using SMOS simulated observations, and results are presented in terms of retrieved soil moisture RMSE and retrieved optical depth RMSE over four master homogeneous scenarios: 1) bare dry soil, 2) bare wet soil, 3) vegetated dry soil, and 4) vegetated wet soil. The main conclusions can be summarized as follows:

- Over bare soils, this study shows that adding ancillary information of soil roughness ($h_s$) on the cost function considerably improves the accuracy of $s_m$ retrievals. It is in good agreement with other L-band retrieval studies [Pardé et al., 2004; Davenport et al., 2005]. With the suggested uncertainty of 0.05 on ancillary $h_s$ data, and of 2 K on $T_s$ data ($\sigma_{T_s} = 2$ K, from thermal infrared observations or meteorological models), SMOS science requirements could be met in the case of using $T_I$ ($s_m$ RMSE of 0.02 m$^3$/m$^3$ and 0.04 m$^3$/m$^3$ are obtained over dry and wet soils, respectively). Using $T_{vv} - T_{hh}$, however, a $s_m$ RMSE of $\approx 0.08 - 0.09$ m$^3$/m$^3$ is obtained over both dry and wet soils.

- As expected, there is a strong decrease of the brightness temperatures sensitivity to $s_m$ in the presence of vegetation. Results indicate that adding vegetation albedo does not cause $s_m$ and $\tau$ retrievals to vary significantly and $\sigma_{\omega} \rightarrow \infty$ is proposed. Note that $\omega$ information is not needed in the particular nominal vegetation case studied ($\tau = 0.24$ Np and $\omega = 0$), but could be needed in the general case of heterogeneous areas and dense vegetation covers [Pardé et al., 2004; Davenport et al., 2005]. In contrast, the uncertainty on the auxiliary optical depth data used on the $CF$ is highly affecting $s_m$ retrievals; $s_m$ RMSE increases with $\sigma_{\tau}$, converging to $\approx 0.11 - 0.14$ m$^3$/m$^3$ for vegetation-covered dry soil and of $\approx 0.10 - 0.11$ m$^3$/m$^3$ for wet soil, when $\sigma_{\tau} \rightarrow \infty$. From these results, and considering the auxiliary sources available, a constraint of $\sigma_{\tau} = 0.1$ Np in the $CF$ is recommended. With this constraint, a $s_m$ RMSE of 0.11 m$^3$/m$^3$ is obtained over vegetation-covered scenarios using $T_{vv} - T_{hh}$, and of $\approx 0.06 - 0.07$ m$^3$/m$^3$ using $T_I$.

- The use of $\tau$ ancillary information on the $CF$ is critical to obtain VWC maps from $\tau$ retrievals with the required accuracy (0.2 kg/m$^2$). Retrieved $\tau$ RMSE increases monotonically with the uncertainty of the $\tau$ ancillary information used ($\sigma_{\tau}$) on the $CF$, converging to $\approx 0.8 - 0.9$ Np using $T_{vv} - T_{hh}$ and to $\approx 0.5$ Np using $T_I$, in the case of high uncertainty on the vegetation parameters ($\sigma_{\tau} = 3$ Np, $\sigma_{\omega} \rightarrow \infty$). With the suggested $\tau$ and $\omega$ constraints ($\sigma_{\tau} = 0.1$, $\sigma_{\omega} \rightarrow \infty$), a $\tau$ RMSE of 0.2 Np is obtained using $T_{vv} - T_{hh}$ and of 0.1 Np using $T_I$. $\tau$ retrievals in a previous overpass could be used as auxiliary information in retrievals at time $t$, as in Wigneron et al. [2000], Pardé et al. [2004]. If no $\tau$ auxiliary information is available, an alternative approach is presented in Meesters et al. [2005], where $\tau$ is retrieved from passive observations at 6.6 GHz using only land surface temperature as ancillary information.

- Soil moisture and vegetation optical depth retrievals show a better performance if the minimization is formulated using the Stokes parameter $T_I$ than using the Earth
This result suggests that the dual-polarization mode should not *a priori* be discarded, since $T_I$ in the dual-polarization mode should have better radiometric sensitivity than in full-polarimetric mode. In addition, retrievals using $T_I$ are more robust to geometric and Faraday rotations than $T_{vv} - T_{hh}$. Note that this effect has been perfectly corrected in the simulations, but can be critical from an operational point of view.

- It must be remarked that, if *a priori* information on the land surface conditions can be available, restrictions on $h_s$, $T_s$, and $\tau$ are highly recommended. The better the accuracy of these auxiliary sources, the better are the $s_m$ and $\tau$ retrievals that could be obtained. All things considered, the required uncertainty levels for auxiliary input data are $\sigma_{h_s} = 0.05$, $\sigma_{T_s} = 2$ K, and $\sigma_{\tau} = 0.1$ Np.

This study has presented a concise error analysis of the SMOS soil moisture retrieval algorithm, and an optimal retrieval configuration for SMOS has been devised. Results preference the use of the first Stokes parameter, and the use of constraints on $h_s$, $T_s$, and $\tau$ with associated uncertainties $\sigma_{h_s} = 0.05$, $\sigma_{T_s} = 2$ K, and $\sigma_{\tau} = 0.1$ Np. But then, what are current uncertainties of available global datasets that could be used as sources for ancillary data? are auxiliary data available with the required uncertainty bounds? the answer to these questions is complex at this point; there are global datasets that could provide the auxiliary information needed, namely, ECOCLIMAP for $h_s$ or vegetation characteristics, Global Land Cover Characterization (GLCC) or MODIS-derived Leaf Area Index (LAI) for vegetation optical depth, AVHRR or METEOSAT-derived global albedo and ERA40 or ERAINTERIM reanalysis of the different parameters from the European Center for Medium-range Weather Forecasts (ECMWF). However, very little information about its associated uncertainty is available or has been evaluated at the time of writing. In the last version of the SMOS Algorithm Theoretical Bases Document (ATBD) the use of auxiliary information from ECOCLIMAP and ECMWF forecasts is recommended, but no precise information of its uncertainty can be found. Due to this lack of information, a discussion regarding the uncertainty of the existing global datasets and its possible use as auxiliary input data has not been included. Still, the results presented in this work can timely help to define the SMOS operation mode, which will be decided at the end of the commissioning phase, and to define the soil moisture retrieval scheme and the auxiliary data needed in the operational SMOS Level 2 Processor. These are crucial issues that have to be addressed to retrieve accurate global soil moisture estimates from SMOS.
4

Analysis of the SMOS soil moisture retrieval algorithm

This chapter analyzes the SMOS soil moisture inversion algorithm, both theoretically and in terms of performance. Different soil moisture retrieval configurations are examined, depending on whether prior information is used in the inversion process or not. Retrievals are formulated in terms of vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations separately and using the first Stokes parameter ($T_I$), over six main surface conditions combining dry, moist and wet soils with bare and vegetation-covered surfaces. A sensitivity analysis illustrates the influence that the geophysical variables dominating the Earth’s emission at L-band have on the precision of the retrievals, for each configuration. It shows that, if adequate constraints on the auxiliary data are added, the algorithm should converge to more accurate estimations. SMOS-like brightness temperatures are also generated by the SMOS End-to-end Performance Simulator (SEPS) to assess the retrieval errors produced by the different cost function configurations. Better soil moisture retrievals are obtained when the inversion is constrained with prior information, in line with the sensitivity study, and more robust estimates are obtained using $T_I$ than using $T_{vv}$ and $T_{hh}$.

4.1 Introduction

The SMOS mission is the first-ever satellite dedicated to provide global measurements of soil moisture. Its payload is MIRAS, a novel 2-D interferometric radiometer that provides brightness temperature measurements of the Earth at different polarizations and incidence angles (see Section 1.3.1). SMOS-derived soil moisture products are expected to have an accuracy of 0.04 m$^3$/m$^3$ over 50 x 50 km$^2$ and a revisit time of 3 days. Also, there is a high interest in obtaining VWC maps with an expected accuracy of 0.2 kg/m$^2$ every 6 days from SMOS observations [Mission Objectives and Scientific Requirements of the SMOS mission, 2003]. Previous studies have pointed out the need to combine SMOS brightness temperatures ($T_B$) with auxiliary data to achieve the required accuracy and several retrieval configurations have been proposed [Pellarin et al., 2003; Pardé et al., 2004; Camps et al., 2005]. However, the optimal soil moisture retrieval setup needs yet to be optimized.

The dielectric constant of soils is highly related to the soil moisture content $s_m$, and also depends on the soil type [Wang and Schmugge, 1980; Dobson et al., 1985]. In addition to the
soil dielectric constant, other soil and vegetation parameters are known to play a significant role in the L-band microwave emission and therefore must be accounted for in the retrieval process, namely vegetation optical depth $\tau$, from where vegetation water content maps can be derived [van de Griend and Wigneron, 2004], vegetation albedo $\omega$, soil surface temperature $T_s$, and soil surface roughness (parameterized using the soil roughness parameter $h_s$). In this study, different Bayesian-based retrieval configurations have been examined depending on whether a priori information of these geophysical variables is used in the inversion process or not. Retrievals have been formulated in terms of vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations separately, and using the first Stokes parameter ($T_I$), over six main surface conditions combining dry, moist and wet soils with bare and vegetation-covered surfaces. Hence, this study analyzes four critical aspects which will provide valuable information for the inversion of soil moisture from L-band passive microwave observations:

1. The use of no a priori information in the CF vs. the use of a priori information about all the auxiliary parameters excluding $s_m$ on the cost function.

2. The effect of the presence of a vegetation canopy.

3. The effect of the soil moisture content (dry/moist/wet).

4. The retrieval formulation using the vertical and horizontal polarizations separately or using the first Stokes parameter.

In Section 4.2, a description of the scenarios, the forward model and the optimization scheme used in this study to analyze the retrieval of soil moisture from L-band passive observations is provided. A sensitivity analysis of the inversion algorithm is afterwards presented in Section 4.3. It illustrates the influence that the geophysical variables dominating the Earth’s emission at L-band have on the precision of the retrievals, for the different retrieval configurations. In Section 4.4, the performance of the different retrieval configurations is analyzed using SMOS-like $T_B$ generated with the SEPS. The L2 Processor Simulator (see Section 1.3.1), in turn, is used to retrieve soil moisture from SEPS synthetic $T_B$. The sensitivity analysis and the analysis with simulated SMOS data are necessary to characterize the different cost function configurations both theoretically and in terms of performance. In Section 4.5 the main results of this work are summarized, and their applicability to upcoming SMOS data on an operational basis is discussed.

4.2 Methodology

Soil moisture inversion from passive microwave observations is complex, since the microwave emission from soils depends strongly on its moisture content, but also on other surface characteristics such as soil type, soil roughness, surface temperature and vegetation cover, and their contributions must be carefully de-coupled in the retrieval process. The geophysical model function used on this study to mimic the Earth’s emission at L-band – the so-called forward model– is thoroughly described in Section 2.2. Particularly, (i) the effect of surface roughness on the microwave emission has been corrected using (2.27), with $Q_s = n = 0$, according to Wigneron et al. [2001]; (ii) the vegetation contribution has been modeled using (2.32), where it is assumed that vegetation canopy is in equilibrium with soil temperature, and $\tau$ and $\omega$ are polarization and angle independent; and (iii) the dielectric
mixing model in Wang and Schmugge [1980] has been used to relate soil moisture to soil emissivity.

Six master scenarios (bare dry/moist/wet soil and vegetation-covered dry/moist/wet soil) have been defined to evaluate how the soil moisture retrievals can be affected by both the presence of a canopy layer and the soil moisture content itself. These scenarios are homogeneous, described by parameters $s_m$, $T_s$, $h_s$, $\tau$ and $\omega$, which are constant in all the area; soil moisture values of 0.02 m$^3$/m$^3$, 0.2 m$^3$/m$^3$, and 0.4 m$^3$/m$^3$ have been used for dry, moist and wet soil, respectively, the roughness parameter $h_s$ has been set to 0.2 – which represents a rather smooth surface–, and nominal values are given to the vegetation parameters $\tau = 0.24$ Np and $\omega = 0$ [SMOS Algorithm Theoretical Bases Document, 2007].

A summary of the parameters’ value for each scenario is given in Table 4.1. Soil texture was assumed to be equal to the mean global clay and sand fractions derived from ECOCLIMAP [Masson et al., 2003], which are 20.4% and 48.3%, respectively, while soil porosity was assumed to be equal to 38%.

### Table 4.1

Selected original values of soil moisture ($s_m$), soil roughness ($h_s$), soil temperature ($T_s$), vegetation albedo ($\omega$) and vegetation optical depth ($\tau$) for the six master scenarios. $\sigma^0_{p_i}$ is the nominal uncertainty of parameter $p_i$.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$s_m$ [m$^3$/m$^3$]</th>
<th>$h_s$</th>
<th>$T_s$ [K]</th>
<th>$\omega$</th>
<th>$\tau$ [Np]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare dry soil</td>
<td>0.02</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>moist soil</td>
<td>0.2</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>wet soil</td>
<td>0.4</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Vegetation-covered dry soil</td>
<td>0.02</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0.24</td>
</tr>
<tr>
<td>moist soil</td>
<td>0.2</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0.24</td>
</tr>
<tr>
<td>wet soil</td>
<td>0.4</td>
<td>0.2</td>
<td>300</td>
<td>0</td>
<td>0.24</td>
</tr>
</tbody>
</table>

The SMOS multi-angular retrieval algorithm approach is described in Section 2.3. In this study, retrievals have been formulated using the vertical and horizontal polarizations separately, and using the first Stokes parameter. Up to date, the formulation of the SMOS-derived soil moisture retrieval problem in the Earth’s reference frame (using $T_{vv} - T_{hh}$) is the preferred one [Pardé et al., 2004; Saleh et al., 2009]. Thus, the formulation in terms of $T_I$ is presented as an alternative approach, since retrievals using $T_I$ are unaffected by geometric and Faraday rotations, which is critical from an operational point of view. Also, retrievals using $T_I$ could benefit of having less angular dependency than $T_{vv} - T_{hh}$, therefore reducing the degrees of freedom during the inversion process, which could lead to better soil moisture retrievals.

To explore the effect of adding a priori (background) information of other geophysical variables on the minimization process, the two Bayesian-based CFs in Table 4.2 have been formulated: $CF_1$ represents the case in which no a priori information is added, i.e. the cost function consists of an observational term and all parameters are free in the minimization; and $CF_2$ stands for the case in which a priori information of all auxiliary parameters is added, excluding $s_m$. Note that, in addition to using or not auxiliary information in the retrievals, it is important to have a good knowledge of the quality of the prior information. Thus, in the present study, $T_s$ is assumed to be known by means of thermal infrared observations and/or meteorological models with an accuracy of 2 K, and the accuracies of $h_s$, $\omega$ and $\tau$ estimations are comprehensively set according to 1) the simulated study in Chapter 3, where a large number of retrieval configurations, depending on the a priori information used in...
the retrievals and its associated uncertainty were tested, and 2) the field experiments in Monerris [2009].

### Table 4.2

<table>
<thead>
<tr>
<th></th>
<th>( \sigma_{s_m} ) [m(^3)/m(^3)]</th>
<th>( \sigma_{h_s} )</th>
<th>( \sigma_{T_s} ) [K]</th>
<th>( \sigma_\omega )</th>
<th>( \sigma_\tau ) [Np]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CF_1 )</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>( CF_2 )</td>
<td>100</td>
<td>0.05</td>
<td>2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

### 4.3 Sensitivity analysis

To get a visual understanding of the \( CF \) shape under different configurations, a set of retrieval setups has been formulated from (2.34), and the most interesting sections (2-D contours) are visualized showing the behavior of the minima in 2-D cuts through a 5-D \( CF \), where the 5-D are the parameters of the forward model, namely \( s_m, T_s, h_s, \omega \) and \( \tau \). These contour plots indicate in the first place that the \( CF \) has only one minimum and converges to the original values, as expected. Note that it is important to ensure that the minimization algorithm will be approaching the “true” solution, and not a local minimum. Also, the \( CF \) can be interpreted as the misfit of the measurements with the solution lying on the geophysical model function surface. Therefore, the shape of its minimum determines the precision of the retrieval. The broader the minimum, the larger is the effect of noise and the less accurate are the retrieved parameters, since we are ignoring all the neighboring solutions, which have a comparable probability of being the true state (as represented by the original \( s_m, h_s, T_s, \omega \) and \( \tau \) in Table 4.1) [Portabella and Stoffelen, 2004; Gabarró et al., 2009].

The weights of (2.34) were set according to Table 4.2, with \( \sigma_{T_B} = 2 \) K. The original parameters (“measured”) were set according to the simulated scenario (see the parameters’ original values for each scenario in Table 4.1) and the forward model on Section 2.2 was used to simulate \( T_B^{mea} \) for incidence angles between \( 0^\circ \) and \( 65^\circ \). Likewise, this was done to obtain \( T_B^{mod} \) over the ranges \( 0 \leq s_m \leq 0.5 \) m\(^3\)/m\(^3\), \( 250 \leq T_s \leq 350 \) K, \( 0 \leq h_s \leq 5 \), \( 0 \leq \tau \leq 3 \) Np, and \( 0 \leq \omega \leq 0.3 \) [SMOS Algorithm Theoretical Bases Document, 2007]. Hence, when the scenario’s original values are used \( T_B^{mod} \) equals \( T_B^{mea} \), which corresponds to the \( CF \)’s absolute minimum. Note that the axes on the figures have been normalized to the parameters’ original values \( \pm 3 \cdot \sigma^0_p \) to cover the 99.7% of the values the retrieved parameters could have and properly compare the different contours. Since the purpose of this experiment is to evaluate the sensitivities (gradients) of the different cost-function configurations, no bias errors are assumed in measurements or references; the effect of having an \( a \ priori \) value which is far from the true state is analyzed in Section 4.4.

Figure 4.1 shows \( CFs \) formulated using the first Stokes parameter over a bare dry soil scenario for the case where no constraints are added (Fig. 4.1 (a) and (b)) and for the case where \( a \ priori \) information about all the auxiliary parameters, except for \( s_m \), is added (Fig. 4.1 (c) and (d)). It can be seen that the minimum in the case of no constraints is elliptical with its major axis covering almost the entire range of roughness parameter and soil temperature values for the contour line \( CF = 1 \). This indicates a low sensitivity to
4.3. Sensitivity analysis

Figure 4.1 Cost functions formulated using $T_I$ over a bare dry soil scenario. Contours of $h_s$ vs. $s_m$ (a) and $T_s$ vs. $s_m$ (b), with no constraints on the cost function ($CF_1$). Contours of $h_s$ vs. $s_m$ (c) and $T_s$ vs. $s_m$ (d), adding constraints on all parameters, except for $s_m$ ($CF_2$).

$h_s$ and $T_s$ and a high sensitivity to $s_m$. When the constraints are used the minimum is better defined, i.e. there is a higher probability of finding the true state. This effect is also manifested on vegetation-covered simulations (see Fig. 4.2). Therefore, assuming that both the real errors in $T_B$ and the reference values are Gaussian, a constrained $CF$ should lead to a more accurate $s_m$ retrieval than a non-constrained $CF$. Also, it is important to note that the position of the minimum does not change when adding constraints on the $CF$.

The presence of a sparse vegetation layer is examined in Fig. 4.2. It can be noticed that the contours plotted are clearly widened if compared to those on Fig. 4.1, which indicates a higher uncertainty in the soil moisture retrievals over vegetation-covered surfaces, as expected. The vegetation canopy attenuates the soil emission and diminishes the forward model sensitivity to $s_m$; as the observed soil emissivity decreases with an increase in vegetation biomass, the soil moisture information contained in the microwave signal decreases [Ulaby et al., 1981].

The difference between $CF$s simulated over a bare dry, moist, and wet soil scenario can be seen in Fig. 4.3. The cost function sensitivity to $h_s$ is the highest on wet soils (Fig. 4.3 (e)) and the lowest on dry soils (Fig. 4.3 (a)). In contrast, the cost function sensitivity to $T_s$...
Chapter 4. Analysis of the SMOS soil moisture retrieval algorithm

Figure 4.2 Cost functions formulated using $T_l$ over a vegetation-covered dry soil scenario. Contours of $h_s$ vs. $s_m$ (a) and $T_s$ vs. $s_m$ (b), with no constraints on the cost function ($CF_1$). Contours of $h_s$ vs. $s_m$ (c) and $T_s$ vs. $s_m$ (d), adding constraints on all parameters, except for $s_m$ ($CF_2$).

is the highest on dry soils (Fig. 4.3 (b)) and the lowest on wet soils (Fig. 4.3 (f)). Therefore, constraints on both $h_s$ and $T_s$ should be needed to improve the accuracy of soil moisture retrievals over bare soils under diverse moist conditions. This result can also be extended to vegetation-covered scenarios, where the same behavior has been observed in the $CF$s. Note that the plots on Fig. 4.1 and Fig. 4.3 are in good agreement with other L-band retrieval studies, where adding constraints on $h_s$ and $T_s$ was also shown to be preferable [Pardé et al., 2004; Davenport et al., 2005].

Regarding the vegetation parameters, Fig. 4.4 shows that the $CF$ sensitivity to $\tau$ is the highest over vegetation-covered wet soils and decreases as the soil under the vegetation canopy dries out, as can be easily appreciated in the contour line $CF = 10$. This indicates that better $\tau$ retrievals should be expected over wet than over dry soils. The soil contribution to the overall above-canopy emission is lower under wet than over dry soil conditions (because of the lower soil emission), and the canopy contribution thus becomes relatively larger. This could probably lead to the higher sensitivity for canopy parameters that are observed under wet conditions.

The effect of adding restrictions on $\tau$ and $\omega$ in the $CF$ is not clearly visible in the contours
4.3. Sensitivity analysis

Figure 4.3 Cost functions formulated using $T_{vv} - T_{hh}$ with no constraints. Contours of $h_{s}$ vs. $s_{m}$ (a) and $T_{s}$ vs. $s_{m}$ (b) over a bare dry soil scenario. Contours of $h_{s}$ vs. $s_{m}$ (c) and $T_{s}$ vs. $s_{m}$ (d) over a bare moist soil scenario. Contours of $h_{s}$ vs. $s_{m}$ (e) and $T_{s}$ vs. $s_{m}$ (f) over a bare wet soil scenario.
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Figure 4.4 Cost functions formulated using $T_{vv} - T_{hh}$ with no constraints. Contours of $\tau$ vs. $s_m$ (a) over a vegetation-covered dry scenario. Contours of $\tau$ vs. $s_m$ (b) over a vegetation-covered moist scenario. Contours of $\tau$ vs. $s_m$ (c) over a vegetation-covered wet scenario.

on Fig. 4.4, probably because the restrictions imposed on these variables are not very severe ($\sigma_x = \sigma_{\omega} = 0.1$). However, it is shown to actually improve $s_m$ and $\tau$ retrievals when applied to SMOS-like simulated data on Section 4.4.2.

Comparing Figs. 4.1(a) and (b) with Figs. 4.3(a) and (b), it can be observed that the $CF$ sensitivity to $T_s$ is higher when using the $T_{vv} - T_{hh}$ than when using $T_I$ (narrower, better defined minimum, less solutions with a comparable probability of being the true state), whereas the sensitivity to $h_s$ remains the same. No remarkable differences have been found between the two formulations over vegetation-covered scenarios.

4.4 Analysis with simulated SMOS data

4.4.1 Simulation strategy

L-band 2-D multi-angular brightness temperatures over land have been simulated over the six main surface conditions of Table 4.1 using SEPS. Next, these data have been used as
input to the L2 Processor Simulator, where retrievals have been performed using the two CF configurations of Table 4.2, formulated in terms of vertical ($T_{vv}$) and horizontal ($T_{hh}$) polarizations separately and using the first Stokes parameter ($T_1$). Note that over the bare soil scenarios $\tau = \omega = 0$ will not be retrieved. It is important to outline that SEPS simulated error on $TB$ includes all the instrument specific features (measured antenna pattern, measured receivers’ frequency response, thermal drifts, etc.) and all the realistic features induced by the image reconstruction algorithms, such as biases and the pixel-dependent radiometric accuracy [SEPS Architectural Detailed Design Document, 2006].

Retrievals on the L2 Processor Simulator have been performed under the following guidelines and assumptions:

- The geophysical models and the ancillary used in the L2 processor Simulator are the same as in SEPS, so that the effect of the model used is not affecting the results.

- The performance of the CF configuration is not dependent on $\sigma_F$, since the absolute accuracy of the radiometric measurements is available on the SEPS output and is used in L2 Processor Simulator.

- To reduce the computational time, the search limits of the retrieved variables in the CF have been reduced within reasonable bounds, namely $0 \leq s_m \leq 0.5 \text{ m}^3/\text{m}^3$, $250 \leq T_s \leq 350 \text{ K}$, $0 \leq h_s \leq 5$, $0 \leq \tau \leq 3 \text{ Np}$, and $0 \leq \omega \leq 0.3$ [SMOS Algorithm Theoretical Bases Document, 2007].

- The reference values of the parameters on the CF ($p_{\theta}$) are randomly determined from a normal distribution with the nominal standard deviations in Table 4.1, added to the original values.

- Homogeneous pixels have been assumed in the simulations to evidence the contribution of each parameter in the results and facilitate the analysis. However, further studies will be required to assess the limitations imposed by heterogeneity of vegetation cover and soil characteristics within a satellite footprint.

### 4.4.2 Simulation results

The mean, standard deviation, and RMSE of the retrieved soil moisture ($s_m^{ret} - s_m^{orig}$) are shown in Table 4.3 for the bare soil scenarios and in Table 4.4 for the vegetation-covered scenarios defined in Table 4.1. The soil moisture retrieval configurations that meet the SMOS science requirement of $s_m$ RMSE $\leq 0.04 \text{ m}^3/\text{m}^3$ are marked in bold. It can be seen that in the case of no constraints ($CF_1$), the $s_m$ RMSE is far from the 0.04 m$^3$/m$^3$ benchmark: a retrieval error of $\approx 0.10$ to $0.21$ m$^3$/m$^3$ is obtained over bare soils and of $\approx 0.11$ to $0.24$ m$^3$/m$^3$ over vegetation-covered soils.

Table 4.3 shows that the $s_m$ retrieval error over bare soil scenarios is considerably improved when constraints on $h_s$ and $T_s$ are added ($CF_2$): $s_m$ RMSE retrievals of $\approx 0.07$ to 0.09 m$^3$/m$^3$ are obtained using $T_{vv} - T_{hh}$ and of $\approx 0.03$ to 0.05 m$^3$/m$^3$ using $T_1$. This result is in line with Fig. 4.1 and with other L-band retrieval studies [Pardé et al., 2004; Davenport et al., 2005]. The special case of having $h_s=1$ on the bare soil scenarios has also been simulated. Results show that a higher roughness leads to an increased $s_m$ RMSE in all the scenarios and configurations studied, and only in the case of using $T_1$ and $CF_2$ the $s_m$ retrieval error is below 0.05 m$^3$/m$^3$. Table 4.4 shows that the $s_m$ retrieval error over vegetation-covered scenarios ($\tau = 0.24 \text{ Np}$ and $\omega = 0$) is also improved when constraints on
Table 4.3 Retrieved mean, standard deviation and root mean square soil moisture error of simulated SMOS observations over the bare soil scenarios in Table 4.1, using the cost-function configurations of Table 4.2, formulated on the Earth’s reference frame or using the first Stokes parameter. Soil moisture retrieval configurations with $s_m$ RMSE $\leq 0.04$ m$^3$/m$^3$ are marked in bold.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Retrieved $s_m$ error</th>
<th>$CF_1$ ($h_s=0.2$/$h_s=1$)</th>
<th>$CF_2$ ($h_s=0.2$/$h_s=1$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Earth</td>
<td>Stokes</td>
<td>Earth</td>
</tr>
<tr>
<td>Bare Dry Soil</td>
<td>Mean</td>
<td>0.149/0.185</td>
<td>0.106/0.140</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.157/0.179</td>
<td>0.164/0.160</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.216/0.257</td>
<td>0.196/0.211</td>
</tr>
<tr>
<td>Bare Moist Soil</td>
<td>Mean</td>
<td>0.069/0.059</td>
<td>0.018/0.056</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.122/0.160</td>
<td>0.134/0.143</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.140/0.171</td>
<td>0.135/0.154</td>
</tr>
<tr>
<td>Bare Wet Soil</td>
<td>Mean</td>
<td>-0.056/-0.100</td>
<td>-0.081/-0.090</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.084/0.142</td>
<td>0.096/0.130</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.101/0.173</td>
<td>0.125/0.158</td>
</tr>
</tbody>
</table>

Table 4.4 Retrieved mean, standard deviation and root mean square soil moisture error of simulated SMOS observations over the vegetation-covered scenarios in Table 4.1, using the cost function configurations of Table 4.2, formulated on the Earth’s reference frame or using the first Stokes parameter.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Retrieved $s_m$ error</th>
<th>$CF_1$</th>
<th>$CF_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Earth</td>
<td>Stokes</td>
<td>Earth</td>
</tr>
<tr>
<td>Dry Soil + Canopy</td>
<td>Mean</td>
<td>0.169</td>
<td>0.170</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.162</td>
<td>0.169</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.235</td>
<td>0.240</td>
</tr>
<tr>
<td>Moist Soil + Canopy</td>
<td>Mean</td>
<td>0.076</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.143</td>
<td>0.121</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.162</td>
<td>0.153</td>
</tr>
<tr>
<td>Wet Soil + Canopy</td>
<td>Mean</td>
<td>-0.062</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.119</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.134</td>
<td>0.109</td>
</tr>
</tbody>
</table>
4.4. Analysis with simulated SMOS data

Table 4.5 Retrieved mean, standard deviation and root mean square vegetation optical depth error of simulated SMOS observations over the vegetation-covered scenarios in Table 4.1, using the cost function configurations of Table 4.2, formulated on the Earth reference frame or using the first Stokes parameter.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Retrieved $\tau$ error</th>
<th>$CF_1$</th>
<th>$CF_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Earth</td>
<td>Stokes</td>
</tr>
<tr>
<td>Dry Soil + Canopy</td>
<td>Mean</td>
<td>0.439</td>
<td>0.369</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.888</td>
<td>0.606</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.991</td>
<td>0.709</td>
</tr>
<tr>
<td>Moist Soil + Canopy</td>
<td>Mean</td>
<td>0.224</td>
<td>0.100</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.732</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.765</td>
<td>0.356</td>
</tr>
<tr>
<td>Wet Soil + Canopy</td>
<td>Mean</td>
<td>0.187</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>Std. dev.</td>
<td>0.714</td>
<td>0.208</td>
</tr>
<tr>
<td></td>
<td>RMS</td>
<td>0.738</td>
<td>0.209</td>
</tr>
</tbody>
</table>

$h_s$, $T_s$, $\omega$, and $\tau$ are used ($CF_2$): $s_m$ RMSE retrievals of $\approx 0.11$ to $0.13 \text{ m}^3/\text{m}^2$ are obtained using $T_{vv} - T_{hh}$ and of $\approx 0.05$ to $0.09 \text{ m}^3/\text{m}^2$ using $T_I$. This result is in agreement with Fig. 4.2. Hence, simulation results show that the use of adequate constraints on the $CF$ improve the accuracy of $s_m$ retrievals in all the cases studied, and that the formulation in terms of $T_I$ is advantageous. Note that the improvement in $s_m$ retrievals when using $CF_2$ is specially noticeable in all the scenarios under dry soil conditions, where a remarkably high $s_m$ RMSE is obtained using $CF_1$. In fact, lower $s_m$ RMSE is obtained over wet soils than over dry soils (bare and vegetation-covered), except for the case of bare soil retrievals using $T_I$ and $CF_2$. This could be due to the reduced sensitivity of the dielectric constant at low moisture levels [de Jeu et al., 2008].

Vegetation optical depth retrievals are analyzed in Table 4.5. It shows that a notable improvement on $\tau$ RMSE is obtained when adequate constraints on the $CF$ are used ($CF_2$) than when all parameters are free ($CF_1$). Also, results indicate that better $\tau$ retrievals should be obtained over wet soils than over dry soils, in agreement with Fig. 4.4. It can also be seen that better $\tau$ retrievals are obtained using $T_I$ than using $T_{vv} - T_{hh}$ in all scenarios and configurations, specially under moist and wet soil conditions. From 2.30, the optical depth can be linearly related to the VWC using the so-called $b$ parameter, which depends mainly of crop type and frequency. At L-band, $b = 0.15 \text{ m}^2/\text{kg}$ was found to be representative of most agricultural crops, with the exception of grasses [van de Griend and Wigneron, 2004]. This value has been used in this study to evaluate if VWC maps with an accuracy of $0.2 \text{ kg/m}^2$ could be obtained from the $\tau$ retrievals in Table 4.5. Thus, using this approach and considering that no constraints are added, VWC with an accuracy of $\approx 4.9$ to $6.6 \text{ kg/m}^2$ could be obtained using $T_{vv} - T_{hh}$ and of $\approx 1.4$ to $4.7 \text{ kg/m}^2$ using $T_I$. If constraints are added, the accuracy of VWC improves to $\approx 1.9$ to $2.2 \text{ kg/m}^2$ using $T_{vv} - T_{hh}$ and to $\approx 0.4$ to $0.6 \text{ kg/m}^2$ using $T_I$. These results show that the formulation in terms of $T_I$ and the use of constraints on the $CF$ substantially improve $\tau$ retrievals, although the VWC requirement of $0.2 \text{ kg/m}^2$ is not fully satisfied.

It must be remarked that, in the results presented on Tables 4.3, 4.4, and 4.5, all pixels
Chapter 4. Analysis of the SMOS soil moisture retrieval algorithm

Figure 4.5 Retrieved soil moisture RMSE of simulated SMOS observations versus pixel position in the swath. Simulations over the dry (red, dashed lines), moist (green, solid lines), and wet (blue, dashed-dotted lines) scenarios of Table 4.1. First row: bare soil scenarios, second row: vegetation-covered scenarios. Left column: with no constraints on the cost-function ($CF_1$), right column: adding constraints on all parameters, except $s_m$ ($CF_2$). In each plot: first Stokes parameter (left side) and Earth’s reference frame (right side). Vertical lines denote the Narrow Swath.
4.4. Analysis with simulated SMOS data

Figure 4.6 Retrieved vegetation optical depth RMSE of simulated SMOS observations versus pixel position in the swath; Simulations over the vegetation-covered dry (red, dashed lines), moist (green, solid lines), and wet (blue, dashed-dotted lines) scenarios of Table 4.1, (a) with no constraints on the cost-function ($C_{F1}$), and (b) adding constraints on all parameters, except $s_m$ ($C_{F2}$). In each plot: first Stokes parameter (left side) and Earth’s reference frame (right side). Vertical lines denote the Narrow Swath.

in the SMOS FOV are considered, regardless of the number of measurements on each pixel. However, due to the SMOS observation geometry, all pixels in the FOV do not have the same properties: as the pixel’s distance to the ground-track increases, the pixel is imaged fewer times, its angular variation is reduced, and the instrument’s noise increases [Camps et al., 2005]. This fact indicates that better accuracies should be expected if only the central part of the FOV – the so-called Narrow Swath (640-km) [Barré et al., 2008] – is considered. However, note that the use of Narrow Swath implies a temporal resolution of 7-days, which will limit the applicability of the data. Still, the possibility of increasing the accuracy of the retrievals by considering a narrower swath should not be neglected. Hence, the retrieval performance has been explored further in Figs. 4.5 and 4.6, as a function of the ground-track distance.

Figure 4.5 illustrates the soil moisture retrieval performance vs. the pixel position, for all the retrieval configurations and scenarios studied. On the left-hand side of each plot simulation results correspond to the use of the first Stokes parameter, and on the right-hand side to the use of the Earth reference frame. Figures 4.5 (a) and (b) show results over bare soil scenarios using $C_{F1}$ and $C_{F2}$, respectively. Figures 4.5 (c) and (d) show results over vegetation-covered scenarios using $C_{F1}$ and $C_{F2}$, respectively. Vertical lines denote the Narrow Swath. These plots effectively show how the $s_m$ RMSE increases with the distance to the ground-track. Also, it can be seen that the use of adequate constraints ($C_{F2}$) dramatically improves soil moisture retrievals. Note that either in the case of considering the nominal or the Narrow Swath, the use of $C_{F2}$ and formulation in terms of $T_I$ should provide more accurate soil moisture retrievals.

Likewise, Fig. 4.6 illustrates the vegetation optical depth retrieval performance vs. the pixel position, for all the retrieval configurations and scenarios studied. When no constraints are added (Fig.4.6 (a)), the retrieval error rapidly increases beyond the Narrow Swath width. If adequate constraints are added (Fig.4.6 (b)), the error dependence on the ground-track distance is reduced, specially in the case of using $T_I$. As in the case of soil moisture retrievals,
the use of adequate constraints \((CF_2)\) and the formulation in terms of \(T_I\) should lead to more accurate \(\tau\) retrievals in the case of considering either the nominal or the Narrow Swath.

### 4.5 Discussion and conclusions

The SMOS mission has the unique capability to map the Earth’s surface soil moisture globally using L-band multi-angular and dual-polarization/full-polarimetric observations. In this paper, the soil moisture inversion algorithm from SMOS observations has been analyzed through the use of different cost function configurations covering four critical aspects: 1) the use of auxiliary information on the cost function, 2) the effect of the presence of a vegetation canopy, 3) the effect of the soil moisture content (dry/moist/wet), and 4) the retrieval formulation in terms of \(T_{vv} - T_{hh}\) (Earth reference frame) or \(T_I\) (the first Stokes parameter).

First, the sensitivity of the different cost function configurations to the geophysical variables dominating the L-band emission (\(s_m, h_s, T_s, \tau\) and \(\omega\)) has been examined by looking at the shape of the most interesting cuts (2-D contours). Then, a simplified version of the operational SMOS Level 2 Processor has been used to test the accuracy of the different retrieval setups with realistic SMOS-like brightness temperatures generated by SEPS. Simulated results are consistent with the theoretical study, therefore reinforcing the conclusions of this work, which can be summarized as follows:

- The use of adequate ancillary information on the cost function significantly improves the accuracy of \(s_m\) retrievals, and is needed to satisfy the SMOS science requirement of \(0.04 \, \text{m}^3/\text{m}^3\). Using \(CF_2\) constraints (Table 4.2), \(s_m\) RMSE retrievals of \(\approx 0.07\) to \(0.09 \, \text{m}^3/\text{m}^3\) are obtained using \(T_{vv} - T_{hh}\), and of \(\approx 0.03\) to \(0.05 \, \text{m}^3/\text{m}^3\) using \(T_I\) over bare soil scenarios. As expected, there is a strong decrease of the brightness temperatures sensitivity to \(s_m\) in the presence of vegetation, and \(s_m\) RMSE retrievals of \(\approx 0.11\) to \(0.13 \, \text{m}^3/\text{m}^3\) are obtained using \(T_{vv} - T_{hh}\), and of \(\approx 0.05\) to \(0.09 \, \text{m}^3/\text{m}^3\) using \(T_I\) (with \(\tau = 0.24, \omega = 0\)).

- The use of adequate constraints on the cost function \((CF_2)\) highly improves the accuracy of \(\tau\) estimations and it is therefore critical to derive VWC maps from SMOS at the required accuracy of \(0.2 \, \text{kg/m}^2\). Preliminary calculations indicate that VWC maps with an accuracy of \(\approx 1.9\) to \(2.2 \, \text{kg/m}^2\) could be estimated from \(\tau\) retrievals using \(T_{vv} - T_{hh}\), and of \(\approx 0.4\) to \(0.6 \, \text{kg/m}^2\) using \(T_I\).

- More accurate soil moisture estimates have been obtained over wet soils than over dry soils (bare and with low vegetation), except for the case of retrievals using \(T_I\) and \(CF_2\). Regarding \(\tau\) retrievals, better estimates have been obtained over wet soils in all the configurations.

- Better \(s_m\) retrievals have been obtained when using \(T_I\) than when using \(T_{vv} - T_{hh}\). Also, the formulation in terms of \(T_I\) leads to better \(\tau\) retrievals in all the configurations. These results suggest that, although \(T_{vv} - T_{hh}\) is the formulation generally adopted in most studies, the use of \(T_I\) should not be disregarded. In addition, \(T_I\) is more robust in the presence of geometric and Faraday rotations (at any spatial scale) than \(T_{vv} - T_{hh}\). These effects have been perfectly corrected on the simulations, but are critical from an operational point of view.
Due to SMOS observation geometry, better accuracies could be obtained if only the Narrow Swath (640-km, the central part of the FOV) is used. The use of adequate constraints ($CF_2$) and the retrieval formulation in terms of $T_I$ provide the most accurate $s_m$ and $\tau$ retrievals over all scenarios in the case of considering either the nominal or the Narrow Swath.

From an operational perspective, it should be pointed out that the forward model used in SEPS and in the L2 Processor Simulator is not as complex as the one used in the ESA’s SMOS Level 2 Processor (the L-MEB model). The L2 processor Simulator uses the $\tau - \omega$ model –which is the core of the L-MEB model–, and does not take into account any specific land cover parametrization for heterogeneous pixels. The main difference in the forward model is in the optical depth formulation, that in L-MEB is dependent on the incidence angle and the vegetation structure. In this study, it is considered that most vegetation covers are randomly oriented, and the optical depth parametrization has been simplified (see Section 4.2). However, note that the optimization algorithm used in the L2 Processor Simulator is exactly as described in the SMOS Algorithm Theoretical Bases Document [SMOS Algorithm Theoretical Bases Document, 2007]. Thus, the results presented in this work are potentially applicable to SMOS data.

Following the successful deployment of SMOS in orbit, continuous efforts will be needed to consolidate an optimal soil moisture retrieval configuration. The present study has analyzed the soil moisture inversion algorithm, both theoretically and in terms of performance with simulated data; it addresses key aspects for the retrieval of accurate soil moisture estimations from SMOS, and the results presented can be readily transferred to the operational Level 2 Processor to produce the much needed global maps of the Earth’s surface soil moisture.
Spatial resolution enhancement of SMOS data: a deconvolution-based approach

A deconvolution scheme to improve the spatial resolution of future SMOS data is presented. Different deconvolution techniques using improved Wiener, Constrained Least Squares and wavelet filters that may include different levels of auxiliary information in the reconstruction process have been developed and results of its application to simulated SMOS brightness temperatures and to passive L-band airborne observations are presented. With these techniques, the product of spatial resolution and radiometric sensitivity of SMOS-like images was improved in a 49% over land pixels and in a 30% over sea pixels. Results with airborne field experimental data confirm that with these methods it is possible to improve the radiometric sensitivity of the observations as well as to improve the coast line definition.

5.1 Introduction

The SMOS mission is an unprecedented initiative to provide global land moisture and surface salinity mapping; its unique payload is MIRAS, a novel L-band 2-D synthetic aperture radiometer with dual-polarization/fullpolarimetric capabilities (see Section 1.3.1). SMOS provides a totally new type of multiangular Earth observations, characterized by having a different pixel size and orientation, and a different noise level and spatial resolution for each pixel (Fig. 5.1(a)).

SMOS observations have a temporal resolution of 3 days, compatible with the temporal variability of the near surface land moisture over continental surfaces, and a ground spatial resolution of 30–60 km at best. This resolution, while adequate for many global applications, is a limiting factor to its application in regional scale studies. As mentioned in Entekhabi et al. [1999], the use of space-based passive microwave data in hydrological modeling is not straightforward because of the scale discrepancy between the typical spatial resolution of microwave radiometers (several tens of kilometers) and the scale at which most hydrological processes occur (approximately 1–10 km). Therefore, the possibility of assimilating future SMOS data in land surface hydrologic applications relies on the prospect of improving its spatial resolution.

Within this context, different downscaling approaches have been adopted in order to distribute fine-scale land moisture within coarse SMOS observations (see Section 1.4). This
work explores the possibility of improving the spatial resolution of SMOS products by the use of deconvolution algorithms that optimally perform noise regularization and include auxiliary information in the reconstruction process.

The prospective deconvolution algorithms expected to be applied to SMOS’ radiometric measurements should be newly created due to the unique characteristics of the mission instrument and to its specific way of observing the Earth’s surface. In Section 5.2, a linear algebra framework is given to the deconvolution process, and the different algorithms developed are presented. Frequency-domain-based methods and combined frequency-wavelet-domain-based methods have been found to be the most suitable for this task. In Section 5.3, an exhaustive test of these methods using SEPS is shown, and comparisons are made in terms of both spatial resolution and radiometric sensitivity enhancement. Section 5.4 evaluates the performance of the deconvolution approach using airborne field experimental data. In the final section, the most significant results of this study are summarized, and the applicability and usefulness of the presented algorithms to future SMOS data on an operational basis is discussed.

5.2 Deconvolution algorithms

5.2.1 Discrete formulation

Satellite microwave radiometric observations may be expressed as the convolution of the sensor antenna beam projected onto the Earth’s surface with the Earth’s brightness temperatures ($T_B$) integrated over the sensor footprint. Adjacent observations mostly cover the same target features on the ground, but with different contributions to the overall signal, and that overlap can be effectively used to estimate more accurately the $T_B$ of those grid cells. Typically, in a regional scale study, the number of observations outnumbers by far the grid cells for which the unknown $T_B$ has to be estimated. Mathematically, it derives from an ill-conditioned or ill-posed linear problem that must be carefully inverted, and proper
regularization techniques must be considered to have noise amplification under control when
inversion is accomplished [Hansen, 1998]. Consequently, the existence, uniqueness, and sta-
bility of the solution are not guaranteed for the general problem even when noise is not
present. In addition, the presence of noise makes an exact solution unfeasible. In this con-
text and following the lexicographic notation [Andrews and Hunt, 1977], the formation of a
$T_B$ image can be described as:

$$g = h \otimes f + n,$$

where $g$ is a column vector containing the real observations, $f$ is a column vector containing
the unknown $T_B$ at the desired spatial resolution, $n$ is a column vector that includes the
noise, $h$ is the column vector representation of the synthetic antenna response function [Bará
et al., 1998], and $\otimes$ indicates the convolution operator. A discrete convolution formulation
can be derived from (5.1). Assuming that $f$ and $h$ are 2–D periodic functions of periods $M$
and $N$ adequately padded with zeros to avoid overlap between different periods and using
the lexicographic notation as aforementioned:

$$g = H \cdot f + n,$$

where $f, g,$ and $n$ are of dimension $(M \cdot N) \times 1$ and $H$ is of dimension $M \cdot N \times M \cdot N$. This
matrix consists of $M^2$ partitions, each partition being of size $N \times N$ and ordered according
to:

$$H = \begin{bmatrix}
H_0 & H_{M-1} & H_{M-2} & \cdots & H_1 \\
H_1 & H_0 & H_{M-1} & \cdots & H_2 \\
H_2 & H_1 & H_0 & \cdots & H_3 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
H_{M-1} & H_{M-2} & H_{M-3} & \cdots & H_0
\end{bmatrix}.$$ (5.3)

Each partition $H_i$ is constructed from the $i^{th}$ row of the extended function $h$ by a circular
shifting it to the right (see Andrews and Hunt [1977] for more details).

A direct solution of (5.3) is computationally unfeasible; for practical size images, it will
require the inversion of a very high number of simultaneous linear equations. Fortunately,
since the matrix $H$ is block circulant, it can be diagonalized, and the problem can be consider-
ably reduced by working in the frequency domain, where convolution simplifies to scalar
operations [Gonzalez and Woods, 1993]. Using frequency-domain-based deconvolution meth-
ods, the computation time is no longer a limitation, since nowadays, there are very powerful
tools to perform fast Fourier transforms.

### 5.2.2 Frequency-domain algorithms

The Fourier space equivalent of (5.1) can be written as

$$G = H \cdot F + N,$$ (5.4)

where $G$, $H$, $F$, and $N$ are the Fourier transforms of $g$, $h$, $f$, and $n$, respectively.

Linear deconvolution can be stated as the task of finding a linear operator $K$ such that

$$F = K \cdot G.$$ (5.5)

The most elementary deconvolution will be performed by the simple inverse filter, given
by $K = H^{-1}$. However, such filtering tends to be very error sensitive and unstable.
To perform the deconvolution, a constrained least squares (CLS) filter can be developed in which the constraint gives the designer additional control over the process. This approach consists of minimizing functions of the form \( \|Q \cdot f\|^2 \), where \( Q \) is a linear operator on \( f \) subject to the constraint \( \|g - H \cdot f\|^2 = \|n\|^2 \) (from (5.2)). Then, using the method of Lagrange multipliers [Gonzalez and Woods, 1993]:

\[
J(f) = \|Q \cdot f\|^2 + \lambda_1(\|g - H \cdot f\|^2 - \|n\|^2).
\]  

(5.6)

Differentiating (5.6) with respect to \( f \) and setting the result equal to zero yields

\[
\frac{\partial J(f)}{\partial f} = 2Q^TQ \cdot f - 2\lambda_1H^T(g - H \cdot f) = 0,
\]

(5.7)

which leads to

\[
f = (H^TH + \alpha \cdot Q^TQ)^{-1} \cdot H^Tg,
\]

(5.8)

where \( \alpha \equiv 1/\lambda_1 \) for simplification. This parameter must be adjusted such that the initial constraint \( \|g - H \cdot f\|^2 = \|n\|^2 \) is satisfied.

The choice of the linear operator \( Q \) generates different deconvolution techniques. However, in order to work on the frequency domain – as it has been demonstrated to be highly desirable – \( Q \) should be a block-circulant matrix. With this premise, two approaches have been found to provide satisfactory results: the well-known Fourier Wiener filter and the CLS filter.

The Wiener Filter establishes \( Q^TQ = R_f^{-1} \cdot R_n \), where \( R_f \) and \( R_n \) are the correlation matrices of \( f \) and \( n \), respectively. Performing the appropriate operations, it can be expressed in the frequency domain as

\[
K(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \alpha \left[ \frac{S_n(u, v)}{S_f(u, v)} \right]} G(u, v),
\]

(5.9)

for \( u, v = 0, 1, 2, \ldots, N - 1 \), where \( S_n(u, v) \) and \( S_f(u, v) \) are the Fourier transforms of \( R_n \) and \( R_f \), and it is assumed that \( M = N \). Note that, in the absence of noise \( S_n(u, v) = 0 \), the Wiener filter reduces to the simple inverse filter.

In most real applications, \( S_f(u, v) \) cannot be determined, and the whole factor \( \alpha \left[ \frac{S_n(u, v)}{S_f(u, v)} \right] \) is reduced to an experimentally determined constant \( \phi_0 \); hence, the Wiener filter of (5.9) is reduced to the least energy constraint filter [Gonzalez and Woods, 1993]. In the results presented in Section 5.3, the value of \( \phi_0 \) has been selected by optimizing the product of radiometric sensitivity (\( \Delta T \)) and spatial resolution (\( \Delta S \)). In any real or synthetic aperture radiometers, the product \( \Delta T \cdot \Delta S \) is constant. An increase in \( \Delta T \) implies a decrease in \( \Delta S \) and vice-versa [Ulaby et al., 1981; Camps et al., 1998]. Thus, when \( \Delta S \) is improved, noise is indirectly added to the observations, and eventually, if this noise is too high, land moisture cannot be retrieved. In order to avoid this effect, it is usually considered that the optimum tradeoff between spatial resolution enhancement and radiometric sensitivity upholding is given by the minimum \( \Delta T \cdot \Delta S \) [Camps et al., 1998].

The CLS filter includes a smoothing criterion function that varies with frequency and eliminates artifacts. Performing the convenient operations, the CLS filter in the frequency domain can be expressed as

\[
K(u, v) = \left[ \frac{H^*(u, v)}{|H(u, v)|^2 + \alpha \left[ \frac{C(u, v)}{C(u, v)} \right]} \right] G(u, v),
\]

(5.10)
for $u, v = 0, 1, 2, \cdots, N - 1$, where $C(u, v)$ is the Fourier transform of the smoothing criterion function, and it is assumed that $M = N$. In this study, the second order Laplacian operator \cite[Galatsanos and Katsaggelos, 1992]{Galatsanos1992} has been used as the smoothing criterion function.

The choice of the parameter $\alpha$ is a key issue. It controls the degree of smoothness of the solution and represents a tradeoff between fidelity to the signal ($\alpha$ small) and fidelity to the prior information about the solution ($\alpha$ large). When $\alpha$ tends to zero, the filter reduces to the simple inverse filter, and (5.5) becomes the ultrarough solution. When $\alpha$ tends to infinity, (5.5) becomes the ultrasmooth solution \cite[Galatsanos and Katsaggelos, 1992]{Galatsanos1992}. In the results presented in Section 5.3, the value of $\alpha$ has been optimized using as a metric the product $\Delta T \cdot \Delta S$, as in the Wiener case.

Following the least-squares procedure, a novel basis for deriving filters has been developed with the possibility of having an extra constraint to improve its performance. As a first approach, the additional constraint is set to be $\|T_b - H \cdot f\|^2 = \|e\|^2$, where $T_b$ is a $T_B$ model of the image at L-band and $e$ is a tolerance error.

Using L-band $T_B$ and radiative transfer models, reasonably realistic $T_B$ images can be simulated from auxiliary data. For instance, \textit{Merlin et al.} \cite{Merlin2008} used simulated $T_B$ images to disaggregate land moisture fields, and \textit{Camps et al.} \cite{Camps2008b} use synthetic L-band $T_B$ images to reduce the scene-dependent bias and improve the coastline transition in the SMOS image reconstruction algorithm. In Section 5.3, $T_b$ is set to be the $T_B$ image that SEPS internally computes from auxiliary data and uses as the original $T_B$ of the Earth’s surface \cite[Camps, 1996]{Camps1996}. Hence, results show the best possible performance achievable by this novel kind of filters.

Two Lagrange multipliers $\lambda_1$ and $\lambda_2$ are used to include the two constraints so that

$$J(f) = \|Q \cdot f\|^2 + \lambda_1(\|g - H \cdot f\|^2 - \|n\|^2) + \lambda_2(\|T_b - H \cdot f\|^2 - \|e\|^2).$$ (5.11)

Differentiating with respect to $f$, setting the result to zero, and solving it for $f$, the following expression in the spatial domain is obtained:

$$f = (Q^T Q + \lambda_1 H^T H + \lambda_2 H^T H)^{-1} \cdot H^T (\lambda_1 \cdot g + \lambda_2 \cdot T_b).$$ (5.12)

At this point, the Wiener and the CLS concepts can be used to set the value of $Q$, therefore generating two new filters: the Wiener model filter and the CLS model filter, respectively. Making use of the diagonalization procedure, the following expression in the frequency domain can be obtained:

$$K(u, v) = \left[ \frac{H^*(u, v) \cdot (G(u, v) + \rho \cdot T_B)}{(1 + \rho)|H(u, v)|^2 + \alpha |L(u, v)|} \right],$$ (5.13)

where $L(u, v)$ represents $\left[ \frac{S_{\gamma}(u, v)}{S_{\gamma}(u, v)} \right]$ in the Wiener-derived case and $C(u, v)$ in the CLS-derived case, $\alpha \equiv 1/\lambda_1$ and $\rho \equiv \lambda_2/\lambda_1$ for ease of notation, and $T_B$ is the Fourier transform of $T_b$. The parameter $\alpha$ controls the degree of smoothness of the solution, as in previous filters, and $\rho$ controls the fidelity of the solution to the auxiliary information. Note that, if the second constraint is not added ($\lambda_2 = 0$) these new filters reduce to the former Wiener and CLS filters ((5.9) and (5.10)).

Apart from the least squares approach, the options of implementing on the frequency domain deconvolution algorithms that rely on statistics, such as the maximum likelihood or the maximum entropy, have also been thoroughly studied, but the results obtained for extended continuous images are considerably less satisfactory than the results obtained by the least squares technique \cite[Demoment, 1989]{Demoment1989}.
5.2.3 Wavelet-domain algorithms

The possibility of posing the problem on the wavelet domain has also been considered. The strength of the wavelet domain is that it economically represents images containing singularities and spatially localized features such as edges and ridges, in contrast to the high number of Fourier coefficients that will be needed for the same purpose. However, the wavelet transform is not well suited to represent general convolution operators and do not efficiently represent images with a high root mean square error (RMSE). The wavelet-vaguelette deconvolution technique as well as different wavelet-shrinkage-based signal’s estimators [Mallat, 1998] have been applied to SEPS data, but probably because of the noisy nature of SMOS observations and of the colored noise inherent to the deconvolution process itself, they yield to unsatisfactory near-zero estimates. Note that the convolution operator is not diagonalized in the wavelet domain.

Within this frame, a combined Fourier-wavelet regularized algorithm that first performs Fourier regularized inversion and afterward applies wavelet denoising has been developed. It is inspired on the Fourier-wavelet regularized deconvolution (ForWaRD) method [Neelamani et al., 2004], and it is specifically adapted to properly work with future SMOS data. Using a metric based on the product $\Delta T \cdot \Delta S$, an optimal balance between the Fourier and the Wiener shrinkage is found, and the involved parameters are set.

The hybrid ForWaRD algorithm relies on a twofold basis. At the first stage, it exploits the well-adapted representation of the convolution operator in the Fourier domain to control noise amplification. The Wiener, CLS, Wiener model, and CLS model filters presented in Section 5.2.2 are used for this purpose, each one generating a ForWaRD-derived algorithm: Wiener-ForWaRD, CLS-ForWaRD, Wiener-ForWaRD model, and CLS-ForWaRD model, respectively.

At the second stage, the task of noise removal and signal estimation is conveniently achieved using wavelet shrinkage. The wavelet-domain signal estimation in ForWaRD remains effective since the noise corrupting the wavelet coefficients is not excessive, thanks to the previous Fourier regularization. Wavelet shrinkage is performed as follows. First, a rough estimate of the input signal is obtained by using a hard-thresholding technique. Then, this estimate is used to obtain a final refined estimate by employing Wiener estimation on each wavelet coefficient [Neelamani et al., 2004]. This wavelet processing is common to all the ForWaRD-derived algorithms implemented.

5.3 Application to SMOS simulated observations

In order to assess the performance of the deconvolution algorithms developed, a series of tests has been carried out using SEPS to evaluate, on the one hand, the spatial resolution obtained with each method and, on the other hand, the radiometric sensitivity achieved. As previously discussed, the best method is chosen as the one that provides the minimum $\Delta T \cdot \Delta S$. The simulations conducted to this end as well as the representative results are shown in this section.

A common scenario has been set in SEPS to run all simulations. It is located in the Pacific Ocean to avoid coastal effects, and the region under study comprises the upper left area of an SMOS snapshot (Fig. 5.1(b)) so that the variation of the pixels’ spatial resolution, depending on their position in the FOV and their varying shapes, could be easily observed. Accordingly, SEPS has been conveniently modified to accept a synthetic image as input.
5.3. Application to SMOS simulated observations

5.3.1 Spatial resolution enhancement

First, a synthetic image with point sources has been introduced in the area under study and has been processed by SEPS. The different methods have then been applied to the SEPS' output, and the spatial resolution of the results has been calculated as the diameter of the circle with the same area as the 3-dB footprint ($\Delta S$). The top left pixel in Fig. 5.1(b) is taken as the worst case, since it is the pixel with the worst spatial resolution, the highest elongation, and the largest radiometric sensitivity among them. The bottom right pixel in Fig. 5.1(b) is taken as the best case. The results over these two extreme pixels are shown in Fig. 5.2. It can be seen that, after applying the deconvolution filters to the SEPS output, the shape of the pixels becomes rounded, and its spatial resolution is improved. Also, better spatial resolution is achieved when using the Wiener-derived filters than when using the CLS-derived ones. It is remarkable how the inclusion of the $T_B$ model improves the spatial resolution in the worst case pixel. In the best case pixel, however, the inclusion of the model improves the spatial resolution when using Wiener-derived filters and barely worsens it when using CLS-derived ones. Regarding the wavelet processing, it has been found not to affect the spatial resolution of the result.

![Figure 5.2](image_url)  

**Figure 5.2** Best case pixel's contour at -3 dB after applying (a) Wiener-derived methods and (b) CLS-derived methods to Fig. 5.1(b). Worst case pixel's contour at -3 dB after applying (c) Wiener-derived methods and (d) CLS-derived methods to Fig. 5.1(b).
Discretization effects appear in the contour of the original image in Fig. 5.1(b)(c) and (d), due to the internal SEPS interpolation from the synthetic high-resolution input images used in the tests to the SMOS-like low-resolution output images, and to the resampling of SEPS low-resolution output images into a higher resolution geographic grid.

To evaluate the spatial resolution enhancement achieved with the different algorithms in an easier and more intuitive way, a set of synthetic images with vertical bars and alternative values (253 K and 120 K to represent dry land and sea, respectively) have been created with different widths. Horizontal bars have also been created so as to observe the difference between the two directions. These images have been processed by SEPS, and the different deconvolution methods have been applied over the SEPS’ output. Results of these tests for representative bar widths are shown in Fig. 5.3 for Wiener-derived methods and in Fig. 5.4 for CLS-derived methods: 48 km appears to be the minimum bar width that allows one to clearly distinguish all vertical bars with all the Wiener-derived filters; when using CLS-derived filters, the minimum vertical bar width that can be distinguished is 52 km. With respect to horizontal bars, 56 km has been found to be the limiting separation between two bars in order to differentiate them with all the methods, except with Wiener-WaRD and CLS-WaRD. With these two methods, the top and top-left areas of the image are gradually blurred, following the decreasing spatial resolution pattern of SMOS observations (see Fig. 5.1), and only bars of at least 58 km width can be differentiated. Contour lines delineating the original footprint of the pixels on the upper left area of an SMOS snapshot (the area under study) have been overlaid to the images for clarity. The original spatial resolution varies from 50 km in the bottom right region to 80 km in the upper left one; after applying the deconvolution filters, the worst resolution is shown to improve from 80 to 48 km in the vertical direction and to 56 km in the horizontal direction.

It can be noticed that the filters that include the $T_B$ model are able to discriminate the bars sharper and nicer than the other methods. In fact, follow-on experiments have shown that they could distinguish up to 40 km vertical bar widths and 44 km horizontal bar widths. Furthermore, note that better spatial resolutions are obtained with vertical bars than with horizontal bars, since in the area under study the pixels elongate having its major axis nearly in the vertical direction.

### 5.3.2 Radiometric sensitivity evaluation

A RMSE metric has been used to assess the radiometric sensitivity ($\Delta T$) achieved with the different methods. It has been computed in each case with respect to the original synthetic image used as input to SEPS. To this end, a synthetic image with a step from 253 K to 120 K has been generated in the area under study and used as input to SEPS. The different methods have been applied over the SEPS output, and the corresponding $\Delta T$ values have been calculated, one for land pixels and another for sea pixels. The resulting images are shown on Fig. 5.5. The sea-land threshold is centered between 253 K and 120 K so that coastal effects are taken into account in the $\Delta T$ computation. Results will be used in Section 5.3.3 to quantify the effectiveness of the different methods.

In order to visually assess the performance of the different deconvolution schemes, the results of applying all the methods over a realistic scenario are shown in Fig. 5.6(a) for Wiener-derived filters and in Fig. 5.6(b) for CLS-derived ones. An area corresponding to Catalonia and the Balearic Islands in the northeast of Spain has been selected. It comprises a variety of land cover types, orographic features, an abrupt coastline, and the Balearic Islands, which, because of their sizes, are outstanding features upon which the spatial resolution
5.3. Application to SMOS simulated observations

Figure 5.3 Vertical bars of 48 km width as original, SEPS output and results of applying Wiener-derived filters to SEPS output (a). Horizontal bars of 56 km width as original, SEPS output and results of applying Wiener-derived filters to SEPS output (b). Cross sections of the original image, SEPS output, Wiener and Wiener-WaRD outputs of Fig. 5.3(a) (c), and of Fig. 5.3(b) (d). Cross-sections of the original image, SEPS output, Wiener model and Wiener-WaRD model outputs of Fig. 5.3(a) (e), and of Fig. 5.3(b) (f).
Figure 5.4 Vertical bars of 52 km width as original, SEPS output and results of applying CLS-derived filters to SEPS output (a). Horizontal bars of 56 km width as original, SEPS output and results of applying CLS-derived filters to SEPS output (b). Cross sections of the original image, SEPS output, CLS and CLS-WaRD outputs of Fig. 5.4(a) (c), and of Fig. 5.4(b) (d). Cross-sections of the original image, SEPS output, CLS model and CLS-WaRD model outputs of Fig. 5.4(a) (e), and of Fig. 5.4(b) (f).
Figure 5.5 A step image as original, SEPS output and results of applying Wiener-derived filters to SEPS output (a). A step image as original, SEPS output and results of applying CLS-derived filters to SEPS output (b). Cross sections of original, SEPS output, Wiener and Wiener-WaRD outputs of Fig. 5.5(a) (c). Cross sections of original, SEPS output, CLS and CLS-WaRD outputs of Fig. 5.5(b) (d). Cross sections of original, SEPS output, Wiener model, and Wiener-WaRD model outputs of Fig. 5.5(a) (e). Cross sections of original, SEPS output, CLS model, and CLS-WaRD model of Fig. 5.5(b) (f).
improvement can be easily tested. Comparing the SEPS’ output and the output of the different methods, it can be noticed that the shape and boundaries of objects are better distinguishable in the SEPS’ output. However, it is not the focus of this study to improve the coastline definition or the geographic features on the image, but to improve its overall spectral information, since an improvement on the $T_B$ image will lead to higher resolution land moisture retrievals. In Figs. 5.6(c),(d),(e), and (f), the $T_B$ values of Figs. 5.6(a) and (b) at constant latitude are plotted so as to observe the images in higher detail. It can be noted that some ripple appears in the areas close to the land-sea transition, mainly in the seaside. As it is localized, it does not affect inland and in-sea retrievals. The effect of this phenomenon over coastal-area retrievals will be further analyzed using airborne data on Section 5.4.

### 5.3.3 Quantitative results

Simulation results are listed in Table 5.1, where $\Delta T$ is the RMSE between the output analyzed and the original synthetic image with a step from 253 K to 120 K that is used as input to SEPS and $\Delta S$ is the diameter of the circle with the same area as the 3-dB footprint of the worst case pixel, expressed in kilometers. The product $\Delta T \cdot \Delta S$ is the radiometer uncertainty principle \[ Ulaby et al., 1981; Camps et al., 1998 \], and it is taken as the criteria to evaluate the whole performance of the methods since it provides an indication of the best radiometric sensitivity and spatial resolution that can be obtained simultaneously.

<table>
<thead>
<tr>
<th>$T_B$ image</th>
<th>$\Delta S$ [km]</th>
<th>$\Delta T$ [K]</th>
<th>$\Delta T \cdot \Delta S$ [K·km]</th>
<th>$\Delta T$ [K]</th>
<th>$\Delta T \cdot \Delta S$ [K·km]</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEPS output</td>
<td>90.2</td>
<td>13.7</td>
<td>1240</td>
<td>9.86</td>
<td>890</td>
</tr>
<tr>
<td>Wiener</td>
<td>67.1</td>
<td>11.6</td>
<td>778</td>
<td>16.8</td>
<td>1131</td>
</tr>
<tr>
<td>Wiener-WaRD</td>
<td>67.1</td>
<td>11.5</td>
<td>775</td>
<td>16.8</td>
<td>1126</td>
</tr>
<tr>
<td>Wiener model</td>
<td>51.5</td>
<td>13.3</td>
<td><strong>685</strong></td>
<td>13.0</td>
<td><strong>668</strong></td>
</tr>
<tr>
<td>Wiener-WaRD model</td>
<td>51.5</td>
<td>13.3</td>
<td><strong>685</strong></td>
<td>13.0</td>
<td><strong>668</strong></td>
</tr>
<tr>
<td>CLS</td>
<td>70.5</td>
<td>13.8</td>
<td>971</td>
<td>15.7</td>
<td>1108</td>
</tr>
<tr>
<td>CLS-WaRD</td>
<td>70.5</td>
<td>13.7</td>
<td>969</td>
<td>15.7</td>
<td>1105</td>
</tr>
<tr>
<td>CLS model</td>
<td>53.6</td>
<td>14.5</td>
<td>779</td>
<td>14.1</td>
<td>758</td>
</tr>
<tr>
<td>CLS-WaRD model</td>
<td>53.6</td>
<td>14.5</td>
<td>779</td>
<td>14.1</td>
<td>758</td>
</tr>
</tbody>
</table>

In particular, it can be observed that the wavelet filtering slightly improves $\Delta T$ when applied to the Wiener and CLS filters, whereas it does not affect $\Delta T$ when the $T_B$ model is added. Over $\Delta S$, however, the wavelet filtering does not affect in any case.

Regarding the effect of adding the $T_B$ model, it can be noticed that it considerably improves $\Delta S$ in all cases. Over $\Delta T$, however, it has little or no effect. On the whole, adding the $T_B$ model results to be of great advantage in terms of $\Delta T \cdot \Delta S$, particularly over sea pixels, since we get unacceptable high values otherwise.

It must be taken into account that the methods which include a $T_B$ model rely on the effectiveness of the model they use and that the results obtained by these methods and
5.3. Application to SMOS simulated observations

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**Figure 5.6** A realistic scenario as original, SEPS output and results of applying Wiener-derived filters to SEPS output (a). A realistic scenario as original, SEPS output and results of applying CLS-derived filters to SEPS output (b). Cross sections of original, SEPS output, Wiener and Wiener-WaRD outputs of Fig. 5.6(a) (c). Cross sections of original, SEPS output, CLS and CLS-WaRD outputs of Fig. 5.6(b) (d). Cross sections of original, SEPS output, Wiener model, and Wiener-WaRD model outputs of Fig. 5.6(a) (e). Cross sections of original, SEPS output, CLS model, and CLS-WaRD model of Fig. 5.6(b) (f).
shown in Table I are on a best possible basis (the $T_B$ model used is exactly the original $T_B$ model used in the computation of the observables). Thus, further studies with available $T_B$ models will be needed to fully evaluate their performance.

Focusing on the overall performance of the algorithms over land pixels, it can be seen that all methods satisfactorily improve the product $\Delta T \cdot \Delta S$ obtained by SEPS’ output and that best results are obtained when the Wiener model filter is used (marked in bold in Table 5.1). Focusing on the performance of the methods over sea pixels, however, the product $\Delta T \cdot \Delta S$ gets worse than SEPS’ outputs when using the methods without the $T_B$ model, which is undesirable. Again, better results over sea pixels are obtained when the Wiener model filter is used than when the CLS model filter is used.

Comparing results over sea and land pixels, it can be observed that the algorithm has a superior performance over land pixels. While $\Delta S$ remains the same for land and sea pixels, a higher noise is added to sea pixels than to land pixels in the deconvolution process. The higher value of $\Delta T$ over sea pixels is mainly due to the ripple that appears on the coastline, which is more significant on the sea side than on the land side. Note that the transition in the coast line is accounted for when calculating $\Delta T$ (see Section 5.3.2). Nonetheless, land and sea margins could be defined in non-coastal areas so that $\Delta T$ will be considerably reduced.

5.4 Application to airborne observations over the Ebro river mouth

In this Section, the deconvolution techniques are applied to airborne data acquired with the UPC Airborne RadIomEter at L-band (ARIEL) over the Ebro river mouth. The performance of the different methods will be assessed in terms of radiometric sensitivity and coast line width; the feasibility of using a land-sea mask of the observed scene as ancillary information in the deconvolution process to improve coastal retrievals from SMOS observations is analyzed.

5.4.1 Airborne system overview

In order to obtain $T_B$ datasets within the SMOS preparatory activities, several field experimental campaigns using the UPC Airborne RadIometer at L-band (ARIEL) have been conducted [Acevo-Herrera et al., 2009]. ARIEL is a light-weight nadir-looking L-band Dicke radiometer, with a radiometric sensitivity of 0.71 K for an integration time of 100 ms [Valencia et al., 2008]. It is mounted on a remotely controlled aircraft or Unmanned Aerial Vehicle (UAV) of 2.5 m wingspan, 2 m long, and approximately 30 minutes of flight autonomy. A system composed by a Global Positioning System (GPS), a 3-axes inclinometer, gyros and accelerometers determine the position and the attitude of the aircraft and are used to properly geo-reference the radiometric measurements. Data is stored in onboard data-loggers for later processing. The UAV with the ARIEL radiometer can be seen in Fig. 5.7(a).

The ARIEL data processing can be divided into three main tasks: (i) radiometer’s raw output voltages are converted into antenna temperatures through calibration – which is performed by measuring with the antenna pointing to an absorber (hot load) and to the sky (cold load) before and after each flight –, (ii) brightness temperatures ($T_B$) are obtained from antenna temperatures, taking into account the contributions of the atmosphere, and (iii) the $T_B$ are geo-referenced and, in the case of having observations from different overpasses which are geographically coincident, they are adequately interpolated (with footprints weighted
5.4. Application to airborne observations over the Ebro river mouth

with the antenna’s radiation pattern) on a regular grid to conform an image (see Fig. 5.8). Further information on the avionics and on the ARIEL data processing can be found in Acevo-Herrera et al. [2009, 2010].

![Image](a)

![Image](b)

**Figure 5.7** The aircraft with the ARIEL radiometer after a test flight (a). Retrieved antenna temperature histogram (b).

5.4.2 Ebro river mouth field experiment

The test site of this field experiment has been the Ebro river mouth, located 180 km South from Barcelona, because of the large variety of scenarios that can be found in a reduced area: dry land (ground), moist or flooded lands (rice fields), dry sand, fresh water (small ponds), and salty water (sea). It is one of the largest wetland areas (320 km$^2$) in the Western Mediterranean region and is in intensive agricultural use for rice. Flights were performed over the Marquesa beach sea shore and land. The diversity of this area can be noticed on the antenna temperature histogram shown in Fig. 5.7(b). Since flights were conducted during daylight conditions, sun effects on the data have been corrected for.

5.4.3 Downscaling strategy

Flights at different heights were performed over the Ebro River Mouth with the ARIEL radiometer so that L-band observations over this area at different spatial resolutions were acquired. ARIEL $T_B$ images obtained at heights between 40 and 170 m, and between 170 and 300 m are shown on Fig. 5.8(a) and (b), respectively. As a rule of thumb, ARIEL observations have a footprint of approximately 1/3 times the flight height. Accordingly, the observations on Fig. 5.8(a) have a pixel size between $\sim$ 13 and 57 m, and the observations on Fig. 5.8(b) have a pixel size between $\sim$ 57 and 100 m.

The Wiener, CLS, Wiener model, and CLS model filters have been applied to the $T_B$ image on Fig. 5.8(b) to explore the possibility of improving its spatial resolution. The use of wavelets has not been considered in this Section, since it has been shown not to be of any advantage when applied to SMOS-like data in Section 5.3.

The effective antenna pattern function of the ARIEL radiometer has been approximated in the deconvolution filters by a 2-D Gaussian function with the observations’ mean radius as half-width value. And two $T_B$ models of the area have been used as ancillary information on two versions of the Wiener and CLS model filters: 1) a simple $T_B$ model has been obtained
Chapter 5. Spatial resolution enhancement of SMOS data: a deconvolution-based approach

Figure 5.8 ARIEL Retrieved $T_B$ [K] geo-referenced on Google Earth obtained at heights (a) between 40 and 170 m, and (b) between 170 and 300 m.

Figure 5.9 Digital Elevation Model [m] of the Marquesa beach area at 5 m spatial resolution, geo-referenced on Google Earth.

From the 5 m resolution Digital Elevation Model (DEM) shown on Fig. 5.9: a land-sea mask have been first derived from the DEM to define the model sea-land transition and constant values of 120 K and 220 K have been afterwards assigned to sea and land pixels, respectively 2) the image on figure 5.8(a) has been directly used as $T_B$ model on a best-case version of the filters to explore their maximum capabilities. The filter’s parameters have been selected in each case by optimizing the RMSE over land pixels.

5.4.4 Experimental results

To evaluate the spatial resolution achieved with the different algorithms, cross-sections at a constant latitude of the image obtained from ARIEL observations at heights 40-170 m, 170-300 m, and of the images resulting from the application of Wiener-derived and CLS-derived filters to the 170-300 m height image, are presented on Fig. 5.10. It can be observed that the coast line is sharply defined when Wiener and CLS model filters are used, which can lead to better coastal retrievals. It can also be observed that the highest definition is obtained when the 40-170 m height image is used as $T_B$ model (best case). Therefore, it appears that the
more accurate the $T_B$ model used on the filter, the sharper the coast-line definition of the resulting image. However, further studies will be needed to quantify the spatial resolution enhancement obtained when applying the different methods.

**Figure 5.10** (a) Cross-sections of the image obtained from ARIEL observations at heights 40-170 m, 170-300 m, and of the images resulting from the application of Wiener-derived filters to the 170-300 m height image. (b) Cross-sections of the image obtained from ARIEL observations at heights 40-170 m, 170-300 m, and of the images resulting from the application of CLS-derived filters to the 170-300 m height image.

A RMSE metric has been used to assess the radiometric sensitivity achieved with the different methods; it is computed in each case with respect to the $T_B$ image in Fig. 5.8(a), which is used as ground-truth data, and results are listed in Table 1. Over land pixels, it can be observed that all methods satisfactorily improve the radiometric sensitivity of the observations. Over sea pixels, though, the methods practically do not achieve any improvement or even worsen the results. Note that this fact can possibly be due to the fact that the filter’s parameters are set by optimizing the RMSE over land pixels and not over sea pixels. Regarding the effect of adding the $T_B$ model, it can be noticed to considerably improve the RMSE over land pixels. This improvement is specially remarkable both over land and sea pixels when the $T_B$ image in Fig. 5.8(a) is used as $T_B$ model (best case). Therefore, these results indicate that the RMSE obtained with the methods which include a $T_B$ model also relies on the effectiveness of the model they use.

**Table 5.2** RMSE between the different $T_B$ images and the highest spatial resolution $T_B$ image at 40-170 m height, over land and sea pixels

<table>
<thead>
<tr>
<th></th>
<th>170-300 m height</th>
<th>Wiener</th>
<th>CLS</th>
<th>Wiener model/best</th>
<th>CLS model/best</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>28.5</td>
<td>26.6</td>
<td>24.8</td>
<td>23.4/11.4</td>
<td>22.5/11.7</td>
</tr>
<tr>
<td>Sea</td>
<td>24.5</td>
<td>23.4</td>
<td>24.0</td>
<td>26.8/12.4</td>
<td>22.1/14.6</td>
</tr>
</tbody>
</table>
5.5 Conclusions

An efficient deconvolution scheme has been proposed to improve the spatial resolution of future SMOS data, particularly over land, where it is more needed. Six different algorithms have been presented, which nicely explore the possibilities of working on Fourier and wavelet domains and of suitably adding an L-band $T_B$ model of the observed scene as auxiliary information in the reconstruction process. The methods have been applied to synthetic and realistic $T_B$ images processed by SEPS and to airborne field experimental data over the Ebro river mouth so as to visually assess and numerically quantify their performance.

Results over SMOS-like images are shown in terms of the best radiometric sensitivity ($\Delta T$) and spatial resolution ($\Delta S$) that can be achieved simultaneously. They confirm that the developed algorithms could significantly decrease the product $\Delta T \cdot \Delta S$—particularly of the pixels located on the upper left area of an SMOS alias-free FOV—improving the spatial resolution from $\sim 90$ to $\sim 50$ km while keeping the radiometric sensitivity constant. The product $\Delta T \cdot \Delta S$ was decreased in a 49% over land pixels and in a 30% over sea pixels. Also, a trend to round the pixels’ shape and diminish its size has been observed, with higher effects in the pixels located far from nadir. Hence, the deconvolution scheme proposed could potentially normalize the pixels shape and orientation in all the SMOS FOVs as well as improving the radiometric sensitivity and the spatial resolution of SMOS observations. Furthermore, results of its application to airborne field experimental data indicate that these methods could be adjusted in coastal areas to improve the radiometric sensitivity and the coastline definition of the observations.
Downscaling SMOS-derived soil moisture using higher resolution visible/infrared data

A downscaling approach to improve the spatial resolution of SMOS soil moisture estimates with the use of higher resolution visible/infrared satellite data is presented. The algorithm is based on the so-called universal triangle concept that relates visible/infrared parameters, such as Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature ($T_s$), to soil moisture status. It combines the accuracy of SMOS observations with the high spatial resolution of visible/infrared satellite data into accurate soil moisture estimates at high spatial resolution. In preparation for the SMOS launch, the algorithm was tested using observations of the UPC Airborne Radiometer at L-band (ARIEL) over the Soil Moisture Measurement Network of the University of Salamanca (REMEDHUS) in Zamora (Spain), and LANDSAT imagery. Results show good agreement with ground-based soil moisture observations, and illustrate the strength of the link between visible/infrared satellite data and soil moisture status. Following the SMOS launch, a downscaling strategy for the estimation of soil moisture at high resolution from SMOS using MODIS visible/infrared data has been developed. Results of its application to the first SMOS images acquired during the commissioning phase provide a first evidence of its capabilities.

6.1 Introduction

Theoretical, ground-based, and airborne experimental studies have proven that L-band passive remote sensing is optimal for soil moisture sensing due to its all-weather capabilities and the high sensitivity of the Earth emission to soil moisture under most vegetation covers (see Section 2.2). The ESA SMOS mission, in orbit since November the 2nd 2009, uses a novel L-band passive instrument concept to provide accurate global surface soil moisture estimates (see Section 1.3.1). However, due to technological limitations, the spatial resolution of SMOS observations is limited to $\sim 50$ km. This resolution is adequate for many global applications, but restricts the use of the data in regional studies over land, where a resolution of 1-10 km is needed.

The possibility of using visible/infrared sensors for soil moisture sensing has been widely studied in the past, since visible/infrared sensors onboard satellites provide good spatial resolution, and controlled experiments have shown their potential to sense soil moisture
[Idso et al., 1975; Price, 1977; Adegoke and Carleton, 2002; Wang et al., 2007]. However, they are equally sensitive to soil types, and it is difficult to decouple the two signatures. In addition, soil moisture estimates from visible/infrared sensors usually require surface micro-meteorological and atmospheric information that is not routinely available [Cracknell and Xue, 1996; Zhang and Wegehenkel, 2006]. Hence, visible/infrared sensors are commonly used to provide an indirect measurement of soil moisture, but not to retrieve it.

To achieve accuracy and high spatial resolution, it seems natural to try to combine the strength of the microwave and visible/infrared approaches for soil moisture estimation. Recently, a number of studies have documented the emergence of a triangular or trapezoidal shape when remotely sensed surface radiant temperature ($T_s$) over heterogeneous areas are plotted versus vegetation index (VI) measurements; an analysis of this “universal triangle” has led to different methods relating the $T_s$/VI space to land surface energy fluxes and surface soil moisture. A comprehensive review of these methods can be found in Carlson [2007]; Petropoulos et al. [2009]. Particularly, an algorithm for the operational retrieval of high-resolution surface soil moisture from future Visible Infrared Imager Radiometer Suite (VIIRS) and MIS (Microwave Imager Sounder) data, under the National Polar-Orbiting Operational Environmental Satellite System (NPOESS), is underway [Zhan et al., 2002]. It has a definite theoretical basis that links soil moisture to the $T_s$/VI space [Carlson et al., 1994], and was demonstrated using 1-km AVHRR and 25-km SSM/I in Chauhan et al. [2003].

This chapter presents an algorithm to synergistically combine passive L-band observations and visible/infrared satellite data into high resolution soil moisture. The algorithm involves three steps. First, a soil moisture retrieval technique is applied to the brightness temperature images to generate soil moisture maps at low resolution. In the second step, the universal triangle concept is used to link the microwave-derived soil moisture maps at low resolution to the scene visible/infrared parameters (aggregated to the microwave resolution). In the third step, the linking model is used with the visible/infrared parameters at high resolution to disaggregate microwave soil moisture into high resolution soil moisture. In Section 6.2, as part of the downscaling activities conducted at the REMEDHUS Cal/Val site, a previous study and test of the algorithm using passive L-band airborne observations and visible/infrared data from LANDSAT is presented. Following this first experiments, a downscaling strategy for improving the spatial resolution of SMOS soil moisture estimates using MODIS-derived NDVI and $T_s$ data is introduced in Section 6.3. Results of its application to the first SMOS images acquired during the commissioning phase indicate that with this approach it is feasible to improve the spatial resolution of SMOS observations over land; the spatial variability of SMOS-derived soil moisture observations is effectively captured at the spatial resolutions of 32, 16, and 8 km. However, further studies are needed to evaluate the radiometric accuracy of the observations at the different spatial resolutions and therefore establish a downscaling limit. The use of ascending and/or descending SMOS orbits for soil moisture sensing is discussed, and soil moisture estimations are compared to in situ soil moisture data from the Murrumbidgee catchment, in South-eastern Australia. In Section 6.4, the main findings and contributions of this work are summarized, and the operational applicability of this downscaling technique to SMOS is discussed.

### 6.2 Downscaling activities at the REMEDHUS Cal/Val site

Due to the exploratory nature of the SMOS mission, calibration and validation (Cal/Val) of SMOS products is an essential activity. After SMOS commissioning phase, an intense
6.2. Downscaling activities at the REMEDHUS Cal/Val site

Activity by many research groups, coordinated by ESA, will collect in situ data simultaneous to SMOS observations in order to improve the empirical aspects of retrieval algorithms and to validate the products generated from these observations. Also, there is a strong interest in developing and testing downscaling techniques that could enhance the spatial resolution of SMOS data (∼50 km), since soil moisture estimates at a resolution of 1-10 km are needed for regional scale applications [Entekhabi et al., 1999]. Hence, different downscaling experiments have been carried out at the REMEDHUS Cal/Val site [ISMN, 2010], within the GPS and RAdiometric Joint Observations long-term field experiment (GRAJO), to investigate the scaling nature of soil moisture and explore the possibility of improving the spatial resolution of SMOS observations over land.

Flights at different altitudes have been performed over the REMEDHUS area with the UPC Airborne RadiometEter at L-band (ARIEL), and a downscaling approach to improve the spatial resolution of ARIEL observations using higher resolution visible/infrared LANDSAT imagery is evaluated. Results from comparison with ground-truth data show that with this technique it is feasible to improve the soil moisture estimates in terms of spatial resolution (from ∼50 m to 30 m) and accuracy (from 0.11 to 0.06 RMSE). This case study demonstrates the consistency of the visible/infrared relationship with soil moisture status, and the potential of applying this downscaling strategy to SMOS data.

6.2.1 Data description

The GRAJO long-term intensive field experiment was conducted at the REMEDHUS soil moisture network in the semi-arid area of the Duero basin, Zamora, Spain, from November 2008 to April 2010 [Monerris et al., 2009]. REMEDHUS has been selected as a secondary Cal/Val site for SMOS mission, and has also been proposed as a Cal/Val site for the NASA SMAP mission. It has an area of approximately a SMOS pixel (40 x 30 km), it is homogeneous (mostly covered by crops) and counts with a complete and operational network of 23 soil moisture and temperature sensors. Its climate is continental and semiarid, with cold winters and warm summers (12°C annual mean temperature and 400 mm mean rainfall).

Airborne observations

ARIEL is a light-weight L-band Dicke radiometer, with a radiometric sensitivity of 0.71 K for an integration time of 100 ms [Valencia et al., 2008]. It is mounted on an UAV of 2.5 m wingspan and 2 m long, which is able to fly at altitudes up to 400 m and has a flight autonomy of ∼30 minutes. A system composed by a GPS and an inertial motion unit is used to geo-reference the radiometric measurements and monitor the aircraft’s attitude (roll, pitch and yaw), altitude, and speed. Data is recorded into onboard data-loggers for later processing.

The ARIEL data processing mainly comprises three steps: (i) radiometer’s raw output voltages are converted into antenna temperatures through calibration – which is performed by measuring with the antenna pointing to an absorber (hot load) and to the sky (cold load) before and after each flight-, (ii) brightness temperatures ($T_B$) are obtained from antenna temperatures, taking into account the contributions of the atmosphere, and (iii) the $T_B$ are geo-referenced and, in the case of having observations from different overpasses which are geographically coincident, they are adequately interpolated (with footprints weighted with the antenna’s radiation pattern) on a regular grid to conform an image. Detailed information on the avionics and on the ARIEL data processing can be found in Acevo-Herrera et al. [2009, 2010].
Figure 6.1 shows the two ARIEL $T_B$ images that are analyzed on this study, overlapped in an aerial photography from Google Earth. They correspond to two flights undertaken the 25th of March 2009 at 9.30 am (Flight 1, image on the right), and at 4.45 pm (Flight 2, image on the left), and cover an area of $\sim 720 \times 720$ m each. These images have been obtained from ARIEL measurements acquired at heights $140 \pm 30$ m. As a rule of thumb, ARIEL observations have a footprint of approximately 1/3 times the flight height; accordingly, ARIEL $T_B$ on Fig. 6.1 have a pixel size of $\sim 50$ m. However, since ARIEL data will be jointly used with LANDSAT data at a spatial resolution of 30 m, ARIEL observations have been conveniently re-sampled to a 60 x 60 m grid.

**Figure 6.1** ARIEL Retrieved $T_B$ [K] obtained at heights $140 \pm 30$ m (spatial resolution $\sim 50$ m), re-sampled to a 60 x 60 m grid and geo-referenced on Google Earth.

**LANDSAT data**

A LANDSAT 5 satellite image from the 23rd of March 2009, scene 201/031, has been used in the present study. The image has been geometrically corrected using orbital modeling and ten ground control points of the study area (latitude, longitude and height); the radiometric calibration has been performed according to Chander and Markham [2003], and the atmospheric correction according to Richter [1996] and atmospheric standard values.

The Normalized Difference Vegetation Index (NDVI) of the area under study has been obtained as [Rouse et al., 1974]:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}, \quad (6.1)$$

where $\rho_{NIR}$ and $\rho_R$ are the at-surface reflectance of bands 4 (Near-infrared, 0.76 - 0.90 m) and 3 (Visible, 0.63 - 0.69 m), respectively, at 30 m spatial resolution.

The surface radiant temperature ($T_s$) of the area under study has been obtained from band 6 (Thermal, 10.40 - 12.50 m) at 120 m spatial resolution, and has been re-sampled to 30 m.

A land cover map of the study area has been retrieved using a supervised classification by maximum likelihood algorithm, and five classes have been identified:

1. rainfed cereal.
2. irrigated cereal.
3. pasture.
4. unproductive soils comprising building areas, ploughed and tilled plots, vineyards (bare soil at the time), fallow lands and others.
5. shrublands and scattered trees.

The predominant covers are pasture (24.1%) and rainfed cereal (9.4%) for Flight 1, and bare soils (19.8%) and rainfed cereal (10.7%) for Flight 2.

Note that, since LANDSAT acquisition time is 10.40 am, data from Flight 1 (9.30 am) is expected to be more closely linked to the satellite NDVI and $T_s$ information than data from Flight 2 (4.45 pm).

**Ground-based soil moisture**

Soil moisture fields over large areas are not easily described using surface observations, which difficulties the validation of remotely sensed soil moisture observations. In this study, ground measurements of 0-5 cm soil moisture at 20 sampling locations were acquired simultaneously to the airborne observations. These measurements have been interpolated to a 30 x 30 m grid using a spatial kriging interpolation technique [Burgees and Webster, 1980]. The resulting image is used in Section 6.2.4 as ground truth to calculate and compare ARIEL-derived and downscaled soil moisture errors.

**6.2.2 The temperature/vegetation index space**

Figure 6.2 illustrates the polygonal correlation between LANDSAT $T_s$ and NDVI on each flight. The polygon’s edges can be interpreted as the minimum/maximum reached by vegetation cover (NDVI) and soil moisture: bare soil, maximum biomass, completely dry, and fully wetted soil surface. Note that, since the vegetation temperature does not vary spatially, variations in temperature in the triangle reflect only variations in the soil surface, i.e. in the soil surface dryness. Therefore, the coldest and warmest pixels correspond to the wet and dry edges, respectively.

**Figure 6.2** Scatter plots of LANDSAT surface radiant temperature versus LANDSAT NDVI of the areas corresponding to (a) Flight 1, and (b) Flight 2.
The predominance of rainfed cereal on Flight 1 and of bare soils on Flight 2 is clearly seen in Fig. 6.2(a) and Fig. 6.2(b), respectively. Also note that the maximum biomass edge is shorter than the bare soil edge in the two scatter plots, which evidences the low sensitivity of vegetation temperature to changes in soil moisture and the higher sensitivity of bare soil to changes in soil moisture content; the range of $T_s$ decreases as the vegetation cover increases. Another salient aspect of the polygons is that the dry edges slope towards lower temperatures with increasing NDVI, which can be explained by the fact that sunlit vegetation is generally cooler than sunlit bare soil.

The most severe limitation of the triangle concept is that a large number of pixels reflecting a full range of soil surface wetness and fractional vegetation cover is needed to identify a “triangular” shape in the pixel distribution [Carlson, 2007]. It has to be noted that this condition prevents a full validation of the downscaling approach with the field experimental data available in the present study.

### 6.2.3 Downscaling approach

Theoretical and experimental studies have demonstrated that there can be a unique relationship between soil moisture ($s_m$), NDVI, and $T_s$ for a given region under a wide range of climatic conditions and land surface types. This relationship can be expressed through a regression formula such as [Carlson et al., 1994]:

$$s_m = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} a_{ij} \text{NDVI}^i T_s^j,$$

(6.2)

where $n$ should be chosen so as to give a reasonable representation of the data.

In this study, a linking model is developed between the LANDSAT $T_s$/NDVI space and airborne soil moisture estimates using the following approximation of (6.2):

$$s_m = a_{00} + a_{01} T_N + a_{10} F_r + a_{11} T_N F_r + a_{02} T_N^2 + a_{20} F_r^2,$$

(6.3)

where $T_N$ stands for normalized LANDSAT surface radiant temperature and $F_r$ is the fractional vegetation cover [Gutman and Ignatov, 1998], defined as:

$$T_N = \frac{T_s - T_{\text{min}}}{T_{\text{max}} - T_{\text{min}}},$$

(6.4)

$$F_r = \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}},$$

(6.5)

with $T_{\text{max}}$ and $T_{\text{min}}$ being the maximum and minimum $T_s$ values for a particular scene, and, similarly, $\text{NDVI}_{\text{max}}$ and $\text{NDVI}_{\text{min}}$ being the maximum and minimum NDVI values for a particular scene. Normalization is preferred to reduce the dependence of $T_s$/NDVI on ambient conditions, and to allow further comparison of different experiments.

The downscaling approach builds on the VIIRS algorithm concept in Zhan et al. [2002]: it consists of aggregating high resolution visible/infrared land surface parameters to the scale of the microwave observations for the purpose of building a linking model that is afterwards applied at fine scale to disaggregate the passive soil moisture observations into high-resolution soil moisture. The algorithm involves three main steps:

1. The soil moisture at low resolution is retrieved from ARIEL observations through linear regression with the in situ soil moisture samples. Note that this step is used in the present study, but is not required in a possible application to SMOS data.
2. High resolution LANDSAT-derived \( T_N \) and \( F_r \) are aggregated to the scale of the airborne observations (60 m), and (6.3) is used to set up a system of linear equations for the pixels in the area under study. The system is solved to obtain the regression coefficients \( a_{ij} \) of the linking model.

3. Downscaled soil moisture at 30 m spatial resolution is obtained by applying (6.3) with the regression coefficients \( a_{ij} \) obtained in step 2, \( T_N \), and \( F_r \) at 30 m spatial resolution.

The use of the Soil Adjusted Vegetation Index (SAVI) instead of the NDVI in (6.2) was considered as an attempt to eliminate soil-induced variations that could affect the relationship between \( T_s \), vegetation, and soil moisture [Huete, 1988]. However, results showed no significant differences.

![Figure 6.3](image)

Figure 6.3 Linear regression between ARIEL \( T_B \) and coincident ground measurements of 0-5 cm soil moisture acquired during (a) Flight 1, and (b) Flight 2.

6.2.4 Results

The downscaling algorithm has been applied to Flight 1 and Flight 2 data separately. Figure 6.3 shows the correlation between ARIEL \( T_B \) and ground-based soil moisture (\( R^2 \) values of 0.78 and 0.57 are obtained for Flight 1 and Flight 2, respectively). The low correlation on Flight 1 is probably due to its acquisition time (4.45 pm), which is far from LANDSAT overpass time (10.40 am) and therefore can induce significant errors on \( T_s \). These linear regressions are used to retrieve soil moisture maps from ARIEL observations.

Sample results of applying the downscaling technique to ARIEL-derived soil moisture are presented on Fig. 6.4. Comparing with the ground-based soil moisture, it can be seen that both the ARIEL-derived soil moisture fields and the downscaled images reproduce the spatial variations in the soil moisture measurements. The spatial distribution of the error between retrieved and downscaled soil moisture and ground-based soil moisture is further analyzed in Fig. 6.5. It shows that the RMSE between ARIEL-derived soil moisture and ground-based soil moisture is 0.11, and that it is improved in a \( \sim 40\% \) when the downscaling technique is applied.
Chapter 6. Downscaling SMOS-derived soil moisture using higher resolution visible/infrared data

Figure 6.4 Sample results for the visual comparison of soil moisture fields [m$^3$/m$^3$]. From left to right: interpolated ground-based soil moisture, soil moisture retrieved from ARIEL $T_B$, and downscaled soil moisture obtained with the algorithm presented. Upper row: Flight 1; Lower row: Flight 2.

(a) RMSE = 0.112  (b) RMSE = 0.069  (c) RMSE = 0.115  (d) RMSE = 0.064

Figure 6.5 Spatial distribution of the soil moisture error [m$^3$/m$^3$] retrieved using ARIEL $T_B$ on (a) Flight 1 and (c) Flight 2, and obtained with the downscaling algorithm on (b) Flight 1 and (d) Flight 2 observations.
6.3 Downscaling approach for SMOS

Based on the experience gained from the downscaling activities presented in Section 6.2, an approach for improving the spatial resolution of SMOS soil moisture observations using MODIS-derived NDVI and \( T_s \) data has been developed. MODIS has been selected among other operational visible/infrared satellites for its suitable characteristics, mainly, its temporal resolution (1-2 days), data availability (near real time), spatial resolution (1 km), and overpass time (10.30 am for MODIS/Terra satellite). Alternatives present severe incompatibilities to be used in combination with SMOS measurements such as the 12.30 am overpass time of the AVHRR, or the 16-days repeat cycle of ASTER.

The resolution of SMOS observations varies from 30 km at nadir to 90 km at the upper borders of the FOV (see Fig. 1.6). In this work, SMOS observations are combined on a regular grid of 64 x 64 km and are downscaled to a grid of 32 x 32 km. The possibility of going into higher spatial resolutions of 16 and 8 km is also explored. However, future studies are needed to evaluate the radiometric resolution of the soil moisture estimates at the different spatial resolutions, and to establish a downscaling limit, which could be given either by the resolution of the optical sensor (which in the case of MODIS is 1 km), or by the presence of noise affecting the accuracy of the soil moisture estimates.

6.3.1 Data description

At the time of writing (20th April 2010), the SMOS commissioning phase is underway. Therefore, the SMOS Level 1c data available is limited and subject to calibration changes. Also, the SMOS Level 2 Soil Moisture Processor is not operational, so that there is no open access to SMOS-derived soil moisture data. These reasons have prevented a full validation of the downscaling approach in the present context, and further work will be needed to consolidate the algorithm once SMOS enters its operational phase. Nonetheless, this study has been oriented so as to make the most out of the data that is currently available.

SMOS data

SMOS data acquired during the commissioning phase and processed from Level 0 to Level 1c with the UPC MIRAS Testing Software (MTS) [Corbella et al., 2008] is used in the present study. For an initial validation of the algorithm, only horizontally polarized brightness temperatures are considered. Note that horizontal polarization is more sensitive to soil moisture variation than vertical polarization (see Fig. 2.7). Also, this study focuses on observations acquired at a constant incidence angle of 42.5°, which is the fixed incidence angle of SMOS Level 1c browse products [McMullan et al., 2008].

MODIS data

The MODIS instrument operates on both the Terra (10.30 am/10.30 pm) and Aqua (1.30 am/1.30 pm) spacecrafts. On this work, only MODIS/Terra products will be used, due to its closeness to SMOS overpass times (6 am/6 pm). Note that it is particularly critical for the case of \( T_s \). Specifically, the daily MODIS/Terra \( T_s \) and the 16-day NDVI Level 3 product (datasets MOD11C1 and MOD13C1, respectively) have been employed. Both products have a spatial resolution of 0.05° (~5 km at the equator), and have been aggregated to 64, 32, 16 and 8 km for the present study. The NDVI composite is cloud free, whereas the \( T_s \) is not. The option of using the 8-day \( T_s \) composite was discarded, since it is not as representative
Ground-based soil moisture

Ground-based measurements of 0-5 cm volumetric soil moisture from the Australian Airborne Calibration/Validation Experiments for SMOS (AACES) are used to evaluate the algorithm performance. The AACES field experiment took place from January 18 to February 21, 2010, in the Murrumbidgee catchment (-33 to -37 S, 143 to 150 E), in South-eastern Australia, in which the permanent OzNet soil moisture monitoring network (www.oznet.unimelb.edu.au) is located. The comparison of SMOS-derived soil moisture estimates to ground-truth data will be focused on a subset of those stations, located within the Coleambally Irrigation Area, South of Yanco (referred to here as the Yanco region); it is a homogeneous and flat area of approximately 60 km by 60 km area (∼ a SMOS pixel) hosting a network of 13 soil moisture stations deployed all over the region [Young et al., 2008].

6.3.2 Method

The downscaling method for the estimation of soil moisture at high resolution from SMOS using MODIS-derived Ts and NDVI data consists of three main steps, which are described in the following sections.

Step 1: soil moisture at low resolution

The retrieval of soil moisture from SMOS brightness temperatures is performed by inverting a simple radiative transfer model, which is described hereafter.

Research since the mid 1970’s has established and verified the physical bases for passive microwave emission of land surfaces (see Section 2.2). Hence, it is known that the emission of microwave energy is proportional to the product of the surface temperature Ts and the surface emissivity e, which is commonly referred to as the microwave brightness temperature TB:

\[ T_{Bp} = e_p \cdot T_s = 1 - \Gamma_{s,p}, \]  

(6.6)

where the subscript p denotes either vertical (v) or horizontal (h) polarization, and \( \Gamma_{s,p} \) is the reflectivity of the surface.

The emissivity depends on the dielectric constant of the medium \( \epsilon_s \) (\( \epsilon_s = \epsilon'_s + j\epsilon''_s \)) which is, in turn, governed by the soil moisture content. Although the relationship between emissivity and \( T_B \) is linear, the relationship between emissivity and dielectric constant is nonlinear because the water content of the media has a nonlinear effect on the dielectric constant (see Section 2.2.3). The Fresnel equations (2.22) can be used to describe the relationship between reflectivity and dielectric constant in the case of a flat surface and a medium of uniform \( \epsilon_s \).

Since the contribution of the imaginary part of \( \epsilon_s \) in (2.22) is relatively small, the inversion of the Fresnel equations can be simplified if only the real part of \( \epsilon_s \)—effective permittivity \( \epsilon'_s \)—is considered. This way, the Fresnel equations (2.22) can be inverted to estimate the
6.3. Downscaling approach for SMOS

The effective permittivity of the emitting layer [Jackson, 1993]:

\[ \epsilon'_{s,h} = \sin^2 \theta + \cos^2 \theta \left( \frac{\sqrt{\Gamma_{s,h}} + 1}{\sqrt{\Gamma_{s,h}} - 1} \right)^2, \]

\[ \epsilon'_{s,v} = a^2 + a \left( \frac{\sqrt{a^2 - 4b^2 \cos^2 \theta \sin^2 \theta}}{2b^2 \cos^2 \theta} \right), \] (6.7)

where \( a = \sqrt{\Gamma_{s,h}} + 1 \) and \( b = \sqrt{\Gamma_{s,v}} - 1 \), and \( \theta \) is the incidence angle. Note that the use of (6.7) requires the assumption that emissivity is principally related to the real part of the complex dielectric constant; this is mostly true for the case of dry soil, but could induce significant errors in the case of wet conditions [Jackson, 1993].

The soil moisture content can therefore be determined from \( \epsilon'_{s,p} \) by inverting a soil dielectric mixing model, e.g. Wang and Schmugge [1980]; Hallikainen et al. [1985]; Dobson et al. [1985]; Mironov et al. [2004].

The following additional considerations have been incorporated to this inversion procedure to consolidate the soil moisture retrieval technique:

- To account for the effects of vegetation on the observed brightness temperatures, the option of using (2.32) instead of (6.6) has been considered. In the case of using (2.32): (i) it is assumed that vegetation canopy is in thermal equilibrium with soil temperature, (ii) vegetation is assumed to be short/sparse enough so as not to contribute to a significant emission of its own (\( \omega=0 \)), and (iii) \( \tau \) is estimated using (2.31) with \( \alpha=-0.05, \beta=-0.36 \), and MODIS NDVI data [Burke et al., 2001].

- The option of correcting for the effect of surface roughness on the microwave emission from bare soil has also been included. To do so, Fresnel coefficients have been modified using (2.27), where \( Q_s \) and \( n \) have been set equal to zero, according to Wigneron et al. [2001], and \( h_s \) has been set to 0.2 (representing rather smooth surface roughness conditions).

- Three different soil dielectric mixing models will be used to retrieve soil moisture from the effective permittivity: the model in Wang and Schmugge [1980], the model in Hallikainen et al. [1985], and the model in Dobson et al. [1985].

In the present study, this retrieval approach has been applied to SMOS T\( _{hh} \) images at a constant incidence angle of 42.5° to generate soil moisture maps at 64 km. In the nominal case, the inversion procedure takes into account vegetation effects, corrects for surface roughness, and uses the soil dielectric mixing model in Hallikainen et al. [1985] with the mean Australian sand and clay fractions reported in Minasny and McBratney [2007], which are 40% and 28.6%, respectively. The effect of using other configurations (i.e. no roughness correction, no vegetation correction, or the use or other soil dielectric mixing model) is only considered when comparing with in situ measurements in Section 6.3.3.

Step 2: linking model

A linking model based on the triangle concept has been developed to relate SMOS-derived soil moisture to MODIS-derived NDVI and \( T_s \) (aggregated to 64 km).

As discussed in Sections 6.1 and 6.2.2, NDVI and \( T_s \) are proven indicators of the vegetative and thermal state of the land surface. Carlson et al. [1994] demonstrated that the
relationship between \( s_m \), NDVI, and \( T_s \) for a particular region can be described using the regression formula in (6.2). In Section 6.2, the approach in (6.3) was effectively used to define the linking model between LANDSAT \( T_s/NDVI \) data and ARIEL observations. In the context of SMOS, SMOS brightness temperatures have been added to the right side of (6.2) to capture soil moisture variability and strengthen the relationship between land surface parameters and soil moisture. Thus, (6.2) is modified to:

\[
s_m = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=0}^{n} a_{ijk} \text{NDVI}^i T_s^j T_B^k.
\]  
(6.8)

Using (6.4) and (6.5), the following approximation of (6.8) has been defined as linking model between SMOS observations and MODIS-derived NDVI and \( T_s \) data:

\[
s_m = a_{000} + a_{001} T_B N + a_{010} T_N + a_{100} F_r + a_{002} T_B^2 + a_{020} T_N^2 + a_{200} F_r^2 + a_{011} T_N T_B N + a_{101} F_r T_B N + a_{110} F_r T_N,
\]  
(6.9)

where \( T_B N \) are the normalized SMOS brightness temperatures:

\[
T_B N = \frac{T_B - T_{B\text{min}}}{T_{B\text{max}} - T_{B\text{min}}},
\]  
(6.10)

with \( T_{B\text{max}} \) and \( T_{B\text{min}} \) being the maximum and the minimum \( T_B \) values for a particular scene.

Three main semi-empirical relationships can be found in literature to derive vegetation fraction from NDVI: Baret et al. [1995], Carlson and Ripley [1997], and Gutman and Ignatov [1998]. No significant differences have been found on the algorithm performance when using these three alternatives, and Gutman and Ignatov [1998] has been adopted for simplicity.

The linking model in (6.9) is used to set up a system of linear equations for all the pixels in the image. This system is solved to obtain the regression coefficients \( a_{ijk} \) –which are specific of the scene being analyzed.

**Step 3: soil moisture at high resolution**

SMOS-derived soil moisture maps at 32 km are obtained by applying (6.9) with the regression coefficients \( a_{ijk} \) (from step 2), \( T_N \) and \( F_r \) aggregated to 32 km, and SMOS \( T_B N \) resampled to a 32 x 32 km grid. Similarly, soil moisture maps at 16 or 8 km are obtained by applying (6.9) with the regression coefficients \( a_{ijk} \), \( T_N \) and \( F_r \) aggregated to 16 km or 8 km, and SMOS \( T_B N \) resampled to a 16 x 16 km or 8 x 8 km grid.

**6.3.3 Results**

The downscaling algorithm in 6.3.2 has been applied to SMOS \( T_B \) images over different regions within Australia to evaluate the algorithm performance under different natural conditions. In this Section, sample soil moisture maps at 64 and 32 km spatial resolution, resulting from the application of the downscaling algorithm to different SMOS images are shown. Results of using (6.3) instead of (6.9) in the SMOS context (Steps 2 and 3 of the algorithm) have been included so as to compare the effect of adding or not SMOS \( T_B \) to the linking model. The use of ascending and/or descending SMOS orbits for soil moisture retrieval is discussed. Then, soil moisture estimations at 64 and 32 km are compared to
6.3. Downscaling approach for SMOS

Figure 6.6 Sample results of the application of the algorithm to a SMOS image over western Australia, from December 8, 2009 (6 am). SMOS $T_B$ [K] on a 16 x 16 km grid (a). SMOS $T_B$ image [K] on a 64 x 64 km grid (b). MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [m$^3$/m$^3$] at 64 km (e). SMOS-derived soil moisture maps [m$^3$/m$^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images correspond to clouds masking MODIS $T_s$ measurements.
in situ soil moisture data from the Murrumbidgee catchment, in South-eastern Australia. Also, the possibility of going into higher spatial resolutions of 16 and 8 km is explored.

Note that the date on the SMOS and MODIS images used in this Section are expressed in UTC, whereas the satellite overpass is expressed in local time.

**Soil moisture maps**

Figure 6.6 shows the results of applying the downscaling algorithm to an SMOS $T_B$ image over western Australia, from December 8, 2009. This image could be representative of a bare soil or poorly vegetated scenario (the NDVI in Fig. 6.6(d) is less than 0.5 in all the area). It can be seen that when using the linking model in (6.3) (Fig. 6.6(f)), the downscaling method is not able to capture the soil moisture variability in Fig. 6.6(e). This is consistent with previous studies using the well-known triangle concept, which have reported the method’s limitation of requiring a large number of pixels reflecting a wide range of fractional vegetation and moisture conditions [Carlson, 2007]. However, Fig. 6.6(g) shows that, when adding the SMOS $T_B$ to the linking model, the method is capable of reproducing the variability seen in the low-resolution SMOS observations.

There are some pixels within the SMOS $T_B$ image in Fig. 6.6 that have remarkably lower $T_B$ (higher soil moisture content) that their surroundings. Particularly, in the region above the cloud mask in Fig. 6.6(b) there is an isolated green pixel at nearly the center of the image, an isolated yellow pixel in the top-right, and an orangish area in the left side of the image; in the region below the cloud mask, there are salient dark blue pixels near the coast line and an isolated blue pixel inland, on the left. In Fig. 6.7, these areas have been identified using coloured rectangles in two aerial photographs covering the regions above (Fig. 6.7(a)) and below (Fig. 6.7(b)) the cloud mask in Fig. 6.6(e), from Google Earth. It can be seen that the areas marked with yellow, orange and dark blue rectangles correspond to sharp changes in land cover and/or topography, that are effectively captured by SMOS.
6.3. Downscaling approach for SMOS

Figure 6.8 Sample results of the application of the algorithm to a SMOS image over eastern Australia, from February, 17, 2010 (6 am). SMOS $T_B$ image [K] on a 16 x 16 km grid (a), SMOS $T_B$ image [K] on a 64 x 64 km grid (b), MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [m$^3$/m$^3$] at 64 km (e). SMOS-derived soil moisture maps [m$^3$/m$^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images are due to clouds masking MODIS $T_s$ measurements.
Chapter 6. Downscaling SMOS-derived soil moisture using higher resolution visible/infrared data

The areas marked with the green and blue rectangles contain the lake Disappointment and the lake Defroy, respectively, two salty lakes with dimensions of approximately 20 x 30 km. Therefore, through simple comparison to aerial photography, it can be seen that the most outstanding features of the region have been nicely detected by SMOS, and also captured at a higher spatial resolution with the downscaling algorithm using the linking model in 6.9.

![Figure 6.9 Scatter plots of MODIS surface radiant temperature versus MODIS NDVI, from Fig. 6.6 (a), and Fig. 6.8 (b).](image)

Sample results of the application of the algorithm to an area exhibiting a full range of fractional vegetation cover is shown in Fig. 6.8. Comparing with the 64 km soil moisture map in Fig. 6.8(e), it can be observed that the method adding the SMOS $T_B$ to the linking model (Fig. 6.8(g)) nicely captures the spatial patterns in soil moisture, and that they are only partially reproduced when using the linking model in (6.3) (Fig. 6.8(f)). Specially, note that the areas not reproduced are those exhibiting extreme low or wet moisture conditions.

Figure 6.9 illustrates the polygonal correlation between MODIS $T_s$ and NDVI observations for the areas studied on Fig. 6.9(a), and Fig. 6.9(b). It evidences the wider range of soil surface temperature and fractional vegetation cover present in the image on Fig. 6.8, if compared to the image on Fig. 6.6. According to Carlson [2007], the main weakness of the triangle method is that it requires some subjectivity in identifying the dry edge (or warm edge) and the bare soil and maximum biomass extremes; identification is more easily obtained if a sufficient number of pixels with varying surface wetness and vegetation cover are present in the image. In this study, however, the edges of the polygon have been detected automatically from MODIS data, regardless of the scene. This could be certainly limiting the performance of the downscaling method when using the linking model in (6.3), but seems to be no longer a limitation when using the linking model in (6.9).

Ascending vs. descending orbits

SMOS is in a Sun-synchronous (polar) orbit, so that it passes over areas on the Earth’s surface at the same local solar time (6 am/6 pm). The overpass time was particularly chosen so as to minimize the effect of temperature gradients within the soil and vegetation on soil moisture retrieval. Still, it is generally assumed that thermal equilibrium and near uniform conditions in the near surface soil layers and overlying vegetation are more likely to be true at 6 am than at 6 pm. Note that the presence of temperature gradients could seriously affect
6.3. Downscaling approach for SMOS

![Image of downscaling approach for SMOS](image)

(a) SMOS $T_B$ [K]
(b) SMOS $T_B$ [K]
(c) MODIS $T_s$ [K]
(d) MODIS NDVI
(e) $s_m$ [m$^3$/m$^3$]
(f) $s_m$ [m$^3$/m$^3$]
(g) $s_m$ [m$^3$/m$^3$]

Figure 6.10 Sample results of the application of the algorithm to a SMOS image over central Australia, from December 8, 2009 (6 pm). SMOS $T_B$ image [K] on a 16 x 16 km grid (a). SMOS $T_B$ image [K] on a 64 x 64 km grid (b). MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [m$^3$/m$^3$] at 64 km (e). SMOS-derived soil moisture maps [m$^3$/m$^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images correspond to clouds masking MODIS $T_s$ measurements.
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Figure 6.11 Sample results of the application of the algorithm to a SMOS image over south-eastern Australia, from February, 17, 2010 (6 pm). SMOS $T_B$ image [K] on a 16 x 16 km grid (a). SMOS $T_B$ image [K] on a 64 x 64 km grid (b). MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [m$^3$/m$^3$] at 64 km (e). SMOS-derived soil moisture maps [m$^3$/m$^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images are the result of clouds masking MODIS $T_s$ measurements.
the performance of the soil moisture retrieval algorithms, since they are usually built upon the assumption that vegetation canopy is in equilibrium with soil temperature. Thus, in the early-stage of the SMOS mission in which we are now, it is important to confirm this general assumption, as well as to decide whether soil moisture retrievals should be performed using only ascendent orbits, using only descendent orbits, or using both of them.

Figures 6.10 and 6.11 show sample results of the application of the downscaling algorithm to SMOS images acquired on descending orbits. On these two cases, night time MODIS $T_s$ (10.30 pm) have been used for being closer than day time MODIS $T_s$ (10.30 am) to the SMOS overpass on descending orbits. Focusing on the Step 1 of the algorithm (Fig. 6.10(e) and Fig. 6.11(e)), it appears that the inversion technique is not able to resolve changes in soil moisture and is mostly underestimating it. Therefore, based on these analysis, SMOS images from ascending orbits seem to be far more adequate for land applications than SMOS images from descending orbits. However, this finding needs to be confirmed with the specific retrieval technique that has been developed for SMOS, which makes full use of its dual-polarization and multi-angular characteristics, and include auxiliary information from global land surface parameters datasets (see Section 2.3, and Chapters 3, and 4). These images also indicate that, as expected, the performance of the downscaling algorithm is critically depending upon the soil moisture estimates obtained on Step 1; if soil moisture maps at 64 km do not effectively capture soil moisture changes, soil moisture maps at 32 km are not able to capture them either.

Comparison with in situ measurements

During the AACES field experiment, a significant rainfall event occurred on February 5 and 6, 2010. Two SMOS ascending $T_B$ images – one captured before the rainfall event (January 22) and one at the end of the experiment (February 19)– over the Yanco region will be compared to in situ soil moisture measurements so that the algorithm performance will be assessed in extremely hot dry (January 22) and moderately dry (February 19) conditions.

![Figure 6.12](image_url)

**Figure 6.12** Spatial variability of 0-5 cm soil moisture measurements (6 am) of the 13 Yanco stations on days (a) January 20-24, 2010, and on (b) February 17-21, 2010.

It is important to remark that validating soil moisture estimation results is not straightforward, since there are some unresolved issues concerning the comparison of in situ measurements with soil moisture maps. The difficulty lies not only in the estimation process, but
also in the representativeness of the \textit{in situ} soil moisture measurements. Note that the penetration depth of the microwave signal depends on the soil moisture content itself. Therefore, the thickness of the soil layer contributing to the emitted radiation can significantly vary with moisture conditions (see Section 2.2.3 and Monerris [2009]). This fact could affect the representativeness of the soil moisture samples taken at a specific depth regardless surface conditions. In addition to this, the spatial distribution of soil moisture depends on soil parameters that are not distributed homogeneously in the area (e.g., soil texture, vegetation, topography, etc). And also, it should be taken into account that soil moisture could change very rapidly in the top layer. In view of these uncertainties, a study of the temporal and spatial variability of the 13 Yanco soil moisture stations the days immediately before and after the two SMOS images were acquired has been performed to analyze the consistency of the \textit{in situ} data and, to some extent, of the validation approach.

Figure 6.12 shows the measured soil moisture variability at Yanco stations on January 20-24 (a), and on February 17-21 (b). It can be observed that there is a definite pattern in the spatial variability of soil moisture that repeats itself on all Yanco stations on the two different periods studied. This variability could be the result of changing soil properties of the area. Note that this pattern is common for the case of extremely dry and moderately dry conditions of Fig. 6.12(a), and Fig. 6.12(b), respectively, on all the stations except for 8 and 9. Still, the spatial variability appears to be consistent. The temporal variability of soil moisture measurements and the mean daily rainfall at Yanco stations from January 20 to February 21, 2010, is shown in Fig. 6.13. It can be seen how the soil moisture network nicely captures the two rainfall events occurred during these days.

Figures 6.14 and 6.15 illustrate the performance of the downscaling algorithm on two SMOS images covering the Murrumbidgee catchment, acquired on January 22 and February 19, respectively. It can be noted that the method using the linking model in (6.3) in these two scenes is better capturing the soil moisture variability of SMOS-derived soil moisture estimations at 64 km than in the previous cases on Fig. 6.6 and 6.8. This can be due to the wide range of vegetation and moisture conditions present within the area, that allows for
6.3. Downscaling approach for SMOS

Figure 6.14 Sample results of the application of the algorithm to a SMOS image covering the Murrumbidgee catchment, from January 22, 2010 (6 am). SMOS $T_B$ image [K] on a 16 x 16 km grid (a). SMOS $T_B$ image [K] on a 64 x 64 km grid (b). MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [$m^3/m^3$] at 64 km (e). SMOS-derived soil moisture maps [$m^3/m^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images correspond to clouds masking MODIS $T_s$ measurements.
Chapter 6. Downscaling SMOS-derived soil moisture using higher resolution visible/infrared data

Figure 6.15 Sample results of the application of the algorithm to a SMOS image covering the Murrumbidgee catchment, from February 19, 2010 (6 am). SMOS $T_B$ image [K] on a 15 x 15 km grid (a). SMOS $T_B$ image [K] on a 64 x 64 km grid (b). MODIS-derived $T_s$ [K] (c) and NDVI (d) maps aggregated to 32 km. SMOS-derived soil moisture map [$m^3/m^3$] at 64 km (e). SMOS-derived soil moisture maps [$m^3/m^3$] at 32 km using the linking model in (6.3) (f), and using the linking model in (6.9) (g). Empty areas in the images correspond to clouds masking MODIS $T_s$ measurements.
### Table 6.1 SMOS-derived soil moisture retrievals [% vol] over the Yanco region at 64 km (~ one pixel) and 32 km (~ two pixels, averaged) spatial resolution, using different soil moisture retrieval configurations.

<table>
<thead>
<tr>
<th>Day of measurement</th>
<th>s_m retrieval configuration</th>
<th>s_m at 64 km (Step 1)</th>
<th>s_m at 32 km (from (6.3))</th>
<th>s_m at 32 km (from (6.9))</th>
</tr>
</thead>
<tbody>
<tr>
<td>22-Jan-2010</td>
<td>Nominal</td>
<td>2.46</td>
<td>2.73</td>
<td>3.13</td>
</tr>
<tr>
<td>(averaged in situ s_m = 2.18)</td>
<td>Wang</td>
<td>14.05</td>
<td>12.48</td>
<td>12.37</td>
</tr>
<tr>
<td></td>
<td>Dobson</td>
<td>1.58</td>
<td>1.40</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>h_s = 0</td>
<td>6.29</td>
<td>5.78</td>
<td>6.29</td>
</tr>
<tr>
<td></td>
<td>τ = 0</td>
<td>0</td>
<td>0.97</td>
<td>1.47</td>
</tr>
<tr>
<td>19-Feb-2010</td>
<td>Nominal</td>
<td>5.05</td>
<td>4.36</td>
<td>3.86</td>
</tr>
<tr>
<td>(averaged in situ s_m = 5.84)</td>
<td>Wang</td>
<td>14.48</td>
<td>12.83</td>
<td>12.05</td>
</tr>
<tr>
<td></td>
<td>Dobson</td>
<td>2.30</td>
<td>2.02</td>
<td>1.63</td>
</tr>
<tr>
<td></td>
<td>h_s = 0</td>
<td>8.25</td>
<td>7.16</td>
<td>6.54</td>
</tr>
<tr>
<td></td>
<td>τ = 0</td>
<td>2.51</td>
<td>1.36</td>
<td>1.71</td>
</tr>
</tbody>
</table>

a better definition of the triangle and, therefore, a better regression. Consequently, these results reinforce the scene-dependent performance of the universal triangle approach. Still, note that there are some particular features of the low resolution soil moisture image (e.g. the extremely dry areas) that are reproduced by the approach using SMOS TB in the linking model, but are not captured by the method using the linking model in 6.3.

Zooming in, Table 6.1 focuses on the performance of the algorithm on the pixels coincident with the Yanco region (~ one pixel of 64 x 64 km, ~ two pixels of 32 x 32 km). It shows the results of applying the nominal retrieval configuration and four variations of it in the Step 3 of the algorithm: the nominal configuration uses the dielectric mixing model in Hallikainen et al. [1985], $h_s = 0.2$, and $\tau$ estimated using (2.31) with $\alpha=-0.05 \beta=-0.36$, and MODIS NDVI data [Burke et al., 2001]; Wang configuration uses the dielectric mixing model in Wang and Schmugge [1980]; Dobson configuration uses the dielectric mixing model in Dobson et al. [1985]; no roughness is considered in the configuration $h_s = 0$, and no vegetation effects are corrected in the configuration $\tau = 0$.

On January 22, ground-based $s_m$ measurements from 13 $s_m$ stations present an average of 2.18 m$^3$/m$^3$, a standard deviation of 2.18 m$^3$/m$^3$, and minimum and maximum values of 0 and 6.33 m$^3$/m$^3$, respectively. On February 19, ground-based $s_m$ measurements from 11 $s_m$ stations report an average of 5.84 m$^3$/m$^3$, a standard deviation of 3.91 m$^3$/m$^3$, and minimum and maximum values of 0 and 12.16 m$^3$/m$^3$, respectively. Hence, comparing soil moisture retrievals at 64 km (in Table 6.1) with the mean of the ground-based $s_m$ measurements, it can be seen that the nominal configuration is the one retrieving the closest $s_m$ values, with an error of ~ 10% in the two days studied. The Wang model clearly overestimates the soil moisture, whereas the Dobson model seems to underestimate it. This is consistent with the study in Monerris [2009, chap. 5], where the Dobson model offered better results than the Wang model over sandy soils –note here that sandy soils are predominant within the Yanco region [Young et al., 2008]. When soil roughness is not corrected for ($h_s=0$), the soil surface is considered to be flat (therefore having a higher reflectivity –lower emissivity– than rough terrain), and, as expected, the soil moisture is overestimated. When the attenuation by vegetation is not compensated ($\tau=0$), results are also coherent: the soil emissivity is
assumed to be higher than it actually is, and, therefore, the soil moisture is underestimated. Regarding the accuracy of soil moisture estimations at 32 km, results from all configurations evidence that they are critically depending on the accuracy of the soil moisture estimations at 64 km. Comparing with ground-based measurements, the downscaling technique appears to overestimate soil moisture in extremely dry conditions, and to underestimate it in moderately dry conditions. However, an statistical analysis including a sufficient number of comparisons ground-truth vs. SMOS estimates is needed to evaluate the performance of the method in terms of radiometric resolution. Future work should definitely focus on developing an algorithm error budget.

Downscaling limit

As said, the possibility of obtaining soil moisture maps at higher spatial resolutions (up to 1 km) using the downscaling technique presented in this Chapter is subject of further research that validates the accuracy of the soil moisture retrievals at the different spatial scales. Still, the feasibility of going into higher spatial resolutions has been analyzed. To do so, sample soil moisture maps at 16 and 8 km spatial resolution have been obtained from the SMOS $T_B$ images in Fig. 6.6(a), 6.8(a), 6.14(a), and 6.15(a), and the soil moisture error between retrievals at 32, 16 and 8 km and retrievals at 64 km has been analyzed.

Figure 6.16 illustrates the performance of the downscaling method using the linking model in (6.9) at different spatial resolutions, using the SMOS $T_B$ image on Fig. 6.6(a). The first row shows SMOS-derived soil moisture maps at 32, 16 and 8 km spatial resolutions. It can be seen how the soil moisture variability is captured at the three different spatial scales, although the areas with high moisture conditions at 32 km (in blue) present lower moisture content at 16 and 8 km. The spatial distribution of the soil moisture error between soil moisture retrievals at 32, 16, and 8 km and soil moisture retrievals at 64 km is shown in the second row, and the histogram and statistics of the soil moisture errors is shown in the third row. Note that the soil moisture RMSE at 32 km is 0.039, and that it increases to 0.040 and 0.041 when going into 16 and 8 km, respectively. Thus, for this particular image, the increase in the soil moisture error when going into higher spatial resolutions seems to be negligible.

The standard deviation, bias, and root mean square soil moisture error between soil moisture retrievals at 32, 16, and 8 km, and soil moisture retrievals at 64 km, for the four SMOS $T_B$ images analyzed (from December 8, 2009, and January 22, February 17 and 19, 2010), using the linking models in (6.3) and (6.9), are presented in Table 6.2. It can be observed that the soil moisture error is lower for the soil moisture map at 32 km in all the cases studied, and that it is nearly the same for the soil moisture maps at 16 and 8 km. Still, the increase in RMSE from 32 to 16 and 8 km is moderate: it is of $\sim$ 0.01 for the images acquired on December 8, January 22, and February 19, and $\sim$ 0.03 for the image acquired on February, 17. Also, note that results are slightly better when using the model in (6.9), than when using the model in (6.3). Thus, these results indicate that, using the downscaling technique presented on this Chapter, it is feasible to obtain soil moisture estimates from SMOS at the 1-10 km spatial resolution required for regional applications.
6.3. Downscaling approach for SMOS

![Figure 6.16](image)

Figure 6.16 SMOS-derived soil moisture maps and error statistics at 32, 16, and 8 km spatial resolution over western Australia, from December 8, 2009 (6 am), using the linking model in (6.9). SMOS-derived soil moisture maps [m$^3$/m$^3$] at (a) 32 km, (b) 16 km, and (c) 8 km spatial resolutions. Spatial distribution of the soil moisture error [m$^3$/m$^3$] between soil moisture retrievals at (d) 32 km, (e) 16 km, and (f) 8 km, and soil moisture retrievals at 64 km. Histogram and statistics of the difference between soil moisture retrievals at (g) 322 km, (h) 16 km, and (i) 8 km, and soil moisture retrievals at 64 km. Empty areas in the images correspond to clouds masking MODIS $T_s$ measurements.
Table 6.2 Standard deviation, bias, and root mean square soil moisture error [m$^3$/m$^3$] between soil moisture retrievals at 32 km, 16 km, and 8 km, and soil moisture retrievals at 64 km, from the SMOS $T_B$ images on Fig. 6.6(a), 6.8(a), 6.14(a), and 6.15(a), when using the linking model in (6.3), and when using the linking model in (6.9).

<table>
<thead>
<tr>
<th>Day of measurement</th>
<th>$s_m$(32 - 64 km)</th>
<th>$s_m$(16 - 64 km)</th>
<th>$s_m$(8 - 64 km)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(6.3)</td>
<td>(6.9)</td>
<td>(6.3)</td>
</tr>
<tr>
<td>8-Dec-2009</td>
<td>mean 0.005</td>
<td>0.019</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.039</td>
<td>0.034</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>RMSE 0.039</td>
<td>0.039</td>
<td>0.050</td>
</tr>
<tr>
<td>22-Jan-2010</td>
<td>mean 0.002</td>
<td>0.013</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.049</td>
<td>0.045</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>RMSE 0.049</td>
<td>0.047</td>
<td>0.062</td>
</tr>
<tr>
<td>17-Feb-2010</td>
<td>mean -0.023</td>
<td>-0.024</td>
<td>-0.050</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.064</td>
<td>0.048</td>
<td>0.080</td>
</tr>
<tr>
<td></td>
<td>RMSE 0.068</td>
<td>0.053</td>
<td>0.094</td>
</tr>
<tr>
<td>19-Feb-2010</td>
<td>mean -0.013</td>
<td>-0.013</td>
<td>-0.022</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.054</td>
<td>0.051</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>RMSE 0.056</td>
<td>0.052</td>
<td>0.065</td>
</tr>
</tbody>
</table>

6.4 Discussion and conclusions

Within the SMOS Cal/Val activities, a downscaling algorithm to improve the spatial resolution of airborne passive L-band observations using the relationship between high spatial resolution visible/infrared satellite imagery and soil moisture status was evaluated. Based on this experience, an algorithm for downscaling SMOS observations using MODIS-derived NDVI and $T_s$ data has been developed. Results of its application to four SMOS images acquired during the commissioning phase indicate that it is feasible to improve the spatial resolution of SMOS accurate soil moisture retrievals using higher spatial resolution MODIS visible/infrared data. SMOS observations from ascending orbits seem to be more adequate for land applications than from descending ones. Results from comparison with ground-based soil moisture measurements outline that it is essential to obtain accurate soil moisture estimates from SMOS at low resolution (first step of the algorithm) to afterwards capture soil moisture variability at higher spatial resolutions (steps two and three of the algorithm). SMOS-derived soil moisture maps at 64, 32, 16 and 8 km have been obtained; the soil moisture variability is nicely captured at the different spatial scales, but further research is needed to validate the accuracy of the retrievals at every spatial resolution and establish a downscaling limit.

Following the successful launch of SMOS in orbit, and a satisfactory demonstration of its capabilities during the commissioning phase, this work could potentially contribute to enhance the spatial resolution of SMOS soil moisture estimates, which will be a new and highly relevant research development. Also, these results suggest the prospect use of a visible/infrared sensor as a secondary payload in follow-on space-borne missions dedicated to soil moisture monitoring; the visible/infrared sensor could be highly useful in both the estimation of collocated land surface temperatures to be used in the soil moisture retrievals,
and the improvement of the spatial resolution of the estimates using the universal triangle concept.
A downscaling algorithm to obtain global high-resolution soil moisture estimates from SMAP L-band radar and radiometer observations is presented. The approach is based on change detection and combines the relatively noisy 3 km radar backscatter cross-section and the more accurate 36 km radiometer brightness temperature into an optimal 10 km product. In preparation for the SMAP mission, an Observation System Simulation Experiment (OSSE) and field experimental campaigns using the Passive and Active L and S-band airborne sensor (PALS) have been conducted. By using the PALS airborne observations and OSSE data, the algorithm is tested and an error budget table is developed. When applied to 4-months OSSE data, the downscaling method is shown to perform better than direct inversion of the radiometer brightness temperatures alone, improving the RMSE by 2% volumetric soil moisture content. The algorithm error budget shows that the proposed algorithm meets the SMAP minimum science requirements.

7.1 Introduction

Active and Passive L-band microwave remote sensing provide a unique ability to monitor global soil moisture over land surfaces with an acceptable spatial resolution and temporal frequency [Njoku and Entekhabi, 1996; Schmugge et al., 2002]. Mapping radars are capable of a very high spatial resolution (∼ 3 km in case of SMAP) but, since radar backscatter is highly influenced by surface roughness, vegetation canopy structure and water content, they have a low sensitivity to soil moisture under vegetated conditions. Various algorithms for soil moisture retrieval from radar backscattering have been developed, but they are only valid in low-vegetation water content conditions [Dubois et al., 1995; Shi et al., 1997]. In contrast, the spatial resolution of radiometers is typically low (∼ 40 km), the retrieval of soil moisture from radiometers is well established, and radiometers have a high sensitivity to soil moisture under vegetated conditions [Jackson et al., 1996].

To overcome the individual limitations of the passive and active approaches, the NASA SMAP mission is combining the two technologies (see Section 1.3.2). This chapter describes...
a downscaling algorithm for the retrieval of global high resolution soil moisture estimates from SMAP radar and radiometer data; it aims at combining the high radar resolution and the high radiometer accuracy into an optimal 10 km soil moisture product.

Change detection techniques have been demonstrated to be able to potentially monitor temporal evolution of soil moisture by taking advantage of the approximately linear dependence of radar backscatter and brightness temperature change on soil moisture change (see Section 1.4). The novel approach presented on this study is based on change detection and focuses on the idea of considering the surface soil moisture over a sample 10 km region to be composed of weighted averages of the available radar retrievals within that region and the radiometer retrieval within the radiometer footprint containing the 10 km region. The advantage of this approach is that as more radar retrievals are available within the 10 km region, more spatial structure within a radiometer footprint will become evident and, since the collection of 10 km pixels within the larger scale radiometer footprint is constrained to sum to the value indicated by the radiometer retrieval, the high resolution estimation gracefully keeps the accuracy of the radiometer retrieval.

The theoretical basis and the assumptions behind the change detection algorithm used in this study are presented in Section 7.2. In Section 7.3, field experiment data from the SMEX02 field campaign is used to validate the algorithm main assumptions. The results of applying the algorithm to a 4-months OSSE dataset are shown on Section 7.4. The performance of the method is shown in terms of comparison with synthetic ground truth soil moisture data and with the radiometer data re-sampled to 10 km. An error budget analysis of the algorithm is presented in Section 7.5 and, in the final section, the most significant results of the paper are summarized and the applicability and usefulness of the scheme to future SMAP data on an operational basis is discussed.

### 7.2 Change detection method

The algorithm presented in this study is based on the change detection concept. The 40 km radiometer brightness temperatures are combined with the 3 km radar backscatter observations to obtain 10 km soil moisture observations. It assumes in the first place that soil moisture and the log of radar backscatter are linearly related at a 10 km scale (Assumption I):

\[
\theta(a, t) = \alpha(a) + \beta(a) \cdot \log[\sigma^0(a, t)],
\]

where \( a \) represents the 10 km scale, \( \sigma^0(a, t) \) is the radar backscatter aggregated to 10 km at time \( t \) and \( \theta(a, t) \) is the soil moisture at 10 km at time \( t \). The aggregation could be made in dB, but using this approach the algorithm does not converge for most pixels.

We can form time differences to remove the bias term of (7.1) and space average the result to the radiometer pixel area \( A \) of 40 km, which leads to:

\[
\langle \Delta \theta(a, t) \rangle = \langle \beta(a) \cdot \Delta \log[\sigma^0(a, t)] \rangle,
\]

where \( \langle \cdot \rangle \) stands for the the spatial average of the \( a \) scale pixels contained into the \( A \) scale pixels.

At this point, it is assumed (Assumption II) that slope \( \beta \) and backscatter changes are uncorrelated. Hence, the definition of covariance \( \text{Cov}\{x, y\} = \langle x \cdot y \rangle - \langle x \rangle \cdot \langle y \rangle \) can be used to write (7.2) as,

\[
\langle \Delta \theta(a, t) \rangle = \langle \beta(a) \rangle \cdot \langle \Delta \log[\sigma^0(a, t)] \rangle.
\]
7.3 Test of assumptions using SMEX02 data

Finally, it is assumed that variation on vegetation type occur principally at scales larger than \( A \) (Assumption III), \( \beta(a) = \langle \beta(a) \rangle \), so time differences can be used to write (7.3) as:

\[
\theta(a, t) = \theta(A, t - t_R) + \langle \beta(a) \rangle \cdot \Delta \log[\sigma_0(a, t)], \tag{7.4}
\]

where \( t_R \) is the revisit time of the observations, three days for the SMAP case.

The radar-radiometer change-detection algorithm can be written as either the radiometer-scale soil moisture retrieval \( \theta(A, t - t_R) \) updated with moisture change evident in the higher-resolution radar backscatter change as in (7.4) or, alternatively, the 10 km soil moisture retrieval from the previous algorithm application (orbit pass) \( \theta(a, t - t_R) \) can be used as the first term. However, this latter approach has the risk of accumulating errors from the relatively more noisy radar measurements.

Equation (7.4) constitutes the core of the change detection algorithm. It indicates that a soil moisture estimate at scale \( A \) and at a given time can be obtained as the previous soil moisture estimate plus a change in soil moisture, which is given by the actual radar estimates and the value of the slope \( \langle \beta(a) \rangle \). From (7.3), the slope can be estimated using regression of radiometer and radar data at scale \( A \). Better slope estimations are obtained with time, since more radar and radiometer observations are available. The first estimates are likely to be noisy due to the high uncertainty on the first calculated slopes. However, when a reasonable number of estimates (on the order of a month) are available, the uncertainty on calculating the slope becomes much lower, leading to robust soil moisture estimations (See Section 7.4).

7.3.1 SMEX02 description

Experimental data from the soil moisture experiments SMEX02 are used in this study to validate the three assumptions of the algorithm. The SMEX02 field campaign was conducted in Walnut Creek, a small watershed in Iowa, between June 25th and July 12th, 2002. The PALS sensor was mounted on an aircraft and flown over the SMEX02 region on June 25, 27, and July 1, 2, 5, 6, 7 and 8, 2002 and an extensive dataset of \textit{in situ} measurements of volumetric soil moisture, surface and subsurface soil temperature, soil bulk density and vegetation water content was collected during all the campaign [Limaye et al., 2004]. The PALS coverage during July 1st was partial and \textit{in situ} sampling was not done on July 2nd, so data from these two days were not used in the present study. Since the algorithm proposed in this paper is based on the change of soil moisture over time, it is not feasible to fully test it with data from aircraft-mounted instruments due to cost limitations. However, L-band PALS data and volumetric soil moisture have been properly used to validate the algorithm assumptions on Section 7.3.2. Also, SMEX02 experimental data has been used to estimate the algorithm error budget on Section 7.5.

7.3.2 Validation of the assumptions

In a previous study, it was shown that for the SMEX02 field experiment PALS L-band brightness temperatures and radar backscatter coefficients were well correlated to soil moisture [Narayan et al., 2004]. To specifically illustrate the correlation between soil moisture and radar backscatter assumed in the algorithm development (Assumption I ), on Fig. 7.1,
Figure 7.1 Change in log of PALS observed L-band radar backscatter at $hh$ (a) and $vv$ (b) polarizations plotted versus change in in situ volumetric soil moisture in the 0 to 6 cm soil layer for the period June 25 to June 27 and July 5 to July 7. The change in radar backscatter has been stratified by 0.05% change in volumetric soil moisture.

The change in log of radar backscatter for $hh$ and $vv$ polarizations is compared to the corresponding change in volumetric soil moisture at a resolution of 400-m for the time periods June 25 to June 27 and July 5 to July 7. $R^2$ values of 0.67 and 0.88 are obtained for $hh$ and $vv$ polarizations, respectively, indicating that radar sensitivity to soil moisture is significant even under the dense vegetation conditions encountered in the SMEX02 experiments with the vegetation water content of corn fields being around 4-5 kg/m$^2$ [Narayan et al., 2004]. The higher correlation obtained with the radar vertical polarization is consistent with the literature on radar remote sensing of soil moisture.

Figure 7.2 Error difference between static map of $\beta$ of 400 m aggregated to 1600 m and directly computed static map of $\beta$ at 400 m spatial resolution using radar $hh$ (a) and $vv$ (b) polarizations.

In order to demonstrate with real data that the algorithm’s calculated slope and backscatter changes are uncorrelated (Assumption II), for each day of measurement the slope is calculated using linear regression from (7.3) and the change in log of radar backscatter is
7.3. Test of assumptions using SMEX02 data

Assumption III in the algorithm formulation states that the slope at 10 km resolution equals the mean of the slope over a 40 km pixel ($\beta(a) = \langle \beta(a) \rangle$). The spatial resolutions of 400 m and 1600 m will be used in this part of the study representing $a$ and $A$, for compatibility with PALS data. As an initial evaluation of this point, for each pixel and for all days of measurement, static maps of $\beta$ were calculated using linear regressions with brightness temperatures and radar backscatters at 400 m resolution and at 1600 m (7.3). The 400 m static map of $\beta$ was then aggregated to 1600 m and compared to the maps of $\beta$ using aggregated radar and radiometer measurements at 1600 m. Thus, the error difference between the two maps is essentially the error of assuming homogeneity of $\beta$. Even though the scale ratios with the PALS data are the same as SMAP radar and radiometer pixels, the absolute scales are clearly different. This mismatch may represent an under-estimation of the error due to this assumption. Nevertheless this represents a preliminary test and more detailed testing using other data sets is needed. The results of the tests on Assumption III are shown in Fig. 7.2. Results show an acceptable error, greater for horizontal than for vertical polarization. Still, for quantifying the error that this assumption is adding to the retrievals, another experiment has been conducted: from the static map of $\beta$ at 400 m, the soil moisture estimates for each day are calculated, and the same procedure is followed to retrieve soil moisture estimates from the static map of $\beta$ at 1600 m. Subsequently, histograms of the difference between the soil moisture retrievals acquired using $\beta(a)$ and $\langle \beta(a) \rangle$ are plotted on Fig. 7.3. With an error of $\sim 2\%$, this third assumption results to be the most critical error source for the algorithm.

The airborne campaign duration is too short and the variability in ground conditions is too limited to fully apply the change detection algorithm. Longer-duration data sets with wider range of vegetation conditions are needed. Here we augment the tests of the algorithm assumptions using airborne field experiment data with tests using synthetic observing system simulation experiments.

![Histograms](image)

**Figure 7.3** Histogram of the difference between soil moisture retrieved using static map of $\beta$ of 400 m and using static map of $\beta$ at 1600 m for $hh$ (a) and $vv$ (b) polarizations.
Chapter 7. A change detection algorithm for retrieving high-resolution soil moisture from SMAP

Figure 7.4 Sample results (three days) from the Observation System Simulation Experiment for the comparison of higher resolution (10 km) soil moisture estimates obtained using the active-passive method with synthetic ground truth soil moisture and with lower resolution (40 km) estimates obtained from a typical radiometer.

7.4 Application to OSSE data

7.4.1 OSSE data set

The simulated data used in this study was generated in the Hydros OSSE. The OSSE was designed to mimic as closely as possible the specific Hydros sensor and orbital characteristics and therefore is perfectly valid for SMAP purposes. The experiment was driven by high resolution land surface geophysical variables generated from a distributed land surface model within the Red-Arkansas river basin. They were used to derive a set of Hydros-like simulated brightness temperatures and radar backscatter cross-sections over the area that were then inverted back into soil moisture products using various retrieval algorithms. The OSSE adopts an easily nested fine, medium and coarse resolution grid of 3, 9, and 39 km, respectively. On this study, the OSSE resolutions of 9 km and 39 km will be used closest to SMAP 10 km and 40 km products. Complete OSSE fundamentals and details for radiometer-only soil moisture retrievals are described in [Crow et al., 2005b]. Details regarding the radar and radiometer soil moisture retrievals are provided in [Zhan et al., 2006].

Two sets of OSSE data are used in this study to reproduce a realistic scenario just after SMAP calibration and validation phase: one month dataset is used as background data for the algorithm, representing the data acquired during the commissioning phase; and a four months dataset is processed in near real time, simulating the first four months of data obtained in the operational phase, exactly after the commissioning phase. To meet the expected SMAP accuracies, an error of 4% (Root Mean Square Error or RMSE) is added to
7.4. Application to OSSE data

(a) RMSE = 2.8%
(b) RMSE = 2.2%
(c) RMSE = 3.4%
(d) RMSE = 4.4%

**Figure 7.5** Spatial distribution of the soil moisture error retrieved using the change detection method with $\sigma_{hh}^0$ (a), $\sigma_{vv}^0$ (b), $\sigma_{hv}^0$ (c), and the radiometer only technique (d)

the radiometer retrievals and the normalized deviation $K_p$ of radar backscatters [Chi *et al.*, 1986] is set to 0.15. Independent noise is added in each measurement channel. Since the three radar polarizations ($hh$, $vv$ and $hv$) can be used independently in the algorithm with different outcomes, the three possible solutions will be analyzed. The simulated data will be used to evaluate the algorithm performance in Section 7.4.2 and to calculate the algorithm error budget in Section 7.5.

### 7.4.2 Results

Sample results of applying change detection to the simulated data (with radar and radiometer noise added) are presented in Fig. 7.4 for three consecutive days. Comparing with the original soil moisture distributions and the estimates obtained from the radiometer only technique, it can be seen that the active-passive disaggregation algorithm reproduces much of the variability seen in the *in situ* soil moisture images and that these details are not captured by the radiometer only method.

Using the OSSE data sets as described previously, the performance of the change detection method is evaluated by comparing the retrieved soil moisture values of the 4-months dataset with their corresponding original data and with results from the radiometer only or minimum performance product. Minimum performance is obtained by re-sampling the 40 km radiometer data to 10 km. Fig. 7.5 shows the spatial distribution of the soil moisture RMSE after applying the change detection method and the radiometer only technique. Using the change detection algorithm on the 4-months OSSE the RMSE is reduced to 2%, with better results obtained using radar $vv$ polarization. In addition, for a direct comparison with the minimum performance algorithm, the ratio of the change detection RMSE to the
minimum performance RMSE is shown in Fig. 7.6(a), 7.6(b) and 7.6(c) for $hh$, $vv$ and $hv$ polarizations, respectively. In all the areas of the image with a value less than unity, the active-passive approach outperforms the radiometer only technique. Notice that most estimation errors (value = 1) occur in high vegetated areas where the radar and radiometer soil moisture sensitivity is decreased. This is evidenced on Fig. 7.7, where the algorithm RMSE linear dependance with vegetation water content is shown.

A box plot of the slope for each day of the 4-month dataset is shown on Fig. 7.8. It can be observed that the uncertainty in the estimation of the slope diminishes with time and that vertical polarization leads to more robust estimates than horizontal and mixed polarizations. Hence, as an alternative to real time processing, the possibility of monthly re-processing the data was explored, resulting in marginal improvement. Further studies with real data would be needed to assess the optimal re-processing time and decide whether the re-processing is required.

### 7.5 Error budget

An error budget analysis has been performed in order to identify the error sources of the algorithm and fully quantify its performance. The three assumptions made in the algorithm formulation have been identified as the three algorithm error sources. The total error has then been calculated as the square root of the sum of the squares (RSS) of these three distinct errors.

To account for Assumption I errors, the algorithm-predicted soil moisture is calculated using linear regression of SMEX02 radar backscatter and soil moisture data (from (7.1)). The
7.5. Error budget

Figure 7.7 Plots of change detection RMSE at 10 km stratified by 0.5 kg/m² vegetation water content values.

Figure 7.8 Plots of the mean slope (in black) and mean slope ± the daily slope standard deviation (in red) for vv, hh and hv polarizations, for each day of the 4-month OSSE dataset.
Chapter 7. A change detection algorithm for retrieving high-resolution soil moisture from SMAP

Table 7.1 Results of the error budget analysis (% vol)

<table>
<thead>
<tr>
<th>Errors</th>
<th>Horizontal polarization</th>
<th>Vertical polarization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assumption #1</td>
<td>1.53</td>
<td>1.40</td>
</tr>
<tr>
<td>Assumption #2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Assumption #3</td>
<td>2.20</td>
<td>1.76</td>
</tr>
<tr>
<td>RSS</td>
<td>2.68</td>
<td>2.25</td>
</tr>
</tbody>
</table>

RMSE between the predicted soil moisture and the ground truth soil moisture for horizontal and vertical polarizations are presented in Table 7.1. It must be noted that field sampling errors are inevitably included in the calculations and they considerably worsen the results. Regarding the errors associated to the Assumption II, the OSSE results in Section 7.4.2 show that the covariance does not affect the retrievals and, therefore, the error contribution from this source has been set to zero. Assumption III-related errors are exactly the values of the standard deviation presented in Fig. 7.3. This figure shows the difference between the soil moisture retrieved using the slope at scale $a$ and the soil moisture retrieved using the slope at a scale $A$. Note that Table 7.1 represents the algorithm assumptions error and any radiometer error has to be added to the total by RSS.

7.6 Conclusions

This chapter presents a simple and efficient technique to downscale radiometer soil moisture estimates with the use of simultaneous radar observations within a SMAP-like context. The algorithm is based on a change detection scheme that benefits from the synergy of the radar high spatial resolution and the radiometer high accuracy, leading to a balanced product with enough accuracy and spatial resolution so as to satisfy current meteorology and hydrology needs.

The algorithm has been thoroughly formulated and the assumptions made on the process have been verified using PALS data from the SMEX02 field campaign. Also, it has been successfully applied to a 4-month OSSE data producing significantly better results than radiometer only inversions, with a 2% RMSE improvement. Real time processing of the data has been shown to be feasible having a month of previous observations and, since the algorithm performance improves over time, a monthly re-processing of the data to improve the estimations’ accuracy has been outlined. An error budget analysis of the algorithm estimates a total RSS of 2.68 (% vol) for horizontal polarization and 2.25 (% vol) for vertical polarization, which meet SMAP science requirements for the 10-km product. These results imply that the change detection method presented on this study is a promising approach to achieving higher resolution and more accurate soil moisture retrievals from future SMAP radar and radiometer observations.
Conclusions and future lines

This Ph.D. Thesis has investigated the ability of measuring the Earth’s surface soil moisture from space. Currently, there are two space-borne projects dedicated to soil moisture observation: the ESA SMOS mission, launched in November the 2nd 2009, and the NASA SMAP mission, with a target launch date in 2014. This work has been performed within the preparatory activities of these two missions, involving the analysis of the retrieval techniques, which have an impact on the accuracy of the estimations, and the development of downscaling algorithms to enhance the spatial resolution of the observations.

Chapter 1 describes the motivation of this work and the context in which it has been developed. The basic concepts of passive microwave remote sensing of soil moisture are presented in Chapter 2. The state-of-the-art of the soil moisture retrieval techniques and of soil moisture downscaling algorithms are given in Chapters 1 and 2, respectively. Then, the Thesis is divided into two parts: the first part is focused on studying the SMOS soil moisture inversion algorithm and devising an optimal retrieval configuration, which is crucial for the accuracy of the estimations (Chapters 3 and 4); the second part explores different approaches for the improvement of the spatial resolution of SMOS (Chapters 5 and 6) and SMAP (Chapter 7) observations. This Chapter summarizes the main conclusions of this work, remarks its original contributions, and presents suggestions for follow-on research.

8.1 Main conclusions

The SMOS mission aims at providing the first global views of the Earth’s soil moisture fields with an accuracy of 0.04 m$^3$/m$^3$ over 50 x 50 km$^2$ and a temporal resolution of 3 days. As a secondary objective, SMOS is expected to provide vegetation water content maps with an accuracy of 0.2 kg/m$^2$, from vegetation opacity retrievals. To make full use of SMOS multi-angular dual-polarization/full-polarimetric capabilities and achieve the required accuracy, previous studies have shown the necessity of combining SMOS brightness temperatures with auxiliary information. However, the required auxiliary data and optimal soil moisture retrieval setup need yet to be optimized.

In Chapter 3, the performance of different retrieval configurations has been evaluated using SMOS simulated data, considering the option of adding a priori information from the parameters dominating the land emission at L-band (i.e. soil moisture $s_m$, soil roughness $h_s$, soil temperature $T_s$, vegetation albedo $\omega$ and vegetation opacity $\tau$) with different asso-
Chapter 8. Conclusions and future lines

Associated uncertainties. Also, the impact of using vertical $T_{hh}$ and horizontal $T_{vv}$ brightness temperatures, or using the first Stokes parameter $T_I = T_{hh} + T_{vv}$ in the minimization process has been analyzed. Results suggest an optimal retrieval configuration for SMOS and can be summarized as follows:

- If a priori information on the land surface conditions are readily available, the use of constraints on $h_s$, $T_s$ and $\tau$ with associated uncertainties $\sigma_{h_s} = 0.05$, $\sigma_{T_s} = 2$ K, and $\sigma_{\tau} = 0.1$ Np in the SMOS retrieval algorithm is recommended. The constraints on soil roughness and soil temperature significantly improve the accuracy of $s_m$ retrievals over bare soils. In the presence of vegetation, results confirm that there is a remarkable decrease of the brightness temperature sensitivity to $s_m$; adding information on $\tau$ (and on $\omega$ with $\sigma_{\omega} = 0.1$ in the case of dense vegetation) is critical to obtain accurate $s_m$ and VWC maps.

- Soil moisture and vegetation opacity retrievals using $T_I$ show better performance than retrievals using $T_{hh} - T_{vv}$. Also, retrievals using $T_I$ are more robust to geometric and Faraday rotations than $T_{hh} - T_{vv}$, which can be critical from an operational point of view. Since $T_I$ in the dual-polarization mode has a better radiometric sensitivity than in full-polarimetric mode, results also preference the use of the dual-polarization mode. Hence, although the formulation of the SMOS-derived soil moisture retrieval problem using $T_{hh} - T_{vv}$ (and therefore the use of the full-polarimetric mode) is the preferred one, these results suggest that use of the first Stokes parameter should not be discarded.

In Chapter 4, the SMOS soil moisture inversion algorithm has been further analyzed, both theoretically and in terms of performance with SMOS-like simulated observations. The use of adequate constraints on the cost function (from the study in Chapter 3), has been compared with the use of no constraints, and with the use of $T_{hh} - T_{vv}$, over six main surface conditions combining dry, moist and wet soils with bare and vegetation-covered soils. Simulated results are consistent with the theoretical study, and are listed below:

- The sensitivity analysis shows that the cost function sensitivity to the soil and vegetation parameters dominating the Earth’s emission at L-band ($s_m$, $h_s$, $T_s$, $\omega$, $\tau$) is greatly improved with the use of adequate auxiliary information in the retrieval (from Chapter 3). Results with simulated SMOS data show that the use of these constraints significantly improves the accuracy of $s_m$ and $\tau$ retrievals in all scenarios, and are needed to meet SMOS science requirements over land.

- The cost function formulated using $T_I$ has a higher sensitivity to both soil and vegetation parameters. Better $s_m$ and $\tau$ estimates are obtained if the retrieval is formulated using $T_I$, than if it is formulated using $T_{hh} - T_{vv}$—considering both the case of using or not a priori information in the retrievals. Therefore, results reinforce the idea that the use of $T_I$ should not be discarded.

- The cost function sensitivity to soil roughness is higher on wet soils than on dry soils, with or without vegetation. Results with simulated SMOS data indicate that more accurate $s_m$ and $\tau$ estimates should be expected from wet soils than from dry soils.

- Due to SMOS geometry, better accuracies could be obtained if only the central part of the FOV is used. In this case, also the use of adequate constraints (from Chapter 3) and the formulation in terms of $T_I$ provide the most accurate retrievals.
8.1. Main conclusions

Following the successful deployment of SMOS in orbit, continuous efforts will be needed to consolidate an optimal soil moisture retrieval configuration. Chapters 3 and 4 of this Thesis have analyzed the soil moisture inversion algorithm, both theoretically and in terms of performance with simulated data; they have addressed key aspects for the retrieval of accurate soil moisture estimations from SMOS, and the results presented can be readily transferred to the operational Level 2 Processor to produce the much needed global maps of the Earth’s surface soil moisture.

SMOS and SMAP radiometers have been designed to potentially provide accurate global views of the Earth’s surface soil moisture every 3 days, but, due to technological limitations, their spatial resolution is limited to 40-50 km. Still, the retrieval of soil moisture at a higher resolution (1-10 km) from SMOS and SMAP observations is a highly relevant research area, since it could greatly extend the applicability of the data to regional scales.

A deconvolution scheme to improve the spatial resolution of SMOS radiometric observations has been presented in Chapter 5. Different deconvolution techniques using improved Wiener, Constrained Least Squares, and wavelet filters that may include different levels of auxiliary information in the reconstruction process have been developed. When applied to SMOS simulated observations, and using an L-band brightness temperature model of the observed scene as auxiliary information, the product spatial resolution and radiometric sensitivity of SMOS-like images was improved in a 49% over land pixels and in a 30% over sea pixels. Particularly, the spatial resolution of the pixels located on the upper left area of the FOV was improved from 90 to 50 km, while its radiometric resolution remained constant. Also, a trend to round the pixels’ shape and diminish its size has been observed, with higher effects in the pixels located far from nadir. Hence, the deconvolution scheme proposed could potentially normalize the pixels shape and orientation in all the SMOS FOVs as well as improve the radiometric sensitivity and the spatial resolution of SMOS observations. Furthermore, results from its application to airborne field experimental data indicate that these methods could be applied to coastal areas to improve the radiometric sensitivity and the coast line definition of the observations.

Chapter 6 presents a downscaling strategy for the estimation of soil moisture at high resolution from SMOS using MODIS visible/infrared data. MODIS-derived $T_v$ and NDVI at high spatial resolution are first aggregated to the SMOS scale for the purpose of building a linking model that is afterwards applied at fine scale to disaggregate the passive soil moisture observations into high-resolution soil moisture. The linking model is based on the so-called universal triangle concept that relates visible/infrared parameters to soil moisture status, and has been specially adapted for the SMOS case. Results of its application to the first SMOS images acquired during the commissioning phase indicate that it is feasible to capture soil moisture variability at a higher resolution and provide a first evidence of its capabilities. They also suggest that SMOS data from ascending orbits are more adequate for land applications than descending ones. Results from comparison with ground-based soil moisture measurements show that the retrieval of accurate soil moisture at low resolution from SMOS is critically affecting the algorithm performance. Further studies are needed to develop an algorithm error budget and stablish a downscaling limit, which could be given either by the resolution of the optical sensor (which in the case of MODIS is 1 km), or by the presence of noise affecting the accuracy of the estimations.

Chapter 7 presents a simple and efficient technique to downscale radiometer soil moisture estimates with the use of simultaneous radar observations within a SMAP-like context. It is based on change detection and effectively combines the radiometer high accuracy with the radar high resolution into an optimal balanced product at 10 km. The algorithm has
been thoroughly formulated and the assumptions made on the process have been verified using airborne field experimental data. Also, it has been successfully applied to a 4-month SMAP simulated data producing significantly better results than radiometer only inversions, with a 2% RMSE improvement. Real time processing of the data has been shown to be feasible having a month of previous observations and, since the algorithm performance improves over time, a monthly re-processing of the data to improve the estimations’ accuracy has been outlined. The algorithm error budget shows that the proposed algorithm meets the SMAP minimum science requirements for the 10 km product. Therefore, results imply that the change detection method presented on this study is a promising approach to achieving higher resolution and more accurate soil moisture retrievals from future SMAP radar and radiometer observations.

8.2 Original contributions

The original contributions of this Thesis are listed below:

- Proposal of an optimal retrieval configuration for SMOS, in terms of the auxiliary data that is used in the retrievals, its associated uncertainty, and the formulation using vertical and horizontal polarizations or the first Stokes parameter.

- A sensitivity analysis of the SMOS soil moisture retrieval algorithm, illustrating the influence that the geophysical variables dominating the Earth’s emission at L-band have on the precision of the retrievals over six main surface conditions combining dry/moist/wet conditions with bare/vegetation-covered surfaces, for different retrieval configurations including: (i) the use of adequate constraints, (ii) the use of no constraints, (iii) the formulation in terms of vertical and horizontal polarization, and (iv) the formulation in terms of the first Stokes parameter.

- Development of a deconvolution scheme for the improvement of the spatial resolution of SMOS brightness temperatures.

- Proposal of a downscaling algorithm for SMOS using higher resolution MODIS \( T_s \) and NDVI data. Retrieval of soil moisture maps from the first SMOS observations acquired during the commissioning phase at 60 and 30 km. The possibility of downscaling to higher spatial resolutions is subject of further research that validates the accuracy of the retrievals at the different spatial scales.

- Development of a change detection algorithm that can be potentially used to combine SMAP radar and radiometer data into a 10 km soil moisture product.

8.3 Future lines

The future research lines opened by the work presented on this Thesis are:

- The application of the deconvolution algorithm to SMOS images so as to fully evaluate its possibilities in inland and coastal retrievals.
8.3. Future lines

- In-depth study of the downscaling algorithm on Chapter 6 and potential improvements (e.g. more accurate soil moisture retrieval at low resolution, the use of SMOS observations at different incidence angles and two polarizations); an error budget of the algorithm should be calculated to establish a downscaling limit and evaluate the performance of the soil moisture retrievals at higher resolutions in terms of spatial resolution and radiometric accuracy.

- The prospect use of a visible/infrared sensor in follow-on space-borne missions dedicated to soil moisture monitoring. It could serve both for estimation of collocated land surface temperatures to be used in the soil moisture retrievals, and for the improvement of the spatial resolution of the estimates using the universal triangle concept.

- The possible use of the change detection algorithm on Chapter 7 in the context of the SMOS mission, using satellite infrared land surface temperatures instead of radar observations.

- Study of a potential improvement of the algorithm on Chapter 7, assuming that the radiometer brightness temperatures (instead of the radiometer-derived soil moisture) and the log of radar backscatter are linearly related at a 10 km scale.
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<thead>
<tr>
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<tr>
<td>AACES</td>
<td>Australian Airborne Calibration/Validation Experiments for SMOS</td>
</tr>
<tr>
<td>AIRSAR</td>
<td>AIRborne Synthetic Aperture Radar</td>
</tr>
<tr>
<td>AMSR-E</td>
<td>Advanced Microwave Scanning Radiometer for EOS</td>
</tr>
<tr>
<td>ARIEL</td>
<td>Airborne RadIomEter at L-band</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
</tr>
<tr>
<td>ATBD</td>
<td>Algorithm Theoretical Bases Document</td>
</tr>
<tr>
<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
</tr>
<tr>
<td>CF</td>
<td>Cost Function</td>
</tr>
<tr>
<td>CLS</td>
<td>Constrained Least Squares</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>ECMWF</td>
<td>European Center for Medium-range Weather Forecasts</td>
</tr>
<tr>
<td>ForWaRD</td>
<td>Fourier Wavelet Regularized Deconvolution</td>
</tr>
<tr>
<td>FOV</td>
<td>Field Of View</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GRAJO</td>
<td>GPS and RAdiometric Joint Observations</td>
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<tr>
<td>JERS</td>
<td>Japanese Earth Resources Satellite</td>
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<tr>
<td>ESA</td>
<td>European Space Agency</td>
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<tr>
<td>ISEA</td>
<td>Icosahedral Snyder Equal Area</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>MIRAS</td>
<td>Microwave Imaging Radiometer by Aperture Synthesis</td>
</tr>
<tr>
<td>Acronym</td>
<td>Full Form</td>
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<tr>
<td>MIS</td>
<td>Microwave Imager Sounder</td>
</tr>
<tr>
<td>MODIS</td>
<td>MODeRate resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MTS</td>
<td>MIRAS Testing Software</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NPOESS</td>
<td>National Polar-Orbiting Operational Environmental Satellite System</td>
</tr>
<tr>
<td>OSSE</td>
<td>Observation System Simulation Experiment</td>
</tr>
<tr>
<td>PALS</td>
<td>Passive and Active L- and S-band airborne sensor</td>
</tr>
<tr>
<td>PALSAR</td>
<td>Phased Array Type L-band Synthetic Aperture Radar</td>
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<tr>
<td>REMEDHUS</td>
<td>Soil Moisture Measurement Network of the University of Salamanca</td>
</tr>
<tr>
<td>RFI</td>
<td>Radio Frequency Interferences</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>RSS</td>
<td>square Root of the Sum of the Squares</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<tr>
<td>SEPS</td>
<td>SMOS End-to-end Performance Simulator</td>
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<tr>
<td>SMAP</td>
<td>Soil Moisture Active Passive</td>
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<tr>
<td>SMOS</td>
<td>Soil Moisture and Ocean Salinity</td>
</tr>
<tr>
<td>SSM/I</td>
<td>Special Sensor Microwave/Imager</td>
</tr>
<tr>
<td>TEC</td>
<td>Total Electron Content</td>
</tr>
<tr>
<td>TMI</td>
<td>TRMM Microwave Imager</td>
</tr>
<tr>
<td>TRMM</td>
<td>Tropical Rainfall Measuring Mission</td>
</tr>
<tr>
<td>UAV</td>
<td>Unmanned Aerial Vehicle</td>
</tr>
<tr>
<td>UTC</td>
<td>Coordinated Universal Time</td>
</tr>
<tr>
<td>VIIRS</td>
<td>Visible Infrared Imager Radiometer Suite</td>
</tr>
<tr>
<td>VWC</td>
<td>Vegetation Water Content</td>
</tr>
<tr>
<td>WindSat</td>
<td>Wind Satellite</td>
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</tbody>
</table>
Symbols

**Latin symbols**

- $a$ Spatial scale of 10 km
- $a_{ij}, a_{ijk}$ Regression coefficients
- $A$ Spatial scale of 40 km
- $A_r$ Antenna effective area [m$^2$]
- $A_t$ Total radiating area [m$^2$]
- $b$ Empirical parameter used for the estimation of vegetation optical depth
- $B(\theta, \phi)$ Brightness or radiance [Wsr$^{-1}$m$^{-2}$]
- $B_{av}$ Average Earth’s magnetic field along the propagation path [Wb/m$^2$]
- $B_{bb}$ Total brightness of a blackbody [Wsr$^{-1}$m$^{-2}$]
- $B_f(\theta, \phi)$ Spectral brightness: brightness per unit bandwidth [Wsr$^{-1}$m$^{-2}$Hz]
- $B_i(\theta, \phi)$ Total brightness incident over an antenna [Wsr$^{-1}$m$^{-2}$]
- $B_w$ Noise-equivalent bandwidth [Hz]
- $c$ Speed of light $c = 3 \times 10^8$ [m/s]
- $C$ Smoothing criterion function
- $C_p$ Diagonal matrix containing the variances of the prior estimates of parameters $p_i$
- $C_F$ Covariance matrix of the observations
- $d$ Antenna spacing
- $e$ Tolerance error
- $e(\theta, \phi)$ Emissivity
- $E_h$ Electric field of an electromagnetic wave at horizontal polarization
- $E_v$ Electric field of an electromagnetic wave at vertical polarization
- $f$ Column vector containing the unknown $T_B$ at high resolution
- $f$ Frequency [Hz]
Appendix B. Symbols

\[ F \] Fourier transform of \( f \)
\[ F^{\text{meas}} \] Vector containing the SMOS measured brightness temperatures at different incidence angles
\[ F^{\text{model}} \] Vector containing the SMOS simulated brightness temperatures at different incidence angles
\( t \) Normalized antenna radiation pattern
\( F_{n}(\theta, \phi) \) Fractional vegetation cover
\( F_{r} \) Antenna radiation pattern
\( g \) Column vector containing the radiometer observations
\( G \) Fourier transform of \( g \)
\( h \) Column vector representation of the synthetic antenna response function
\( h \) Planck’s constant \( h = 6.63 \cdot 10^{-34} \text{[J·s]} \)
\( h_{s} \) Effective roughness parameter
\( H \) Matrix constructed from circular shifting of \( h \) to express the convolution operation as a product in the time domain
\( H \) Fourier transform of \( h \)
\( I \) First Stokes parameter
\( k \) Wavenumber [rad/m]
\( k_{B} \) Boltzmann’s constant \( k_{B} = 1.38 \cdot 10^{23} \text{[J/K]} \)
\( K \) Generic filter
\( K_{p} \) Normalized deviation of radar backscatters
\( L_{a} \) Atmospheric attenuation
\( m_{g} \) Gravimetric soil moisture
\( m_{v} \) Volumetric soil moisture
\( n \) Column vector representing the noise added to the radiometer measurements
\( n \) Exponential of the cosine dependence of soil emissivity with the incidence angle
\( N \) Fourier transform of \( n \)
\( \text{NDVI}_{\text{max}} \) Maximum NDVI value for a particular scene
\( \text{NDVI}_{\text{min}} \) Minimum NDVI value for a particular scene
\( N_{T} \) Ionospheric total electron content [electrons/m²]
\( p_{i} \) Retrieved physical parameters that may influence the modeled \( T_{B} \)
\( p_{i0} \) Prior estimates of parameters \( p_{i} \)
\( P \) Power collected by an antenna [W]
\( P_{bb} \) Power collected by an antenna surrounded by a blackbody [W]
\( Q \) Linear operator
\[ Q \quad \text{Second Stokes parameter} \\
\]
\[ Q_s \quad \text{Cross-polarization factor} \\
\]
\[ R_f \quad \text{Correlation matrix of } f \\
\]
\[ R_n \quad \text{Correlation matrix of } n \\
\]
\[ s_m \quad \text{Soil moisture} \\
\]
\[ S_f \quad \text{Fourier transform of } R_f \\
\]
\[ S_n \quad \text{Fourier transform of } R_n \\
\]
\[ t \quad \text{Time} \\
\]
\[ t_R \quad \text{Revisit time of the observations} \\
\]
\[ T \quad \text{Physical temperature [K]} \\
\]
\[ T_b \quad \text{Simulated brightness temperature image of the scene observed by the radiometer} \\
\]
\[ T_{hh} \quad \text{Brightness temperature at horizontal polarization, Earth reference frame [K]} \\
\]
\[ T_{lc} \quad \text{Left-hand circular polarized brightness temperature [K]} \\
\]
\[ T_{max} \quad \text{Maximum } T_s \text{ value for a particular scene [K]} \\
\]
\[ T_{min} \quad \text{Minimum } T_s \text{ value for a particular scene [K]} \\
\]
\[ T_s \quad \text{Soil effective temperature [K]} \\
\]
\[ T_v \quad \text{Vegetation effective temperature [K]} \\
\]
\[ T_{vv} \quad \text{Brightness temperature at vertical polarization, Earth reference frame [K]} \\
\]
\[ T_{xx} \quad \text{Brightness temperature at x-axis, antenna reference frame [K]} \\
\]
\[ T_{xy} \quad \text{Cross-polarized brightness temperature, antenna reference frame [K]} \\
\]
\[ T_{yy} \quad \text{Brightness temperature at y-axis, antenna reference frame [K]} \\
\]
\[ T_A \quad \text{Antenna temperature [K]} \\
\]
\[ T_{AP} \quad \text{Apparent brightness temperature [K]} \\
\]
\[ T_B \quad \text{Fourier transform of } T_b \\
\]
\[ T_B \quad \text{Brightness temperature [K]} \\
\]
\[ T_{Bmax} \quad \text{Maximum } T_B \text{ values for a particular scene [K]} \\
\]
\[ T_{Bmin} \quad \text{Minimum } T_B \text{ value for a particular scene [K]} \\
\]
\[ T_I \quad \text{First Stokes parameter in brightness temperature [K]} \\
\]
\[ T_Q \quad \text{Second Stokes parameter in brightness temperature [K]} \\
\]
\[ T_N \quad \text{Normalized soil effective temperature} \\
\]
\[ T_{SC} \quad \text{Downward atmospheric radiation scattered by the Earth’s surface [K]} \\
\]
\[ T_U \quad \text{Third Stokes parameter in brightness temperature [K]} \\
\]
\[ T_{UP} \quad \text{Atmospheric upward radiation [K]} \\
\]
\[ T_V \quad \text{Fourth Stokes parameter in brightness temperature [K]} \\
\]
\[ T_{45} \quad \text{Brightness temperature skewed 45° with respect to normal [K]} \\
\]
Appendix B. Symbols

\( T_{-45} \)  
Brightness temperature skewed -45° with respect to normal [K]

\( U \)  
Third Stokes parameter

\( V \)  
Fourth Stokes parameter

\( V_w \)  
Volume of water in a soil sample [m³]

\( V_T \)  
Total volume of a soil sample [m³]

\( w_d \)  
Dry weight of a soil sample [g]

\( w_w \)  
Wet weight of a soil sample [g]

Greek symbols

\( \alpha \)  
Filter parameter \( \alpha \equiv 1 / \lambda_1 \)

\( \beta(a) \)  
Slope of the linear relationship between soil moisture and the log of radar backscatter at a scale

\( \langle \beta(a) \rangle \)  
Spatial average of the \( \beta(a) \) pixels contained into the \( A \) scale pixels

\( \gamma \)  
Transmissivity of the vegetation layer

\( \gamma_D \)  
Soil penetration depth [m]

\( \Gamma_{o,p} \)  
Fresnel’s soil reflectivity at \( p \)-polarisation (flat surface)

\( \Gamma_{s,p} \)  
Soil reflectivity at \( p \)-polarization

\( \Delta f \)  
Bandwidth [Hz]

\( \varepsilon_s \)  
Complex dielectric constant of soils \( \varepsilon_s = \varepsilon'_s + j\varepsilon''_s \)

\( \varepsilon'_s \)  
Effective permittivity (real part of \( \varepsilon_s \))

\( \eta \)  
Directing cosine with respect to y axis \( \eta = \sin \theta \sin \phi \)

\( \eta_v \)  
Electromagnetic wave impedance of the medium (120π in vacuum) [Ω]

\( \theta \)  
Incidence angle referred to nadir [°]

\( \theta(a, t) \)  
Soil moisture at \( a \) scale at time \( t \)

\( \lambda \)  
Wavelength \( \lambda = c / f \) [m]

\( \lambda_1, \lambda_2 \)  
Lagrange multipliers

\( \xi \)  
Directing cosine with respect to x axis \( \xi = \sin \theta \cos \phi \)

\( \rho \)  
Filter parameter \( \rho \equiv \lambda_2 / \lambda_1 \)

\( \rho_b \)  
Soil bulk density [g/cm³]

\( \rho_{NIR} \)  
At-surface reflectance of LANDSAT band 4 (Near-infrared, 0.76 - 0.90 m)

\( \rho_R \)  
At-surface reflectance of LANDSAT band 3 (Visible, 10.40 - 12.50 m)

\( \sigma_s \)  
Standard deviation of the surface height [m]

\( \sigma_{p_0} \)  
Uncertainty on \( p_0 \)

\( \sigma_{p_0}^2 \)  
Variance of \( p_0 \)

\( \sigma_{F_n} \)  
Radiometric accuracy for the \( n^{th} \) observation

\( \sigma^0(a, t) \)  
Radar backscatter aggregated to \( a \) scale at time \( t \)

\( \tau \)  
Vegetation opacity or vegetation optical depth [Np]
\( \phi \) Azimuth angle referred to nadir [°]
\( \phi_0 \) Filter parameter \( \phi_0 \equiv \alpha \left[ \frac{S_n(u,v)}{S_f(u,v)} \right] \)
\( \varphi \) Faraday rotation angle [rad]
\( \omega \) Vegetation albedo
\( \Omega \) Solid angle [sr]
\( \Omega_p \) Antenna solid angle
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