Department of Meteorology

SATELLITE
REMOTE SENSING
OF SOIL MOISTURE

by

Maria Helena Lopes Roberto Serrano

A dissertation submitted in partial fulfilment of the requirement for the degree of Master of Science in Applied Meteorology

August 2010
Acknowledgements

I would like to thank both my supervisors Prof. Robert Gurney and Dr. Ian Davenport for the warm welcome to the ESSC, their help, guidance, sharp suggestions and comments to my work. The comments made by Dr. Jeff Settle were also very constructive and highly appreciated.

The ground and aircraft based observational data used to undertake this study was collected in the frame of the National Airborne Field Experiment 2006 led by Prof. Jeffrey Walker from the University of Melbourne, Australia.

I thank in special my mother and my husband for the support throughout the year.
Abstract

Microwave remote sensing of soil moisture will, in the near future, bring to the community real advantages. The European soil moisture and ocean salinity (SMOS) and, the American soil moisture active-passive (SMAP) are two satellite missions planned to sense this component of the water balance with new technology that will improve the accuracy of the retrievals. The knowledge of soil moisture at a global scale will allow improvements is weather and climate models, as well as, introduce the opportunity for better management of water resources. The objective of this project is to study how well the zeroth solution \(\tau-\omega\) model performs for semi-arid regions, in the presence of sparse vegetation. This model is widely used to retrieve soil moisture, since it simulates the radiative transfer considering a single layer of vegetation. Microwave observations collected during the National Airborne Field Experiment 2006, were used to estimate the surface parameters to which microwave emission is sensitive. Soil moisture and vegetation optical depth were analysed for the 1\(^{st}\), 3\(^{rd}\), 8\(^{th}\), 10\(^{th}\) and 17\(^{th}\) of November 2006. During this two week period a few rainfall events were registered. The analysis of the model output revealed an error of 3\% to 10\% between sensed and estimated of soil moisture. The biggest error can be associated with dew on the 8\(^{th}\) of November 2006, as a consequence of intercepted water in the vegetation canopy. The \(\tau-\omega\) model does not have parameterisation for intercepted water in the vegetation canopy and, as a result the estimations of soil moisture for days and areas were a precipitation event occurred should present high errors associated. The model was able to identify the increase of soil moisture in the day of the rainfall event and the posterior dry out. However, the model seems to lack accuracy when soil moisture variation is not so evident. For example, it lacked to identify the increase in soil moisture between the 10\(^{th}\) and the 17\(^{th}\) November due to a precipitation event on the 16\(^{th}\) of November, which was identified by the Hydraprobe® sensors. For the analyses of vegetation optical depth, the model output was compared with the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) using either Landsat or MODIS images. An increase in this parameter was suggested by the model and confirmed using the above mentioned remote sensing technique. A downscaling study of soil moisture and vegetation optical depth was done and revealed heterogeneity present in the surface parameters across the area of the transect flight where the PLMR observations were collected.
List of Figures and Tables

Figures

Fig.2.1 Radiation Absorption and scattering components of the relative dielectric effect. 4

Fig. 2.2 Surface Emissivity Spectra function of frequency for Vertical vs Horizontal polarization. 5

Fig. 3.3.1: Image illustrating the soil moisture (HDAS) sensor grid configuration with the transect flight line (Walker et al., 2006). 10

Fig.5.1 Brightness Temperatures output from τ-ω forward model by keeping soil temperature, vegetation optical depth and single scattering albedo fixed, and varying roughness. Plot on the left considers dry soil, and plot on the right considers slightly moist soil. 21

Fig.6.1.1 Rainfall and Soil Moisture in Spring 06 for Yanco farm. 24

Fig.6.2.1 PLMR observations for the 5 days with 6 angles. 25

Fig.6.2.2 PLMR observations for the 5 days with 5 angles. 25

Fig. 7.1.1 Soil moisture changes over 5 days. Dashed blue line obtained by adding the bias between the averaged sensed and estimated soil moisture values over day 1, 3, 10, 17 to the Hydraprobe initial values. 32

Fig.7.2.1 Plot with accumulated NDVI percentage for the 7th and 23rd of November, calculated over the purple area defined in the Landsat image given on the left side. 35
Fig.7.2.2 Changes in vegetation optical depth and soil moisture. Values estimated by τ-ω inverse model using PLMR observations for the 1st, 3rd, 8th, 10th and 17th November.

Fig.8.1 Landsat image of the region where the microwave observations were collected. Blue rectangle highlights the area covered by the transect flight (approximately along 3.5 km); purple rectangles signal the downscaling subareas.

Fig.8.1.1 TSLS IR (grey) and NDVI (color) images of area 1.

Fig.8.1.2 TSLS IR (grey) and NDVI (color) images of area 2.

Fig.8.1.3 TSLS IR (grey) and NDVI (color) images of area 3.

Fig.8.1.4 TSLS IR (grey) and NDVI (color) images of area 4.

Fig.8.1.5 TSLS IR (grey) and NDVI (color) images of area 5.

Fig.8.2.1 Soil moisture estimations using Tao-Omega inverse model versus Hydraprobe, for the 5 sub-areas over 5 days.

Fig.8.3.1: Estimative of vegetation optical depth for 5 sub-areas generated using τ-ω inverse model.

Fig. 8.3.2: Normalized difference vegetation index (NDVI) calculated using Landsat images, after water body correction.

Fig. 8.3.3 Normalized difference vegetation index (NDVI) calculated using MODIS images. In the MODIS image is possible to identify the 5 sub-areas.

Fig. 8.3.4 Enhanced Vegetation Index (EVI) calculated using MODIS images
Tables

Table 5.1 Flight time and temperature for the 5 days. Parameters retrieved with inverse model for the area along the flight line, considering $\omega = 0.06$ and $r = 0.19$. 20

Table 5.2 $\tau-\omega$ model estimates of soil moisture using two soil compositions. 22

Table 6.2.1 Changes in $T_s = T_v$ (given by TOM inverse) versus changes in $T_b$ at different angles. 26

Table 7.1.1 Study of surface temperature constrain in the estimation of soil moisture. 33

Table 8.2.1 Percentage error between estimated and sensed soil moisture (after bias elimination) 46
List of Symbols and Abbreviations

**Symbols**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_b$</td>
<td>Brightness temperature (Kelvin)</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Soil temperature (Kelvin)</td>
</tr>
<tr>
<td>$T_{wo}$</td>
<td>water temperature (Celsius)</td>
</tr>
<tr>
<td>$T_v$</td>
<td>Vegetation temperature (Kelvin)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Soil moisture</td>
</tr>
<tr>
<td>$r$</td>
<td>Soil roughness parameter</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Vegetation optical depth</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Vegetation single scattering albedo</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Nadir view angle</td>
</tr>
<tr>
<td>$e_s$</td>
<td>Emissivity of smooth surface</td>
</tr>
<tr>
<td>$R_s$</td>
<td>Reflectivity of soil surface</td>
</tr>
<tr>
<td>$\Gamma$</td>
<td>Transmissivity</td>
</tr>
<tr>
<td>$R$</td>
<td>Reflectivity</td>
</tr>
<tr>
<td>$R_{\text{smooth,soil}}$</td>
<td>Smooth surface reflectivity</td>
</tr>
<tr>
<td>$R_{\text{rough,soil}}$</td>
<td>Rough surface reflectivity</td>
</tr>
<tr>
<td>$A$</td>
<td>Absorptivity of canopy</td>
</tr>
<tr>
<td>$e_c$</td>
<td>Canopy emissivity</td>
</tr>
<tr>
<td>$\varepsilon_c$</td>
<td>Complex dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon_r$</td>
<td>Relative dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon_0$</td>
<td>Free-space permittivity</td>
</tr>
<tr>
<td>$\varepsilon_r^*$</td>
<td>Dielectric constant/ permittivity</td>
</tr>
<tr>
<td>$\varepsilon_r'$</td>
<td>Dielectric loss factor</td>
</tr>
<tr>
<td>$\varepsilon_r''$</td>
<td>Dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon'_\text{soil}$</td>
<td>Soil dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon'_\text{water}$</td>
<td>Water dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon_{\text{dw}}$</td>
<td>Static diel. Const. of distilled water</td>
</tr>
<tr>
<td>$\varepsilon_e$</td>
<td>High-frequency dielectric constant</td>
</tr>
<tr>
<td>WP</td>
<td>Wilting point</td>
</tr>
<tr>
<td>$t_{wc}$</td>
<td>Transitional soil/ water content</td>
</tr>
</tbody>
</table>
\( \rho_{\text{bulk}} \)  Bulk density
\( \rho_{\text{par}} \)  Particle density
\( f \)  Frequency
\( \lambda \)  Wavelength
\( \text{rel}_{\text{time}} \)  Relaxation time of pure water
\( \sigma^2 \)  Variance of the soil

**Abbreviations**

- **CSIRO**  Australia's Commonwealth Scientific and Industrial Research Organisation
- **ECMWF**  European Centre of Medium-Range Weather Forecast
- **EVI**  Enhanced Vegetation Index
- **H**  Horizontal polarisation
- **IR**  Infrared
- **MODIS**  MODerate resolution Imaging Spectroradiometer
- **MPDI**  Microwave polarisation difference index
- **NAFE’06**  National Airborne Field Experiment 2006
- **NDVI**  Normalised Difference Vegetation Index
- **NIR**  Near InfraRed
- **PLMR**  Polarimetric L-band Multibeam Radiometer
- **PR50**  Polarisation Ratio at 50 degrees
- **RFI**  Radio Frequency Interference
- **RMSE**  Root Mean Square Error
- **SERA**  Small Environmental Research Aircraft
- **SMAP**  Soil Moisture Active Passive
- **SMOS**  Soil Moisture and Ocean Salinity
- **TOM**  Tao Omega Model
- **TRMM**  Tropical Rainfall Measuring Mission
- **TSLS**  Tri-Spectral Line Scanner
- **V**  Vertical polarisation
Table of Contents

Acknowledgements iii
Abstract v
List of Figures and Tables vi
List of Symbols and Abbreviations ix
Table of Contents xi

1 Introduction 1

2 Microwave Remote Sensing of Soil Moisture 2

3 Satellite Missions and Field Experiments 6

3.1 SMOS Mission 7
3.2 SMAP Mission 8
3.3 Field Experiments 8

4 The $\tau$-$\omega$ Zeroth-Order Solution Model 11

4.1 Forward and Inverse Model 12
4.2 Model Parameterisation 12
4.2.1 Vegetation Module 13
4.2.2 Dielectric Mixing Model 15
4.2.3 Smooth Emissivity Model 17
4.2.4 Soil Roughness Model 18

5 Estimation of Model Parameters 19

6 Analysis of Observations 23

6.1 Hydaprobe® Sensed Soil Moisture 23
6.2 PLMR Microwave Observations 24
6.2.1 Effect of Dew and Spray on Microwave Observations 27

7 Analysis of the Zeroth-Order $\tau$-\omega model estimations 31

7.1 Soil Moisture 31
7.2 Vegetation Optical Depth ($\tau$) 34

8 Downscaling estimations 37

8.1 Sub-area characteristics 39
8.2 Soil Moisture 43
8.3 Vegetation Optical Depth ($\tau$) 47

9 Conclusions 52

References 56
Appendix 61
1 Introduction

Soil moisture constitutes an important contribution to the knowledge of a part of the water balance at the global, regional, and local scales. Hence, this information is widely used in hydrological applications helping to quantify the diverse components of the water balance - infiltration, surface runoff, evaporation, deep percolation, and changes in water content of the vadose zone (Davenport et al., 2005). The groundwater storage may have a direct impact on human health, and can influence agriculture activities, economy, military activities and transportation. Therefore, information about the topsoil layer is important to monitor crop conditions, and information about the moisture in deeper soil is crucial for agricultural planning and management of water resources.

Additionally, low levels of soil wetness can lead to drought or wild land fire, whereas saturated soil together with precipitation may increase the risk of flooding. The knowledge of soil moisture is also of extreme importance in weather and climate forecasting. Considering that the atmosphere has millions of degrees of freedom, weather forecasts have a limit of deterministic predictability of around 14 days. Therefore, weather prediction is considered an initial value problem and numerical weather prediction (NWP) models require accurate data about the transfer of soil moisture, energy fluxes in the boundary layer, evaporation and the partitioning of sensible heat flux and latent heat flux to accurately predict the wind circulation and cloud development.

Furthermore an evaporation rate that varies strongly and consistently with soil moisture tends to lead to a higher coupling strength between atmosphere and surface (Guo et al., 2005). Specific knowledge of surface wetness patterns on a regional scale can additionally aid in the forecast of thunderstorm location, maximum and minimum temperatures and identify restricted visibility related with haze, smog and fog. Models of ecosystem and carbon cycle processes require soil moisture because it regulates both soil respiration and plant water stress, which affects stomata conductance and carbon uptake. There are also benefits for the modulation of dust generation and trace gas fluxes from earth’s surface (Koster et al., 2009). For military defense, too, soil moisture affects everything from low-
level fog forecasts to the calculation of density altitude, or lift capacity of aircraft\(^1\). Satellite remote sensing of soil moisture is a key factor to understand land-atmosphere coupling. Large-scale observational products using microwave radiometry are an effective method of monitoring soil moisture heterogeneity (Gao et al., 2004).

## 2 Microwave Remote Sensing of Soil Moisture

Remote sensing provides researchers and the community with the possibility to monitor changes in land and ocean around the globe, especially where in-situ observations are limited or non-existent. Microwave remote sensing enables satellite to get observations day and night regardless of the lighting conditions, and at selected frequencies, microwave emissions have a good cloud penetration which proves to be an immensely advantage over the oceans, which are on average 70% covered by clouds. Microwave sensors are used for retrieval of soil moisture because they are insensitive to vegetation.

The two main properties of microwave radiation are polarisation and frequency. Polarisation varies with the wavelength and with the physical characteristics of the emitting or reflecting material, which in turn allows the discrimination between solid, liquid, and frozen elements on both land and ocean surfaces. Microwave remote sensing covers both active and passive forms of operation. Passive instruments (radiometers) sense the naturally emitted microwave radiation in their field of view, measuring the emanating electromagnetic radiation from the earth’s surface or physical objects. The sensors require a large field of view in order to detect low level of emitted microwave radiation. The low spatial resolution is a consequence of the Rayleigh criterion, which is a diffraction limit on the resolution of sensors based on the wavelength of the radiation and the size of the observing “aperture”. The smallest angle \( \alpha \) that can be resolved is calculated as \( \sin (\alpha) = 1.22 \times \) (wavelength / aperture diameter for circular apertures). Active microwave systems include imaging (radar) and non-imaging sensors (altimeters, scaterometers). This type of

\[^1\] http://spectrum.mit.edu/issue/2010-summer/measuring-moisture/
sensor has its own source of illumination and measures the difference between the power emitted and the power received from the target.

Space borne microwave radiometry is an important technique for obtaining global estimates of parameters important to the hydrological cycle and land-surface energy coupling (surface temperature, soil moisture, vegetation). The need for frequent information of soil moisture at fine resolution scale is in fact imperative for the improvement on model outputs.

Microwave are electromagnetic waves with wavelengths ranging from one meter to one millimetre, or equivalently, with frequencies between 0.3 and 300 GHz. Electromagnetic waves travel at the speed of light $c$, and their frequency $f$ and wavelength $\lambda$ are related by $c = f\lambda$. In order to obtain an estimation of the soil moisture, the sensor measures the soil’s naturally emitted microwave radiation, and traduces that information into brightness temperature.

The brightness temperature is the apparent temperature of the surface assuming a surface emissivity of 1.0, which is equivalent to assuming the target is a blackbody, hence the brightness temperature is defined as the temperature a blackbody would be in order to produce the radiance identified by the sensor. The Planck’s law describes the spectral radiance at all wavelengths emitted in the normal direction from a blackbody, and it is given by the following expression

$$I(f, T) = \frac{2hf^3}{c^2} \frac{1}{e^{hfT} - 1}$$  \hspace{1cm} (1)

where $I$ is the blackbody spectral radiance, $T$ is the blackbody temperature, $h$ is the Planck’s constant, $f$ is the frequency, and $k$ is the Boltzmann’s constant. The brightness temperature can be obtained by applying the inverse of the Planck function to the perceived radiation. In the limit of very high temperatures or small frequencies, in which $hf / kT << 1$, we can use the Rayleigh-Jeans law, that describes the spectral radiance of electromagnetic radiation from a blackbody at a given temperature through classical arguments. This law consists in an approximation of Planck’s law using the power series expansion, and is given by a simpler expression

$$I(f, T) = \frac{2f^2kT}{c^2} .$$  \hspace{1cm} (2)
When in the presence of flat, smooth and bare soil surfaces of known composition, the retrieval of soil moisture can be straightforward. However, there are factors that challenge the retrieval process. Vegetation, soil surface roughness and soil type interfere with the signal emitted from the surface. Vegetation emits its own microwave radiation which can be confused with the desired soil emission. It acts to increase the emissivity of the surface below, hence increasing the microwave brightness temperature as well, making the surface appear dryer than it really is. Fortunately, both surface roughness and vegetation have very specific polarisation effects on the microwave signal.

Several mechanisms can contribute to the interaction of radiation with matter. Within the microwave region the rotation of molecular dipoles is the most important interaction of radiation with matter. As can be seen in figure 2.1, the scattering component is dominant when compared with the loss term and grows rapidly with decreasing frequency from about 100 GHz down to about 1GHz.

**Fig. 2.1** Radiation Absorption and scattering components of the relative dielectric effect. **Source:** www.comet.ucar.edu

The increase in scattering at lower frequencies is especially noticeable for water with its strong electric dipole and is primarily responsible for the higher reflectance (lower emissivity) observed for water.
Other factors that influence the level of interaction of radiation with matter are molecular composition, temperature and frequency.

For the retrieval of soil moisture, both surface roughness and vegetation polarisation effects on the microwave signal are useful.

Figure 2.2 compares frequency, and vertical and horizontal polarisations effects for different surfaces. The degree of polarisation for a wet surface becomes more evident at lower frequencies. For land covered by a vegetation canopy, there is some polarisation at lower frequencies but the degree of polarisation is less when compared to bare wet land. Also, we notice that emissivity for vegetation is greater.

Short wavelength systems suffer atmospheric attenuation, hence are unsuitable for spaceborne systems. Furthermore, due to their relatively low penetration capability, they tend to produce scattering from vegetation layers, obscuring the soil moisture signal. Spaceborne microwave remote sensing of soil moisture uses long wave/low frequency channel because it penetrates deeper in the soil, it is less affected by vegetation and surface roughness, and also has the advantage of a greater dielectric effect.

Fig. 2.2 Surface Emissivity Spectra function of frequency for Vertical vs Horizontal polarisation. Source: www.comet.ucar.edu.

However, lower frequency channels have inherent poor spatial resolution because they require large footprint for detection. Another vulnerability of lower frequency systems is
radio frequency interference (RFI); for example in North America the interference with cell phone frequency allocation is common.

In a broad spatial area different characteristics of soil type and roughness, and vegetation type and layers may be present (Davenport et al., 2005). The understanding of how these characteristics influence the brightness temperature will enable the retrieval of soil moisture to be more accurate.

In recent years, improved models have been developed describing the relationship between the brightness temperature and land surface parameters, with the use of a range of frequencies, polarisations, viewing angles and downscaling algorithms leading to an increase interest in the potential of microwave radiometry for global observation of land surfaces.

3 Satellite Missions and Field Experiments

Remote sensing of soil moisture using microwave radiometer sensors applies the theory that different dielectric values are associated with dry and wet soil surfaces. The sensitivity to surface dielectric properties increases at lower microwave spectrum. Past and currently operating satellite missions that provide soil moisture information include: Scanning Multichannel Microwave Radiometer (SMMR) at 6.63 GHz on Nimbus-7 (1978-1987); the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave Imager (SSM/I) at 19.3 GHz (1987); Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) at 10.65 GHz (1997); Advanced Microwave Scanning Radiometer (AMSR) on Earth Observing System (EOS) Aqua satellite (AMSR-E) at 6.9 GHz (2002); and Europeans Soil Moisture and Ocean Salinity (SMOS) mission at 1.4 GHz (2009) (Gao et al., 2004). NASA’s Soil Moisture Active-Passive (SMAP) mission, with frequencies 1.26 GHz and 1.41 GHz respectively for radar and radiometer instruments, is currently schedule to launch in 2014. The next two sections of this chapter will describe in more detail the SMOS and SMAP missions. Both these missions use novel microwave sensors, and should
provide a better understanding of global soil moisture distribution. This information will improve NWP model accuracy and help constrain current climate-change models, which disagree about which areas across the globe will have more stored soil moisture, and which have less. The last section of chapter 3 mentions some of the field experiments undertaken to collect data for validation and calibration of satellite data. The observations used in this project were collected during the National Airborne field Experiment 2006; hence a brief summary of this experiment objectives and a description of the different sets of data collected will be given. Detailed information about the observations used for this project work can be found in chapter 6.

3.1 SMOS Mission

Soil moisture and ocean salinity mission (SMOS) was launched on 2\textsuperscript{nd} November 2009. This satellite acquires data at 35 km resolution at centre of its field-of-view every 3 days. It has on board a microwave imaging radiometer using aperture synthesis (MIRAS). It works in L-band (21cm – 1.4 GHz), acquires data at horizontal and vertical polarisations, and has a multi-incidence angle capability ranging from 0 to 55 degrees from nadir\textsuperscript{2}. The satellite orbit is Sun-synchronous, dawn/dusk, quasi-circular at 758 km altitude. The problem associated with low frequencies in a space based receiver revolves around the fact that in order to have a reasonably spatial resolution (30-50 kilometers) it is necessary a very large antenna (5-10 meters) that is very hard to fit in a standard satellite. In order to overcome this difficulty an aperture synthesis approach that was already in use by radio-astronomers was adopted that, in order to detect small signals from point sources in space, routinely links radio-telescopes located in different locations to simulate a larger antenna than they actually have. The MIRAS instrument on board SMOS has 3 foldable arms, each 3 meters long that open in a Y shape, and carry in total 69 small antennas that will provide measurements as a single large antenna\textsuperscript{3}. For the retrievals the SMOS Level 2 soil moisture

\textsuperscript{2} \url{www.esa.int/esaLP/ESAL3B2VMOC_LPsmos_2.html}
\textsuperscript{3} \url{www.sciencedaily.com/releases/2009/11/091102111845.htm}
algorithm was implemented. The modulation of soil and vegetation parameters is present in L-band microwave emission of the biosphere model (L-MEB) which uses the multi-angle incidence to retrieve the surface parameters applying a minimization of a cost function obtained between the measured and modeled brightness temperatures at the different angles (Wigneron et al. (2007)).

### 3.2 SMAP Mission

The Soil Moisture Active-Passive mission (SMAP) is scheduled to launch in 2014 and will provide real data at high resolution, every two to three days. In addition, it will also present information about whether the soil is frozen or not. The orbit will be near-polar, sun-synchronous at 690 kilometers. SMAP’s active measurements of soil moisture will provide a spatial resolution of about 10 kilometers. This high resolution is achieved by combining two L-band sensors aboard the satellite. The radiometer captures low-frequency microwaves naturally emitted at the surface of the planet at 30 kilometers resolution, and the radar (SAR) actively beams low-frequency microwaves to the surface and captures what is reflected back with a resolution of 1 to 3 kilometers. The data is collected at 40° from nadir with different polarisations.⁴

### 3.3 Field Experiments

Projects around the world complement the validation and calibration of satellite missions: SGP (Southern Great Plains), SMEX (Soil Moisture Experiment) were implemented in the United States, and coSMOS (Campaign for Validating the operation of SMOS) was implemented in Europe. The National airborne field experiment 2006 (NAFE’06) was a campaign conducted in southern Australia in November 2006 to collect

sets of data for the validation of the SMOS mission. The main objective of the NAFE’06 experiment was to evaluate if the Murrumbidgee river catchment area was suitable for SMOS calibration and validation, as well as to develop downscaling algorithms and test multi-angle and multi-spectral retrieval approaches and assimilation techniques to apply when the satellite data becomes available on-line. Since the collection of data sets requires a high level of effort and costs, an international collaboration was established for the collection and analysis of the data for a better coordination of satellite, airborne and ground based data. The NAFE’06 study area comprises three separate regions of the Murrumbidgee catchment (Yanco, Kyeamba Creek and Yenda).

This project only uses data collected on the Tubbo farm (Y7) in the Yanco area. The Yanco study area is 3600 km² in area (60x60 km) and it is located in the western plains of the Murrumbidgee catchment. The topography is mostly flat; the main soil type is clay, red brown earth, sands over clay, and deep sands (Walker et al., 2006). Approximately one third of the area comprises the Coleambally Irrigation Area (CIA) that is constituted by more than 500 farms than produce rice, maize and soybeans (local summer), as well as wheat, barley, oats, and canola (local winter). Tubbo farm, however, is covered mostly by native pasture and grazing.

Walker et al. (2006), state that according to the Digital Atlas of Australian soils, the soil is characterised by “plains with domes, lunettes, and swampy depressions, and divided by continuous or discontinuous low river ridges associated with prior stream systems—the whole traversed by present stream valleys; layered soil or sedimentary materials common at fairly shallow depths: chief soils are hard alkaline red soils, grey and brown cracking clays”. For the downscaling resolution study of SMOS, NAFE’06 has collected intermediate resolution data to account for the natural heterogeneity of land surface with the objective of filling the gap between point-scale and space based measurements. For this purpose, a small environmental research aircraft (SERA) was equipped with a Polarimetric L-band Multibeam Radiometer (PLMR) instrument and a thermal imager with the capacity to obtain high resolution measurements together with other complementary instruments (full wave form lidar, NDVI scanner and an 11 Megapixel digital camera). The flights were planned to maximize the concurrent Moderate resolution Imaging Spectroradiometer (MODIS) overpass.
MODIS is a scientific instrument launched by NASA on board the Terra (EOS AM) Satellite, and the Aqua (EOS PM) satellite. MODIS data is captured in 36 spectral bands ranging in wavelength from 0.4 \( \mu \text{m} \) to 14.4 \( \mu \text{m} \) and at varying spatial resolutions (2 bands at 250 m, 5 bands at 500 m and 29 bands at 1 km). They provide images of the entire Earth every 1 to 2 days, and measurements in large-scale global dynamics including changes in Earth's cloud cover, radiation budget and processes occurring in the oceans, on land, and in the lower atmosphere.

In this project the brightness temperature data obtained using a PLMR receiver, measured using both V and H polarisations at six incidence angles, along the flight track, using a frequency of 1.413GHz, which have accuracy better than 1K. Across the study period (1\(^{st}\) to 17\(^{th}\) of November) there were rainfall events on the 2\(^{nd}\) - 3\(^{rd}\), 12\(^{th}\) - 13\(^{th}\), and 16\(^{th}\) of November. In order to validate the soil moisture values and its spatial distribution, a set of sensors were distributed in a grid-based pattern (see fig.3.3.1). Walker et al. (2006) consider spatial variability of ground measurements at 1 km resolution to be less than 10% vol.

**Fig. 3.3.1:** Image illustrating the soil moisture (HDAS) sensor grid configuration with the transect flight line (Walker et al., 2006).
For each multi-incidence flight made across Tubbo Farm, the near surface soil moisture measurements were collected using the Hydraprobe® Data Acquisition System (HDAS)$^5$, which were connected to a pocket PC with Bluetooth connection to GPS for real-time positioning and data logging. These were roving measurements with the objective of retrieving the percentage of soil moisture, as well as its spatial distribution. The remaining soil moisture measurements (deeper soil levels) were made in a 3 by 1 km area at 50m/250m resolution (fig.3.3.1).

In order to calibrate Hydraprobe® measurements, volumetric measurements were collected at each farm and compared with the HDAS data. For each day of sampling, 5 soil samples will be taken for each soil moisture sampling grid.

4 The $\tau$-$\omega$ Zeroth-Order Solution Model

In the scientific literature it is possible to find a number of models that estimate the microwave emission from surface parameters (Ulaby et al., 1986). They constitute an approximation of the vector radiative transfer equation, with different parameterisations representing the interaction between radiation and matter. Microwave remote sensing of soil moisture relies on the big contrast in the dielectric effect of dry soil and water, approximately 4 and 80 respectively. The sensitivity to this effect increases for lower microwave frequencies (Gao et al., 2004). The $\tau$-$\omega$ model zeroth-order solution of the radiative transfer equations in a vegetation layer is so called because it neglects radiation scattered into the beam, and it is based on two main parameters: optical depth ($\tau$) and single scattering albedo ($\omega$). The effects of canopy attenuation are taken into consideration for given boundary conditions of a vegetation layer over a soil surface. The objective of section 4.1 is to identify the model parameters, and to distinguish two different applications of the $\tau$-$\omega$ model. Section 4.2 will describe the physical components of the model.

4.1 Forward and Inverse Model

The τ-ω model has five parameters that represent the surface characteristics: τ vegetation optical depth, ω vegetation single scattering albedo, Θ is the soil moisture, T_s soil temperature, T_v vegetation temperature (T_s and T_v are assumed to be the same) and r surface roughness. If we assume that the model is a faithful representation of reality, then the set of brightness temperatures generated by the model represents the measurements of a multiple-look-angle radiometer instrument.

The forward model generates a set of both horizontal and vertically polarized brightness temperatures, at multi-angle view, which represent the user’s choice of soil and vegetation circumstances given by the model parameters. The forward model is extremely useful to understand the uncertainties that may result from an incorrect choice of parameters. The inverse model is applied to retrieve the surface parameters that can produce a set of curves that best match the observed brightness temperatures sensed by a microwave instrument.

For this project work, I have used a set of aircraft borne brightness temperatures collected with PLMR instrument by NAFE’06 team. The objective of the study is to verify how well the inverse model estimates the ground parameters; by comparing the model parameter output with ground based observations of soil moisture values, as well as to understand how well the model identifies the growth of vegetation, by using EVI and NDVI vegetation indexes and high definition photos taken on the field site.

4.2 Model Parameterisation

It is possible to retrieve the soil moisture signal from terrestrial microwave emission, and this provides a useful resource to understand the spatial and temporal distribution of this surface characteristic globally.
In the presence of bare soil, based on the Rayleigh-Jeans approximation, microwave remote sensing measures the brightness temperature ($T_b$) emitted by the surface according to $T_b = e_s T_s$, where $T_s$ is the physical temperature of the surface layer and $e_s$ is the emissivity of a smooth surface, defined as $e_s = 1 - R_s$, where $R_s$ is the reflectivity of the soil surface. In this case, in order to determine the brightness temperature of the soil using the $\tau$-$\omega$ forward model, both $\tau$ and $\omega$ would be set to zero, eliminating the radiative effect of the vegetation layer.

However, terrestrial microwave emission is also very sensitive to vegetation cover of the soil. The vegetation layer has the potential of attenuating the soil emitted radiation and can cause diffuse scattering of both the radiation emitted by the soil and that due to its own self-emission. Both scattering and absorption of a vegetation element are function of the dielectric properties of the element, direction of the wave’s electric field relative to the elements geometry and the size of the element relative to the wavelength of the incident wave (Ulaby et al., 1986). This model ignores the difference between soil and vegetation temperatures, which can exceed 7 K (Jackson et al., 1982). However the area of study considered in this study is not densely vegetated, so this difference should be small.

### 4.2.1 Vegetation Module

In the presence of one canopy layer, the radiative transfer characteristics of a vegetation layer can be expressed in terms of the transmissivity ($\Gamma$) and single scattering albedo ($\omega$). According to van de Griend et al. (1996), the following relationship between vegetation parameters can be established:

$$\Gamma + R + A = 1$$

(3)

Where, $R$ is the reflectivity, and $A$ is the absorptivity of a vegetation canopy. Furthermore, in a canopy the emissivity equals absorptivity, so canopy emissivity can be written as:

$$e_c = 1 - R - \Gamma$$

(4)
The transmissivity of the vegetation layer is considered the fraction of the layer not obscured by leaf elements; hence 1- $\Gamma$ is the fraction of leaf coverage within the layer. Transmissivity is given by $\Gamma = \exp(-\tau)$, where $\tau$ is the canopy optical depth. However, the optical depth for a slant path is known as $\tau' = \tau / \cos\alpha$ where $1 / \cos\alpha$ reflects the longer slant path length through the vegetation canopy with $\alpha$ the zenith angle. Hence, in the vegetation module the vegetation transmissivity is parameterized as:

$$\Gamma = \exp(-\tau/\cos\alpha)$$

The $\tau$-$\omega$ model radiative transfer equation for a single vegetation layer is given by the combination of three components. The upwelling brightness temperature is the sum of soil emitted radiation multiplied by the transmissivity of the canopy (6); the vegetation upwards radiation given by the canopy emissivity multiplied by the canopy temperature (7); and finally the vegetation downwards emission which is reflected by the surface and attenuated by the vegetation layer (8):

$$T_b = e_s \times T_s \times e^{\frac{\tau}{\cos\alpha}} +$$

$$+ (1 - \omega) \times T_v \times \left(1 - e^{\frac{\tau}{\cos\alpha}}\right) +$$

$$+ (1 - e_s) \times (1 - \omega) \times T_v \times \left(1 - e^{\frac{\tau}{\cos\alpha}}\right) \times e^{\frac{\tau}{\cos\alpha}}$$

where, $e_s$ is the soil emissivity, $\alpha$ is the look angle from nadir, $T_s$ is the soil temperature and $T_v$ is the vegetation temperature. The single scattering albedo ($\omega$) is considered the leaf surface reflectivity so, following Kirchhoff’s law using the hypothesis of thermal equilibrium, the absorptivity of the canopy ($A$) is given by

$$A = 1 - \omega$$
The \( \tau - \omega \) model radiative transfer equation accounts for multi-angle view as well as for vertical and horizontal polarisations.

### 4.2.2 Dielectric Mixing Model

Soil consists of a combination of soil particles, air, bound and free water. As soil moisture increases, free water around soil particles increases too, and it is this free water that has a dominant effect on the dielectric properties. The dielectric effect accounts for the majority of the reflection and scattering as radiations interacts with the surface molecules.

Microwave remote sensing of soil moisture is sensitive to the large contrast between the dielectric properties of liquid water and dry soil marking high correlation between the complex dielectric constant \( \varepsilon_c \) and the volumetric soil moisture (\( \theta \)). The complex dielectric constant is property of the medium and is commonly expressed in terms of the free-space (vacuum) permittivity \( \varepsilon_0 \) : \( \varepsilon_c = \varepsilon_r \varepsilon_0 \), where \( \varepsilon_r \) is the relative dielectric constant and \( \varepsilon_0 = 8.85 \times 10^{-12} \text{ Fm}^{-1} \) (farads per meter).

The relative dielectric constant \( \varepsilon_r \) (relative because it is compared with the permittivity of the vacuum) is a complex number consisting of a real part \( \varepsilon_r' \) (permittivity or dielectric constant, related with the stored energy within the medium) and an imaginary part \( \varepsilon_r'' \) (dielectric loss factor): \( \varepsilon_r = \varepsilon_r' - j\varepsilon_r'' \), where \( j = \sqrt{-1} \). For most environmental remote sensing applications the imaginary (loss term) is relatively small, so that the focus remains on permittivity term. Wang and Schmugge presented in 1980 an empirical model for the complex dielectric permittivity of soil as a function of water content. It requires the estimation of the percentage of clay and sand in the soil. Initially for all soil types the dielectric constant increases slowly until it reaches a volumetric moisture transition point that varies with the soil type. After the transition point the dielectric constant increases steeply with moisture.

The soil dielectric mixing model computes the soil dielectric constant as a function of volumetric moisture, soil texture, frequency of detection and surface soil temperature. This dielectric mixing model also considers the effect of bound water on the dielectric constant,
and it is limited to lower frequencies (1-5 GHz) (de Rosnay & Drusch, 2008). The dielectric constant model of the soil used here is based on the Wang & Schmugge (1980) model, assuming an average soil texture of 30% sand and 40% clay, following soil classification given by Australia’s Commonwealth Scientific and Industrial Research Organisation (CSIRO) for the Wagga Wagga region. It incorporates the wilting point (WP) of soil in terms of volumetric water content (cm$^3$/cm$^3$), and is given by the following expression

\[
WP = 0.06774 - 0.00064 \times \text{sand} + 0.00478 \times \text{clay}
\]  

(10)

with the transitional soil/water content defined as

\[
t_{wc} = 0.47 \times WP + 0.165
\]  

(11)

and the delta factor is given by

\[
\Delta = -0.57 \times WP + 0.481
\]  

(12)

Since, initially for all soil types the dielectric constant increases slowly until it reaches a volumetric moisture transition point (which varies with the soil type), and after reaching the transition point the dielectric constant increases steeply with moisture, the soil dielectric constant is given by the following two equations. The first applies for the dielectric value of the soil up to the point it reaches the transition water content and the second for there after:

\[
\varepsilon'_{\text{soil}} = wc \times \left( \varepsilon'_{\text{ice}} + (\varepsilon'_{\text{water}} - \varepsilon'_{\text{ice}}) \times \Delta \times \frac{wc}{t_{wc}} + \left( 1 - \frac{\rho_{\text{bulk}}}{\rho_{\text{part}}} \right) - wc \right) \times \varepsilon'_{\text{air}} + \left( \frac{\rho_{\text{bulk}}}{\rho_{\text{part}}} \right) \times \varepsilon'_{\text{sp}}
\]  

(13)

\[
\varepsilon'_{\text{soil}} = t_{wc} \times \left( \varepsilon'_{\text{ice}} + (\varepsilon'_{\text{water}} - \varepsilon'_{\text{ice}}) \times \Delta \right) + (wc - t_{wc}) \times \varepsilon'_{\text{water}} + \left( 1 - \frac{\rho_{\text{bulk}}}{\rho_{\text{par}}} \right) - wc \times \varepsilon'_{\text{air}} + \left( \frac{\rho_{\text{bulk}}}{\rho_{\text{par}}} \right) \times \varepsilon'_{\text{sp}}
\]  

(14)
It assumes $\rho_{\text{bulk}} = 1.3$ g cm$^{-3}$ (bulk density), $\rho_{\text{par}} = 2.65$ g cm$^{-3}$ (particle density), and $\varepsilon'_{\text{water}} = 3.2$ (dielectric constant bound water), $\varepsilon'_{\text{air}} = 1$ (dielectric constant air), and $\varepsilon'_{\text{sp}} = 5.5$ (dielectric constant soil particles).

Dobson et al. (1985) published another dielectric mixing model that is used in the Community Microwave Emission Model of the European center of medium-range weather forecast (ECMWF) (de Rosnay & Drusch, 2008), it yields a very good fit to measurements above 4 GHz but at 1.4 GHz it does not parameterize in perfection the dielectric properties of bound water.

The real part of the relative dielectric constant of water is derived by modified version of the Debye equation (Ulaby et al., 1986):

$$\varepsilon'_{\text{water}} = \varepsilon_\infty + \frac{(\varepsilon_s^{dw}(T_w) - \varepsilon_\infty)}{(1 + rel_{\text{time}} \times f) \times (rel_{\text{time}} \times f)}$$

where $\varepsilon_\infty = 4.9$ is the high-frequency dielectric constant (Lane & Saxton, 1952), $f = c/\lambda$ with $c=3\times10^8$ m/s is the frequency , and $\varepsilon_s^{dw}(T_w)$ is the static dielectric constant of distilled water as described by Klein & Swift (1976), which is given by

$$\varepsilon_s^{dw}(T_w) = 88.045 - 0.4147 \times T_w + 6.295 \times 10^{-4} \times T_w^2 + 1.075 \times 10^{-5} \times T_w^3$$

with $T_w$ the temperature of water in degrees Celsius. To conclude the calculation of soil dielectric constant, the expression for the relaxation time of pure water (Stogryn, 1970) is

$$rel_{\text{time}} = 1.1109 \times 10^{-10} - 3.824 \times 10^{-12} \times T_w + 6.938 \times 10^{-14} \times T_w^2 - 5.096 \times 10^{-16} \times T_w^3$$

### 4.2.3 Smooth Emissivity Model

The soil emissivity model describes the relationship between soil emissivity and soil dielectric constant. Emissivity is calculated for vertical and horizontal polarisation using
Fresnel equations relating reflectivity to dielectric constant and look angle. The Fresnel equations represent the behaviour of light moving throughout a medium of differing refractive indices. The horizontal and vertical polarisations of soil reflectivity are given by the following expressions:

\[
R_{\text{soil hor}} = \cos(a) - \sqrt{\varepsilon_{\text{soil}}' - \left(\sin(a)\right)^2} \\
R_{\text{soil ver}} = \cos(a) + \sqrt{\varepsilon_{\text{soil}}' - \left(\sin(a)\right)^2}
\]

where “a” is nadir angle of view and \(\varepsilon_{\text{soil}}'\) is the soil dielectric constant.

### 4.2.4 Soil Roughness Model

Higher soil roughness generally is associated with higher emissivity. By considering a Gaussian distribution for soil roughness with zero mean, and variance \(\sigma^2\), Choudhury et al. (1979), derives the relationship between smooth surface and rough surface reflectivity as being:

\[
R_{\text{rough}} = R_{\text{smooth}} e^{-r \cos^2(a)}
\]

and the soil roughness parameter \(r\):

\[
r = 4\sigma^2 \left(\frac{2\pi}{\lambda}\right)^2
\]
where, $\lambda$ is the wave length. Expression (18) is calculated in the $\tau$-$\omega$ model at horizontal and vertical polarisations.

5. Estimation of Model Parameters

The $\tau$-$\omega$ inverse model is commonly used for the estimation of soil moisture when in the presence of a vegetation layer. The PLMR data used to run the model comprises a set of 10 brightness temperatures corresponding to H and V polarisation sensed observations at 5 view angles from nadir. Originally the PLMR observations set had 6 view angles, however after analysing it one of the angles were removed due to calibration error. A large number of PLMR measurements were taken, each with a field-of-view of 250m. Only those PLMR measurements which had a field-of-view enclosing a Hydraprobe® measurement site were analysed here. For each of the days, this extracted about one to four hundred of these observations, which were first averaged for each look angle, and the averaged result of brightness temperatures per day was afterwards used in the inverse model run to estimate the soil moisture, the vegetation optical depth, the soil temperature (assumed to be the same as the vegetation temperature), by keeping soil roughness and single scattering albedo parameters fixed. The soil temperature ($T_s$) was constrained to the values of the top 5cm of soil, obtained in the experiment (see table 5.1).

Wigneron et al. (2008) showed that the estimation of surface temperature can be significantly improved by using additional information on the soil temperature at depth with an error reduction from $\sim 4$ to $\sim 1.8$ K. In the same study, no improvement was reached using air temperature instead of surface temperature. Also, it mentioned that information about soil properties, can lead to improvements of approximately $0.2$ K in the estimation of surface temperature.

However, the $\tau$-$\omega$ model does not have the parameterisation of surface temperature in depth, so only soil surface temperature was used.
Both these $\omega$ and $r$ parameters were assumed to be homogeneous throughout the area of study, which is the area along the transect flight line (multi-incidence). Empirical values for single scattering albedo are present in literature, and vary for different crops, between 0.04 and 0.12. Becker and Choudhury (1988, in van de Griens (1993)) considered 0.05 for their study in Africa.

The Tubbo farm is covered mostly by native pasture and grazing; hence low values of single scattering albedo were tested using the inverse model. The results from the different model runs were analysed considering the fitting root mean square error generated together with the surface parameters. The best approximation to the PLMR brightness temperatures was obtained for the $17^{th}$ November, with $\omega = 0.06$ and $r = 0.19$. For this value of roughness the corresponding soil height standard deviation is 0.07 m. Both these parameters were considered fixed and used in the estimations for the remaining days (table 5.1).

A poor choice of roughness can yield large uncertainty in the estimated soil moisture, especially if in presence of a wet surface (Choudhury et al., (1979)). In fact, using the $\tau$-$\omega$ forward model to estimate the brightness temperature while maintaining fixed $T_s = 293$ K, $\tau=0.2$, $\omega=0.06$, and varying soil roughness between zero and 0.3, it was obtained for $\theta=0.1$ (dry soil) changes in $T_b$ varying from 1 K to 7 K and, for $\theta = 0.3$ (moist soil) changes

---

**Table 5.1** – Flight time and temperature for the 5 days. Parameters retrieved with inverse model for the area along the flight line, considering $\omega = 0.06$ and $r = 0.19$.

<table>
<thead>
<tr>
<th>Date</th>
<th>PLMR flights</th>
<th>Tao-Omega Model retrieved variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nov’06</td>
<td>Time (hh:mm)</td>
<td>$T_s$ (K)</td>
</tr>
<tr>
<td>1</td>
<td>05:17 - 06:46</td>
<td>292 - 295</td>
</tr>
<tr>
<td>3</td>
<td>17:02 - 18:31</td>
<td>301 - 308</td>
</tr>
<tr>
<td>8</td>
<td>04:50 - 06:21</td>
<td>291 - 292</td>
</tr>
<tr>
<td>10</td>
<td>17:15 - 18:42</td>
<td>307 - 314</td>
</tr>
<tr>
<td>17</td>
<td>18:16 - 19:45</td>
<td>300 - 308</td>
</tr>
</tbody>
</table>
varying between 4K and 19K. These possible changes were higher at 0° nadir view angle at both V- and H- polarizations (fig.5.1).

**Figure 5.1** Brightness Temperatures output from τ-ω forward model by keeping soil temperature, vegetation optical depth and single scattering albedo fixed, and varying roughness. Plot A considers dry soil, and plot B (next page) considers moist soil.

However, information about soil roughness or texture was not included in the set of data collected during the NAFE’06 field experiment.
Nevertheless, looking at HD photos from the scene, it is possible to identify roughness heterogeneity along the transect line of the flight but there is a lack of numerical information to back up a realistic analysis. Thus, even conscious of the level of uncertainty that soil roughness can bring to the estimation of brightness temperature; this parameter was considered homogeneous in the area of study.

Monerris et al. (2006) have studied the soil moisture retrieval dependence from soil type and moisture profiles using L-band radiometry. They have collected dual-polarisation observations of six smooth bare soil fields at five incidence angles during 22 days at different depths (0, 5, 10, and 15 cm) in order to obtain the goodness of two dielectric mixing models (Wang & Schmugge, Dobson) in comparison to an expression for the dielectric constant derived from laboratory measurements for the 6 different soil types studied. They have found that the values of retrieved soil moisture using Wang & Schmugge dielectric mixing model have good results for loamy and ferromagnetic soils, but worse results when applied to sandy soils. Dobson’s dielectric mixing model has offered better results for dry and sandy soils which tend to dry faster. The expressions obtained in laboratory have proved themselves better than the models except for soils with high sand composition. The $\tau$-$\omega$ model was run both using at first 60% sand and 20% clay, and after using a more accurate composition of the local soil composition for the Wagga Wagga region, which is 30% sand and 40% clay. The results shown in table 5.2 suggest that changes in soil composition affect the estimation of soil moisture, and that was especially true for the 3rd of November when there was precipitation.

**Table 5.2** $\tau$-$\omega$ model estimates of soil moisture using two soil compositions.

<table>
<thead>
<tr>
<th>Day</th>
<th>Hydraphobe</th>
<th>Sand 60% Clay 20%</th>
<th>Sand 30% Clay 40%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0,03</td>
<td>0,08</td>
<td>0,10</td>
</tr>
<tr>
<td>3</td>
<td>0,12</td>
<td>0,21</td>
<td>0,26</td>
</tr>
<tr>
<td>8</td>
<td>0,05</td>
<td>0,04</td>
<td>0,05</td>
</tr>
<tr>
<td>10</td>
<td>0,03</td>
<td>0,14</td>
<td>0,16</td>
</tr>
<tr>
<td>17</td>
<td>0,09</td>
<td>0,13</td>
<td>0,15</td>
</tr>
</tbody>
</table>
The changes for vegetation optical depth were not as significant as for soil moisture. This suggests that if soil moisture retrieval using $\tau$-$o$ model is sensible to soil composition, then the estimation of soil moisture would be difficult in regions where the soil is not well mapped.

6   Analysis of Observations

For a future comparison of model performance, it is necessary to first take a look at the quality of the observations available. The information provided by the Hydraprobe® sensed soil moisture, the PLMR microwave observations along with soil, air temperature and relative humidity are the links that allow the comparison of the model estimations with the reality of the conditions in a given place at a given time. Extra care has to be taken before using for example the microwave observations in the model to get estimates for soil moisture as it will be shown in section 6.2. In section 6.1, the analysis of Hydraprobe sensed soil moisture measurements will be discussed. Some of the questions to answer will be: are the instruments giving a faithful representation of the soil moisture distribution in the overall area of study? What are the instrument errors?

6.1   Hydraprobe® Sensed Soil Moisture

An initial analysis of the data collected revealed that a considerable number of Hydraprobe® sensors were outputting zero percentage of soil moisture, even short days after rainfall. This fact leads us to conclude that the calibration process used has proved itself insufficient and some information was lost.

Therefore, the comparison of the model with the sensed soil moisture will be limited. The soil moisture records were averaged for each day, after the removal of multiple null
observations. The objective was to bring these values closer to reality. The top 5cm soil moisture for the farm follows the trend in fig.6.1.2, which identifies the rainfall events and posterior dry outs.

Fig. 6.1.1: Rainfall and Soil Moisture in Spring 06 for Yanco farm. (Walker et al., 2006)

6.2 PLMR Microwave Observations

The initial PLMR data set constituted 12 brightness temperatures resultant from H- and V- polarisations observations at 6 view angles from nadir (see figure 6.2.1). However, after plotting the brightness temperature curves for the 5 days an irregularity was identified for the V-polarised observations collected at about 9 degrees from nadir. Therefore, assuming the irregularity in the curves to be due to calibration error, both H- and V- polarised 9 degree angle were removed from the set of brightness temperatures. In fact, after the
measurements of nadir 9 ° angles were removed the fitting RMSE for day 1, 3, 8 and 10 improved and, changes were reflected in all T_s, 0, τ parameters leading to a reprocessing of the data and consequent change in the analysis.

**Figure 6.2.1** PLMR observations for the 5 days with 6 angles

In figure 6.2.2 the resultant brightness temperature curves for the five days can be analysed. In order to interpret these curves it is important to understand that they represent a set of surface parameters (soil and vegetation temperature, soil moisture, soil roughness, vegetation optical depth and single scattering albedo, free water in the vegetation, etc).

**Figure 6.2.2** PLMR observations for the 5 days with 5 angles
An initial look at the brightness temperatures suggests that there is great difference between them over the different days, except for the ones sensed on the 1$^{\text{st}}$ and 8$^{\text{th}}$ of November. Using the forward model to analyse the impact of changing the surface temperature, maintaining all the other surface parameters fixed, it was found that the changes in brightness temperatures are directly proportional to the changes in surface temperature (even in absolute terms) and, this happens all over the angles (0°-40°). So one of the questions to pose is: do the changes in the PLMR brightness temperature curves correspond only to the retrieved changes in $T_s$ between the days?

Table 6.2.1 has the surface temperature (rounded to the nearest integer) retrieved by the inverse $\tau$-\(\omega\) model (considering an initial temperature constrain given by surface sensors at the time of the flights) and, the PLMR brightness temperatures (rounded to the nearest integer) sensed for the different days at different angles and polarisation.

<table>
<thead>
<tr>
<th>TOM Model</th>
<th>$T_s$ (kelvin)</th>
<th>N1</th>
<th>N3</th>
<th>N8</th>
<th>N10</th>
<th>N17</th>
<th>N3-N1</th>
<th>N8-N3</th>
<th>N10-N8</th>
<th>N17-N10</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLMR</td>
<td>36°</td>
<td>255</td>
<td>236</td>
<td>256</td>
<td>271</td>
<td>267</td>
<td>-19</td>
<td>20</td>
<td>15</td>
<td>-4</td>
</tr>
<tr>
<td></td>
<td>20°</td>
<td>265</td>
<td>248</td>
<td>265</td>
<td>279</td>
<td>272</td>
<td>-17</td>
<td>17</td>
<td>14</td>
<td>-7</td>
</tr>
<tr>
<td></td>
<td>6°</td>
<td>270</td>
<td>255</td>
<td>270</td>
<td>283</td>
<td>277</td>
<td>-15</td>
<td>15</td>
<td>13</td>
<td>-6</td>
</tr>
<tr>
<td></td>
<td>23°</td>
<td>268</td>
<td>252</td>
<td>268</td>
<td>281</td>
<td>274</td>
<td>-16</td>
<td>16</td>
<td>13</td>
<td>-7</td>
</tr>
<tr>
<td></td>
<td>39°</td>
<td>261</td>
<td>243</td>
<td>263</td>
<td>276</td>
<td>269</td>
<td>-18</td>
<td>20</td>
<td>13</td>
<td>-7</td>
</tr>
<tr>
<td>PLMR</td>
<td>36°</td>
<td>279</td>
<td>273</td>
<td>282</td>
<td>294</td>
<td>289</td>
<td>-6</td>
<td>9</td>
<td>12</td>
<td>-5</td>
</tr>
<tr>
<td></td>
<td>20°</td>
<td>274</td>
<td>263</td>
<td>274</td>
<td>287</td>
<td>282</td>
<td>-11</td>
<td>11</td>
<td>13</td>
<td>-5</td>
</tr>
<tr>
<td></td>
<td>6°</td>
<td>273</td>
<td>259</td>
<td>273</td>
<td>285</td>
<td>280</td>
<td>-14</td>
<td>14</td>
<td>12</td>
<td>-5</td>
</tr>
<tr>
<td></td>
<td>23°</td>
<td>273</td>
<td>260</td>
<td>273</td>
<td>286</td>
<td>281</td>
<td>-13</td>
<td>13</td>
<td>13</td>
<td>-5</td>
</tr>
<tr>
<td></td>
<td>39°</td>
<td>279</td>
<td>269</td>
<td>280</td>
<td>292</td>
<td>287</td>
<td>-10</td>
<td>11</td>
<td>12</td>
<td>-5</td>
</tr>
</tbody>
</table>

Considering the column N3-N1, which gives the change in temperatures from the 1$^{\text{st}}$ to the 3$^{\text{rd}}$ of November, it would be expected an increase in the $T_b$ curves of about 12 K,
assuming no changes in surface parameters except temperature wise. Instead, $T_b$ has decreased between 6 K and 19 K depending on the angle and polarisation.

Tests using the $\tau$-$\omega$ forward model indicate that a decrease in brightness temperature so steep to compensate the increase of 13 K in $T_s$, would only be possible if a higher amount of precipitation had fallen on the 3$^\text{rd}$ of November. These facts leave me to conclude that the observations are capturing some information that the model does not recognise.

Previous studies of soil moisture using the $\tau$-$\omega$ model have identified shortcomings when situations of dew and spray occur in the scene of study. The next section will cover some of the main contributions of dew and spray in microwave remote sensing of soil moisture. For now, we suspect that possible the 3$^\text{rd}$ and 17$^\text{th}$ of November microwave observations are affected by spray because they were collected after rainfall events.

Considering now column N8-N3, the decrease by 16 K in surface temperature again is not evident in the change between the corresponding $T_b$.

Another intriguing factor seems to be the high similarity between the $T_b$ from the 1$^\text{st}$ and the 8$^\text{th}$ of November, displayed in figure 6.1.1 and in table 6.1.1 as well. Is it related with the $T_s$ only? On these two days the flights were in the early morning, and surface temperatures did not differ by much. However, parameters like soil moisture and vegetation optical depth are expected to be different from each other in the 1$^\text{st}$ and the 8$^\text{th}$ of November, due to the precipitation event between these days. The hypothesis of dew affecting both the 1$^\text{st}$ and the 8$^\text{th}$ of November is also taken in consideration, but chances are higher for day 8 because the level of soil moisture was higher at that time due to rainfall few days before.

### 6.2.1 Effect of Dew and Spray on Microwave Observations

Considering the information that during the two week period in which the microwave observations were collected there were a few rainfall events, and also the possibility of dew given the flight times on the 1$^\text{st}$ and 8$^\text{th}$ of November, it was found necessary to understand how these meteorological conditions affect the remote sensing of soil moisture when in the presence of a vegetation layer. Dew consists of the condensation of water into droplets
when surface temperature drops and reaches the dew point temperature. Sufficient cooling usually takes place when the loss of radiation from the land surface is higher than the incoming sun’s short wave radiation, in general during clear nights. Typical dew nights have clear skies, light wind, and the presence of humid air near the surface.

It was mentioned in previous chapters of this work that surface microwave emission is sensitive to soil moisture, soil roughness, soil texture (especially clay) and vegetation. In fact, surface naturally emitted electromagnetic energy is also sensitive to the water within the canopy as well as to the effect of “free water” (dew or spray) on the vegetation leaves (Hornbuckle et al., 2007).

Motivation for the study of the natural deposition of water in vegetation surface has hydrologic, biological and economical reasons (dew is part of the water cycle, vital for some ecosystems in arid climates, and the presence of moisture in the foliage of some crops can commence the development of disease), as well as with the fact of how these effects will shape the global satellite remote sensing of soil moisture in order to evaluate and adjust the retrieval models.

It is known that the water contained within the vegetation attenuates the microwave emission from the soil, and this effect is certain to increase with the density and water content of the canopy. In recent years, several experiments were undertaken in a group effort to validate and calibrate the soil moisture satellite missions. Some of these studies analysed how “free water” lying in the vegetation affects the soil moisture retrievals.

In 2003, B. Hornbuckle and A. England published a study on the effect of dew on the $1.4$ GHz frequency brightness temperature. They have compared of the observations with the outputs of a zero-order radiative transfer model (similar to tao-omega), and the results showed that the net effect of dew on maize canopy is to decrease the microwave brightness temperature. This effect was about 2K- 4 K at both H and V polarisations. The evaluations of two different dew events, suggested that the decrease in brightness temperatures was directly proportional to the amount of water lying on the vegetation. The model used in the experiment was similar to the one used in this project and, was not able to predict the brightness temperature reduction and, consequently overestimated the soil moisture.

Other studies on soybean canopy have found that dew increases the brightness temperature. Hornbuckle et al. (2007) have looked into the effect of intercepted
precipitation on the microwave emission of maize and, have found that precipitation intercepted by maize canopy has the opposite effect of dew. The precipitation causes an increase in the brightness temperatures by at least 3 K at H-polarisation and 0.8 K at V-polarisation. This means that in the presence of intercepted precipitation the model will underestimate the soil moisture.

Moreover, this difference is attributed to two hypotheses: dew and intercepted precipitation wet different parts of the maize canopy, or possibility of “free water” on the canopy to assume different forms that have a different impact both on attenuation and scatter of microwave radiation. Another important conclusion is the fact that the size of the vegetation components relative to the wavelength also influences the microwave emission. If the size of the vegetation components is small relative to the wavelength the emission is more enhanced than scattered, and both dew and intercepted precipitation are observed to increase the surface emission, leading to underestimation of soil moisture.

Saleh et al. (2006) have studied the effect of “free water” intercepted by vegetation and mulch on the microwave emission of grass. Intercepted water by vegetation, free water lying on vegetation due to precipitation, is known to enhance vegetation emission reducing soil emission estimates as a consequence. These effects are considered difficult to decouple. Grassland has a large water storage capacity, especially when it has additional debris and mulch. While dry, this layer of debris will not affect the soil microwave emission, however in the presence of intercepted water it will play a strong part in the absorption and emission of energy. In the study, a polarisation ratio was used, PR50, considered sensitive to “free water” in vegetation after rainfall. The polarisation ratio PR50 based on measurements acquired 50 degrees from nadir, is independent from surface temperature and is given by the following expression:

$$PR_{50} = \frac{T_{b50,v} - T_{b50,h}}{T_{b50,v} + T_{b50,h}}$$

In the presence of a grass layer, this ratio decreases both with the dry-out of soil moisture and with the increase of vegetation. The latter will decrease PR50 because it will
attenuate the strong polarisation of soil emission \( T_{h.a.,v}^{soil} \gg T_{h.a,H}^{soil} \) and, increase the depolarized vegetation emission \( T_{h.a.,v}^{veg} \approx T_{h.a.,H}^{veg} \). During a long term observation, this ratio was found to decrease from the time when the rainfall starts, followed by an increase after the evaporation process.

In the above mentioned work (Saleh et al., 2006), it was suggested a flag for the likelihood of interception using the PR50 ratio:

\[
\begin{align*}
PR_{50} & \leq 0.02 & \text{High probability of rainfall events within the last 24h} \\
PR_{50} & \geq 0.031 & \text{Low probability of intercepted water in vegetation (24h after last rainfall)}
\end{align*}
\]

There are however limitations to the use of this flag, especially in two situations: wet soil and sparse vegetation where PR50 is likely to maintain higher than 0.031 even after 24h after last rainfall and, in densely vegetated layer where PR50 is likely to be very low.

In the PLMR microwave observations used in this project to test the \( \tau \)-\( \omega \) model, our maximum nadir angle view is on average 40°. Using this angle to calculate the polarisation ratio, the highest value was obtained (PR40=0.051) for the 3\textsuperscript{rd} of November and the lowest value (PR40=0.029) on the 10\textsuperscript{th} of November. For the 1\textsuperscript{st}, 8\textsuperscript{th} and 17\textsuperscript{th} of November the ratio was between 0.031 and 0.034. The flag values suggested by Sahel et al. (2006) for PR50, obviously will not apply directly to PR40. Nevertheless, in the assumption that PR40 is a good polarisation ratio to draw conclusions on soil moisture, it would be possible to identify the 3\textsuperscript{rd} of November as a likely day for the occurrence of precipitation, without consulting meteorological records.

De Jeu et al. (2005) developed a study to determine the effect of dew on passive observations from space using two month of TRMM data and the Microwave Polarisation Difference Index (MPDI). This index has the same expression as the polarisation index used by Saleh et al. (2006). Field observations from the Wageningen case study identified a diurnal variation in the MPDI (lower values in the morning opposed to higher values in the afternoon) which was explained by the diurnal variation of the external vegetation water content (dew in this case). In theory, for dry soil, MPDI decreases with the increase of vegetation optical depth because soil emission is attenuated by vegetation. For wet soil,
MPDI increases directly with soil moisture, and decreases with the increase of vegetation water content.

Unfortunately, for this project it was only possible to apply this polarisation ratio to identify the soil moisture increase on the 3rd of November. It would have been interesting to apply the polarisation ratio PR50 / MPDI to this case study in order to confirm its application to intercepted water by vegetation due to dew, but angle 50 is not available in our PLMR data set. It would be interesting for NAFE team to include in future field experiments PLMR 50º measurements of surface microwave emissions, especially in early morning flights in order to verify the application of this ratio in the detection and future modulation of dew in radiative models.

Dew is expected to be present more than 50% of the time at the SMOS 6:00 AM CST overpass time, and is a quantity that is known to affect microwave brightness temperatures. For the SMOS mission Kabela et al. (2008) estimate an error bellow 0.05 m³ m⁻³ while for SMAP the error expected to be higher than that.

The next chapter will focus on the analysis of soil moisture and vegetation optical depth model estimations. In section 7.1, it will be interesting to see if the results of the model agree or not with the research on how dew affects the brightness temperature done by Brian Hornbuckle.

7 Analysis of the Zeroth-Order $\tau$-$\omega$ Model Estimations

7.1 Soil Moisture

Soil moisture is an important component of the water balance. Agricultural activities depend directly on the water stored in the soil, especially in some developing countries. Satellite missions plan to retrieve accurate information on soil moisture, and several models are being tested and improved. The zeroth-order solution $\tau$-$\omega$ model is composed of a
vegetation layer, an emissivity model using Fresnel equations relating reflectivity and dielectric constants, the Wang & Schmugge (1980) dielectric mixing model and the Choudhury (1979) soil roughness parameterisation. Looking at figure 7.1.1, it is possible to identify a general overestimation of the soil moisture levels by the model relative to the Hydraphobe® measurements.

**Fig. 7.1.1** Soil moisture changes over 5 days. Dashed blue line obtained by adding the bias between the averaged sensed and estimated soil moisture values over day 1, 3, 10, 17 to the Hydraphobe initial values.

Given the physically unlikely low values of soil moisture measured by the Hydraphbes, we assumed a systematic bias in the Hydraphobe® measurements and calculated the apparent bias omitting the consideration of the values referring to the 8th of November.

The dashed blue line on figure 7.1.1 represents the elimination of the bias between the measured and estimated values of soil moisture, enabling this way a closer analysis. The error between the red (PLMR estimate) and the blue dashed (Hydraphobe® measurement without bias) is now -3% and +3% for days 1 and 10 and of +4% and -4% for days 3 and 17, respectively. Day 8 has still a higher error (10%) associated, that was linked in this project with the possibility of dew.
The errors obtained after the bias removal do not differ much from the manufacturer estimated error of about +/-3% absolute.\(^6\) As mentioned before, it is very likely that dew (8\(^{th}\) of November) and possible spray (3\(^{rd}\) and 17\(^{th}\) of November), meteorological condition not parameterized in the model, can disturb in some way the estimation of soil moisture by the model. Given the characteristics of the observations at hand, it would be interesting to look at measurements taken for a longer period of time and study in more detail how these factors affect the estimation of soil moisture by the model in a field where most vegetation is pasture and short shrubs.

With the objective of studying the surface temperature constrain impact in soil moisture estimates, the model was run using a wider interval for surface temperatures: [Ts -10K, Ts + 10K]. For this model run the error between the Hydraprobe® measurements and model estimates has change from -10% to 2% on the 8\(^{th}\) of November (see table 7.1.1)

<table>
<thead>
<tr>
<th>Days</th>
<th>Bias corrected Hydraprobe</th>
<th>Ts given by MET</th>
<th>Ts +/- 10K</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SM (m3/m-3)</td>
<td>% Error</td>
<td>SM (m3/m-3)</td>
</tr>
<tr>
<td>1</td>
<td>0.13</td>
<td>0.1</td>
<td>-3</td>
</tr>
<tr>
<td>3</td>
<td>0.22</td>
<td>0.26</td>
<td>4</td>
</tr>
<tr>
<td>8</td>
<td>0.15</td>
<td>0.05</td>
<td>-10</td>
</tr>
<tr>
<td>10</td>
<td>0.13</td>
<td>0.16</td>
<td>3</td>
</tr>
<tr>
<td>17</td>
<td>0.19</td>
<td>0.15</td>
<td>-4</td>
</tr>
</tbody>
</table>

This result suggests that the use of a wider interval for surface temperatures to vary should be used because it improves the model estimates of soil moisture when the microwave observations are affected by dew.

The use of a wider interval for surface temperatures did not affect the accuracy of the model estimates for the other days.

7.2 Vegetation optical depth (τ)

The vegetation optical depth determines the attenuation of emitted soil radiation; hence it is a significant parameter to consider when monitoring the soil moisture using passive microwave. It depends largely on the water content within the canopy and, as a consequence on the green vegetation biomass (van de Griend et al., 1993). Recent studies on the effect of intercepted water in vegetation tried to establish a relationship between τ and vegetation water content. For example, de Jeu et al. (2005) established an empirical relationship for τ using both internal and external vegetation water content and, Meesters et al. (2005) derived an analytical expression relating τ with MPDI.

The Normalized Difference Vegetation Index (NDVI) is a remote sensing technique used in diverse ecological studies. This index is derived from the red (RED) and near infrared (NIR) reflectance ratio that reaches the sensor, as \( \text{NDVI} = \frac{(\text{NIR} - \text{RED})}{\text{NIR} + \text{RED}} \).

NDVI ranges from -1 to 1, in which negative values correspond to water bodies, low values around zero are associated with soil reflectance, and values greater than 0.1 are identified as vegetated areas. The above relationship between the different spectral bands has to do with the fact that chlorophyll present in the outer leaf absorbs RED whereas the mesophyll located in the interior of a leaf structure scatters NIR. As a consequence, this remote sensing technique allows environmental researchers to obtain broad information about the local climate effects on vegetation (Pettorelli et al., 2005). Nevertheless, some factors can act to increase RED with respect to NIR and reduce the computed NDVI, such as scattering by aerosols, Rayleigh scattering, sub pixel-sized clouds, large solar zenith angles, and large scan angles\(^7\).

Satellite-derived NDVI is considered an important tool to monitor effective rainfall, derive green vegetation cover and biomass over large areas, however the reliability on the results are dependent upon the complex radiative interaction between atmosphere, sensor view angle and solar zenith angle. Although this index is limited on its applications, it can be used with appropriate consideration of the inherent limitations (du Plessis, 1999).

\(^7\) www.bom.gov.au
In order to analyse the results obtained by the \( \tau - \omega \) model, the ENVI software was used for processing and analyzing geospatial imagery to calculate NDVI using Landsat and MODIS for the area of study. The objective is to understand the developing trend of the vegetation optical depth over the two week period (1\textsuperscript{st} to 17\textsuperscript{th} November 2006). Landsat images from the 7\textsuperscript{th} and 23\textsuperscript{rd} of November 2006, covering the scene of study were considered for the NDVI calculations (fig. 7.2.1). The area of the multi-incident flight was identified and statistics were calculated, revealed a slight increase in the vegetation index. Vegetation optical depth is known to vary with water content.

**Fig 7.2.1** Plot with accumulated NDVI percentage for the 7\textsuperscript{th} and 23\textsuperscript{rd} of November, calculated over the purple area defined in the Landsat image given on the left side.

Figure 7.2.2 shows the variation of soil moisture and \( \tau \) for the 5 days. The values estimated by the model for \( \tau \) are variable throughout the days. Assuming that the estimation of \( \tau \) for the 1\textsuperscript{st} of November was not affected by the presence of dew, then when comparing it to the estimation for the 10\textsuperscript{th} and 17\textsuperscript{th} of November it is possible to identify an increase of at least 0.11. This increase seems to agree with the NDVI calculations for the area of study (see fig. 7.2.1).

It should be mentioned that the NDVI was also calculated using images collected in October, but it was found that it was obviously contaminated by a (not identified) atmospheric noise. This conclusion was taken after examining the October NDVI against consecutives images of November, in which October presented a much higher value.
The observations collected on the 1\textsuperscript{st} of November correspond to surface conditions with a preceding period of drought. In fact meteorological data indicates a period of nearly two months without significant rainfall. Both soil moisture and vegetation optical depth estimations present low values in the beginning of the period of this study (see figure 7.2.2). From day 1 to day 3, $\tau$ estimates maintain and soil moisture increases. This is expected to happen if we consider the rainfall that took place on the 3\textsuperscript{rd} for November to increase moisture in the soil and, bearing in mind the lag period before vegetation responds to the water in the soil, leading to a similar estimation of $\tau$ to as in day 1.

**Fig 7.2.2** Changes in vegetation optical depth and soil moisture. Values estimated by $\tau$-\omega inverse model using PLMR observations for the 1\textsuperscript{st}, 3\textsuperscript{rd}, 8\textsuperscript{th}, 10\textsuperscript{th} and 17\textsuperscript{th} November.

To some extent this makes sense, because during this period of two weeks there were a few rainfall events that have increased the soil moisture at different depths in the ground. Therefore, an increase in vegetation water content and, to some extent the vegetation biomass is expected, hence higher values for $\tau$.

The estimated value of $\tau$ for the 8\textsuperscript{th} of November is very low compared with the other values estimated for the period; hence suggesting that the model has underestimated vegetation optical depth as well as soil moisture for this day. This fact leads to the conclusion that the zeroth-order solution $\tau$-\omega model needs additional improvements to
overcome estimation of soil moisture and vegetation optical depth in the event of intercepted water in vegetation caused especially by dew. In the next chapter, the study of soil moisture and vegetation optical depth will be downscaled to sub-areas of the area of the multi-incidence flight.

8 Downscaling

The resolution of SMOS sensor is adequate for global applications but can be limiting when used at regional scale. For example, most hydrological processes occur at 1-10 km scale, therefore the assimilation of SMOS data in; for example, land surface hydrologic model relies in improvement of its spatial resolution.

Passive microwave instruments have higher sensitivity to near-surface soil moisture, but have lower spatial resolution then active microwave and optical systems. Examples of high resolution sensors (approximately 100m spatial resolution) are the L-band phased Array type L-band Synthetic Aperture Radar (PALSAR) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) which provide data every 30 and 16 days, respectively. Examples of medium spatial resolution products are the C-band Advanced Synthetic Aperture Radar (ASAR) and the Moderate resolution Imaging Spectroradiometer (MODIS) which provide data every 6 and 1-2 days, respectively.

Currently the research community is making an effort to combine passive and active microwave to produce a reliable soil moisture product with medium spatial resolution.

Some studies are based on disaggregation strategies relating to optical-derived soil moisture indices. Stochastic approaches to the problem have the advantage of using less ancillary data, however may not hold valid outside the conditions used for calibration. Deterministic approaches do not have that disadvantage, but require more ancillary data.

Merlin et al. (2008) developed a deterministic approach to the problem. The downscaling scale is 10 km, and the downscaling procedure has several phases: the estimate of soil evaporative efficiency from MODIS data; link soil evaporative efficiency to
near-surface soil moisture via a physically-based scaling function and at last build a downscaling relation. The disaggregation results of 10 km resolution MODIS surface temperature images were compared with soil moisture estimates from L-band microwave observations. The overall root mean square difference between the two was better than 1.8% v/v.

Piles et al. (2009) developed a deconvolution-based model (algorithm-based process used to reverse the effects of convolution on recorded data) to enhance the spatial resolution of SMOS observations while preserving the radiometric sensitivity to soil moisture. A 30-60 km spatial resolution pixel is likely to present high variability of surface topography, soil, vegetation and land use.

Pellenq et al. (2003) developed a surface soil moisture scaling strategy that couples a Soil Vegetation Atmosphere Transfer Model (SVAT-SIMPL) with a hydrological model (TOPMODEL) that redistributes spatially the soil moisture content as a function of topographic and surface properties. This modelling technique was applied to the Nerrigundah catchment in New South Wales, Australia, where ground measurements of near surface soil moisture were collected and used for validation. This method allows retrieval of near-surface soil moisture with a satisfying resolution of 100 m x 100 m.

The objective of this chapter is not to evaluate a downscaling technique in particular. The work developed was with the purpose of study how the τ-ω model accounts for the natural heterogeneity of land surface. The area of the transect flight (fig. 8.1) was divided into 5 sub-areas. The PLMR observations were divided into five subgroups using the respective coordinates and the inverse model was run considering the averaged brightness temperatures for each of the five areas for each day. Parameter estimation followed the same criteria described in chapter 5: surface temperatures were limited to a range established by meteorological information; soil roughness and vegetation single scattering albedo were assumed homogeneous and identical to each of the 5 sub-areas (ω=0.06 and r=0.19).
The area of study is located in the western plains of the Murrumbidgee catchment, hence topography is mostly flat. The soil is mainly constituted by clay, red brown earth, sands over clay, and deep sands (Walker et al., 2006). The transect flight has crossed land mostly covered by native pasture and grazing.

8.1 Sub-area Characteristics

This section will analyse the different characteristics of the 5 sub-areas. For the purpose of analysing the characteristics of the area of study tri-spectral line scanner (TSLS) images as well as high definition images, collected with an 11 Megapixel digital camera, of the scene were analysed.

The NAFE’06 team collected the observations after a period of drought; therefore vegetation distribution is confined to particular areas where underground storage of water might be present. It is possible that at the time the microwave measurements were taken
plants in the scene were going to a period of water stress, state when vegetation reduces the use of radiation to transpiration due to lack of water in the soil. This state leads plants to close stomata, hence reducing their ability to cool. In this state vegetation temperature tends to be closer to air temperature.

**Area 1**

This area is located in the southeast of a waterline and it has, as well, a pond that can be found in brown color in the NDVI color image. The presence of “free water” bodies in the scene where the PLMR measurements were collected might contribute to an over estimation of soil moisture by the model.

Looking at the TLS IR image in figure 8.1.1 it is possible to identify trees of different heights (using tree shades) along the margins of a dried out low river path. Using the NDVI image to complement the analyse it is clear that other form of short vegetation, maybe shrubs, are also present in the scene and follow the trail of what was once the margins of river.

**Area 2**

This area does not present any “free water” body. As described in area 1, vegetation signal is found mainly along a prior stream ridge. It is possible to identify trails used by animals or men without vegetation signal, which are found in the NDVI image in figure 8.1.2 with brown lines.

**Area 3**

Area 3 has the particularity of having a man-made topography depression possibly to hold water in periods of sparse water resources. A dense patch of what seems to short vegetation is present locally along what was in the past the river stream. Trails created by men or by animals are also present.
Fig. 8.1.1: TSLs IR (grey) and NDVI (color) images of area 1

Fig. 8.1.2: TSLs IR (grey) and NDVI (color) images of area 2

Area 4
In this area the NDVI image in figure 8.1.4 has a predominant yellow tone. This means that most of the vegetation is composed by grass passing through a period of water stress. NDVI is directly related with vegetation water content hence in this image the NDVI is very low.
Fig. 8.1.3: TSLS IR (grey) and NDVI (color) images of area 3

Fig. 8.1.4: TSLS IR (grey) and NDVI (color) images of area 4

**Area 5**

Area 5 has similar characteristics as area 4. The NDVI image is mostly yellow, corresponding to low levels of vegetation water content. Nevertheless, it is possible to identify a tree in the right down corner of both IR and NDVI images of figure 8.1.5. The soil is characterised by plains with domes and swampy depressions.
The next section will discuss how the model has handled the estimation of soil moisture for the different areas, each of them contributing to the heterogeneity crossed by the transect flight.

### 8.2 Soil Moisture

In this section the analysis of the soil moisture estimation by τ-ω inverse model will be based on the plots given in figure 8.2.1. The characteristics of each sub-area described in section 8.1 will be used to interpret the results. The last plot in figure 8.2.1 combines the values of soil moisture estimated by the model for each day. The value of soil moisture for area 1 on the 10th is missing because the aircraft did not travel that far northwest.

All the estimates of moisture for each day follow the same trend as the initial estimate soil moisture values using the averaged PLMR observations for all area of the transect flight.
The same problems seem to be present: underestimation of soil moisture on the 8th of November, possibly related to the presence of dew in the morning of the flight and, the lack of response of the model to the increase in soil moisture suggested by the Hydрапrobe® from the 10th to the 17th of November. A curious fact for area 1 is that the model soil moisture estimates for the 3rd and the 8th of November are higher than the ones estimated for the overall area of the transect flight. This might be due to the characteristics of this

Fig. 8.2.1: Soil moisture estimations using Tao-Omega (TOM) inverse model versus Hydрапrobe, for the 5 sub-areas over 5 days.
area, in particular the proximity to water bodies. The flights taken over the different days present different azimuths, hence there is a possibility that in both these days the flights have sampled areas very close to water bodies.

The first five plots in figure 8.2.1 compare the model estimation of soil moisture for a particular area with the model initial estimation for the area of the transect flight. When we compare the sub-area Hydraprobe® sensed soil moisture and the model estimates, all the plots show an overestimation of soil moisture for the 3rd and an underestimation for the 8th of November. If we now compare the model soil moisture estimates for areas 1 and 2 with the estimates for the overall area, we find that the values differ considerably on the 3rd of November. For area 1, the estimate is higher than the estimate for the overall area, possibly an influence of water bodies’ proximity; nevertheless this aspect is also present in the Hydraprobe® trend. For area 2, both model estimations and Hydraprobe® sensed soil moisture are lower than the ones referent to the overall area, this fact can possibly be related with several ridges identified on the surface which can drain water from precipitation events to other neighbouring areas, reducing ground water recharge. Area 1 and area 2 have presented bigger differences both on the PLMR estimated and Hydraprobe® sensed moisture when compared with the respective PLMR and Hydraprobe® values before downscaling. For areas 3, 4 and 5 estimated and sensed soil moisture are closer to the trend defined before the downscaling study, except for day 17 in which estimation of soil moisture parameters presents a spread of values for all regions.

Overall the comparison of the model estimates at different scales identifies the different partial contributions of smaller areas. It seems that topography and the presence of water bodies have the greatest influence in the model estimates of this parameter.

The model keeps missing the increase in soil moisture from the 10th to the 17th of November even at smaller scales, not following the trend suggested by the values sensed by the Hydraprobe®. However it is clear that on day 8 for all the areas the model has underestimated the soil moisture level.

The τ-ω model does not include a parameterisation for intercepted water on the vegetation canopy. Intercepted water in the vegetation associated with dew and spray affect the radiative energy emitted by the surface in a way that the model does not interpret correctly. Extra care is needed when using this model to estimate soil moisture on days
where precipitation has occurred within the previous 24 hours, as well as at the time of the
day when dew is likely to occur. Again, given the physically unlikely low values of soil
moisture measured by the Hydraprobes, it was assumed a systematic bias in the
Hydraprobe® measurements omitting the consideration of the values referring to the 8th of
November.

Table 8.2.1 presents the percentage error for the estimates of soil moisture in the case
where we constrain the surface temperature to observed values, and also in the case in
which we consider a wider interval (+/- 10 K) for the surface temperature to vary. In the
first case only 33% of the observations errors are in the range of ±3% (error indicated by
sensor manufacturer).

**Table 8.2.1 Percentage error between estimated and sensed soil moisture after the bias removal**

<table>
<thead>
<tr>
<th>Day</th>
<th>Percentage error (%) using T, constrain</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-5.2</td>
<td>-2.2</td>
<td>-4.9</td>
<td>-2.6</td>
<td>-3.4</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>7.7</td>
<td>4.4</td>
<td>3.1</td>
<td>4.2</td>
<td>4.1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>-3.8</td>
<td>-6.6</td>
<td>-9.6</td>
<td>-9.1</td>
<td>-11.1</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-</td>
<td>0.0</td>
<td>3.7</td>
<td>3.7</td>
<td>2.4</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>-2.4</td>
<td>-2.2</td>
<td>-1.9</td>
<td>-5.2</td>
<td>-3.0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Day</th>
<th>Percentage error (%) using T, +/- 10K</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-9.8</td>
<td>-2.5</td>
<td>-3.2</td>
<td>-1.4</td>
<td>-5.0</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>18.1</td>
<td>3.1</td>
<td>2.8</td>
<td>2.4</td>
<td>4.5</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>-4.4</td>
<td>2.1</td>
<td>1.1</td>
<td>1.1</td>
<td>-0.7</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-</td>
<td>-0.3</td>
<td>2.4</td>
<td>4.9</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>-4.0</td>
<td>-2.4</td>
<td>-3.2</td>
<td>-7.0</td>
<td>0.4</td>
<td></td>
</tr>
</tbody>
</table>

However, in the second case, when it is used a wider interval for surface temperature to
vary, the errors decrease for day 8. So, without using temperatures constraint, 54% of the
observations have an error in the range of ±3.
Initially, when surface temperature is constrained, it is very interesting to note for day 1, 8 and 17 the model estimates are lower than the Hydraprobe® sensed soil moisture across all sub-areas. This trend does not hold true when we drop the surface temperature constraint. If we focus the analysis on the estimates of soil moisture for the 8th of November, areas 3, 4 and 5 seem to be the more affected when we use the temperature constraint, and are the ones which have better results when the constraint is removed. This can be related with the fact that these areas are likely to have short size vegetation and, if the size of the vegetation components is small relative to the wavelength the emission will be enhanced (leading the model to underestimate soil moisture). The downscaling study of model estimates for soil moisture has permitted to identify the partial contributions of the sub-areas in the overall estimates. The hydrological characteristics of the surface play an important role in the spatial distribution of this important element of water balance. The presence of water bodies seems to produce an overestimation of the model soil moisture estimates. Other factors like surface roughness and variations of soil type at the surface may contribute to the variations in the estimates throughout the sub-areas (differences were identified in HD images of the scene).

8.3 Vegetation optical depth

In this section the estimation of vegetation canopy optical depth by the zeroth-order solution τ-ω model will be discussed. The differences attributed to this parameter when we downscale the PLMR observations to smaller areas will be studied. Likewise the normalized difference vegetation index will be used to infer relationships between the estimated canopy optical depths in different sub-areas of the scene.

Figure 8.3.1 shows the variation of the τ estimates for the 5 areas over the 5 days, as well as the τ estimates for the overall area on each day. The plotted lines show for the 1st of November very similar values of τ for all the areas. For the 10th and the 17th of November the estimates of τ for area 3 are the greatest suggesting that this area has more vegetation, or maybe the type of vegetation contains more water that in other sub-areas. A decrease in
the model estimate of vegetation optical depth for the 8\textsuperscript{th} of November is also present, following the trend identified before for soil moisture, which was linked with the likely presence of dew.

**Fig. 8.3.1:** Estimative of vegetation optical depth for 5 sub-areas generated using τ-ω inverse model.

![Tao estimation over 5 areas](image)

For days 3 and 8, area 1 presents higher estimates for this parameter. However, the only particularity that seems to distinguish area 1 from the others is the proximity to water bodies. This factor affects the estimation of soil moisture and most likely the estimation of vegetation optical depth.

Looking now at fig. 8.3.2 located in the following page, the NDVI calculus done after water correction using Landsat images suggests in general a NDVI increase in the area crossed by the transect flight. When the study of this index is downscaled to smaller areas the results do not always follow the surface characteristics.

Therefore, it is evident that this remote-sensed technique is limited when it is applied to downscaling, especially for small areas like the ones used in this study. Du Plessis (1999), in his study about the relationship between NDVI, vegetation and rainfall mentions that the comparison between total green vegetation cover and NDVI, indicate that changes in total green vegetation cover are much closer to the observed situation in the area of study than the ones indicated by the NDVI.

In the same study, it was also found that the NDVI relate much more strongly to cumulative rainfall than to individual rainfall events. Small rainfall events do not result in a
significant increase in green vegetation cover, especially if rainfall events occur more than 5 days apart. Another fact to consider in the analyses of NDVI is the response time to soil moisture that different vegetation types have. For example, it is not expected to see a great change in trees or shrubs in one or two weeks after a rainfall event. However, surface covered by grass seems to respond more rapidly to soil moisture.

**Fig. 8.3.2:** Normalized difference vegetation index (NDVI) calculated using Landsat images, after water body correction.
The NDVI was also calculated using MODIS images, however it is known that NDVI values at different resolutions may not be comparable (Jiang et al., 2006).

MODIS images have lower resolution than the ones provided by Landsat. That fact is evident in figure 8.3.3 and figure 8.3.4, by looking at NDVI and Enhanced Vegetation Index (EVI) plots generated for the sub-areas using MODIS images, where each of the areas have a very limited number of pixels from each to calculate the vegetation indexes.

**Fig. 8.3.3** Normalized difference vegetation index (NDVI) calculated using MODIS images. In the MODIS image is possible to identify the 5 sub-areas.
The analysis of the plots in figure 8.3.2 identifies area 1, 2 and 3 with the maximum values of NDVI, approximately between 0.22 and 0.28. For areas 4 and 5 the values are lower. This result agrees with the information given by the TLS images of the different areas.

**Fig. 8.3.4 Enhanced Vegetation Index (EVI) calculated using MODIS images**

In figures 8.3.3 and 8.3.4, due to the low definition of MODIS images the same results can not be stated. NDVI calculated using MODIS images also suggests a decrease in
vegetation optical depth for area 5, but that can be the result of lack of precision in the limitation of the different areas (because of the coarseness of the MODIS imagery pixel size compared to the field site).

Agricultural fields may be erroneously included within the MODIS data because area 5 is located on the limits of Tubbo farm. Although EVI is calculated similarly to NDVI, it corrects for some errors caused by aerosols in the reflected light as well as the ground cover below the vegetation.

Another advantage in the application of EVI data is that it does not turn out to be saturated as easily as the NDVI in densely vegetated areas.\(^8\) To conclude, the comparison of the model estimations for vegetation optical depth with NDVI vegetation index have confirmed a general increase in \(\tau\) that usually occurs after a period of rainfall. Images from Landsat have presented themselves more useful to apply to this project especially in the downscaling study, due to higher resolution when compared with MODIS.

9 Conclusions and Suggestions for Further Work

Satellite remote sensing of soil moisture is expected to bring a much needed improvement in accuracy to numerical weather prediction and climate change models. The knowledge of soil moisture global distribution is promised to increase with the observations taken by SMOS and future SMAP satellite missions. A series of models are being tested and improved to that effect. In this project work, the zeroth-order solution \(\tau-\omega\) model was tested with real PLMR microwave observations at multi-incidence angle view collected by NAFE’06 field experiment.

The run of the model for two types of soil composition have suggested an important variation of soil moisture with soil type, hence it is important to apply the closest information available of soil percentage of sand and clay in order to get accurate estimates

\(^8\) http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_4.php
for soil moisture. The estimation of soil moisture will be difficult to do using this model in regions where soil type is not well mapped.

In order to draw conclusions about the estimated soil moisture output it was used Hydraprobe® measurements of soil moisture. After the removal of the bias between the model estimated and Hydraprobe® sensed values for each day in which observations were collected (except the 8th of November 2006) the results of the model for the 1st and the 10th of November did not differ in much to the manufacturer estimated error of about +/-3% absolute, followed by +/-4% for the 3rd and 17th of November and 10% error for the 8th of November. This last error results however is very likely to be a result of dew (8th of November), meteorological condition not parameterized in the model, which can disturb the estimation of soil moisture.

The suggestion of dew on the 8th of November comes from the combination of the big (10%) error on the estimate of soil moisture and the fact that the PLMR measurements were made during an early morning flight. From the analysis it is possible to conclude that the model seems to produce reasonable estimates for soil moisture for the overall area, except for situations where dew affect the surface microwave emission.

The way that dew affects microwave emission is being researched with the purpose of improving the soil moisture estimates given by SMOS. As referred to in section 6.2.1 if the size of the vegetation components is small relative to the wavelength, the emission will be more enhanced than scattered, and dew as in the case of spray is observed to increase the surface emission. In our area of study the grazing (most of land cover) is considered to have on average 30 cm height, as opposed to the 21 cm of the wavelength, nevertheless the increase in surface emission holds true in this analysis.

It would have been interesting to apply the polarization ratio PR50/MPDI to identify the chances of intercepted water in vegetation canopy. Future work can be done to study the PR50 in more detail for areas covered with dry pasture and grazing. So I would suggest that future NAFE field experiments would also include in their data set the PLMR multi-
incidence measurements taken at 50°. This polarization ratio can be one of the tools to use in the interpretation of SMOS satellite-based passive microwave measurements for soil moisture because this nadir angle of view will be part of the data.

Another data set that could be helpful to alert to the possibility of dew will be the information of time of day, air temperature, surface temperature and relative humidity for the area where observations are collected in order to calculate the dew point.

Improvements on the initial $\tau$-$\omega$ model estimations were identified (using RMSE) when soil roughness was used as 0.19 as opposed to 0, when single scattering albedo was used as 0.06 as opposed to 0, hence the accuracy of the model estimations will improve when the fixed parameters are as close as possible to reality.

However the surface temperature is the one that most influences the brightness temperatures and therefore the estimation of soil moisture. Initially, to obtain a good estimate for the values of soil roughness and vegetation single scattering albedo it is extremely helpful to have access to the record of surface temperatures.

Regarding the analysis of vegetation optical depth estimations by the model, an increase in this parameter was identified after the rainfall events that occurred in the 2 week period of the study. This surface parameter depends mainly on vegetation biomass and vegetation water content; hence it can suffer unexpected fluctuation if there is a presence of intercepted water in the vegetation canopy. The verification of model estimates for $\tau$ was done by calculating NDVI and EVI vegetation indexes using both from Landsat or MODIS images. Although bearing in mind the limitations associated with these remote sensing techniques a general increase in the vegetation indexes was identified from the beginning of November until the beginning of December 2006 on the overall area crossed by the multi-incidence flight.

The downscaling study of model soil moisture estimation has lead to the identification partial contributions of sub-area characteristics (especially area 1 and 2) in the estimates for
the overall area. The errors between the estimated and sensed soil moisture have increased when the estimates were downscaled to smaller areas. This proves that the assumption that certain surface parameters (like surface roughness, soil type) are homogeneous does not hold true even in small spatial resolution, and as a consequence greater errors will be associated with the estimates.

The downscaling study for vegetation optical depth has led to identify what seem to be an overestimation of this parameter for area 1 on the 3rd and the 8th of November, when compared with the estimates for the other areas. The model has identified an increase in this parameter for all areas from the 1st to the 17th of November as well, which was confirmed by NDVI calculus using Landsat images (and with MODIS images to some degree, because spatial resolution is lower). If this model was to be used in the remote sensing of soil moisture at a SMOS spatial resolution, then the estimations would benefit from the information of the hydrological behavior of the sub-regions within the pixel scale. The information about soil type seems also of extreme importance for the accuracy of the estimates. Information about the location and dimensions of rivers (or main water bodies) would help to avoid overestimation of soil moisture.
References


Lane, J.A. and J.A. Saxton, 1952: Dielectric dispersion in pure polar liquids at very high radio-frequencies. I. Measurements on water, methyl and ethyl alcohols. Proceedings of the


**Websites**

http://www.comet.ucar.edu/
http://www.esa.int/esaLP/ESAL3B2VMOC_LPsmos_2.html
http://www.ecmwf.int/research/ESA_projects/SMOS/cmem/files/cmem_physics_v1.3_200804.pdf
http://www.ecmwf.int/research/ESA_/cmem_index.html
http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_4.php
Appendix

Hydraprobe® sensed soil moisture measurements

Plots of percentage of soil moisture vs. number of observations

1st November - Percentage SM sensed

3rd November - Percentage SM sensed

8th November - Percentage SM sensed

10th November - Percentage SM sensed

17th November - Per cented SM sensed