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Influence of forest cover fraction on L-band soil moisture retrievals from heterogeneous pixels using multi-angular observations

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Abstract

Airborne L-band data from the Australian National Airborne Field Experiment 2005 (NAFE ‘05) field campaign were used to investigate the influence of fractional forest cover on soil moisture retrievals from heterogeneous (grass/forest) pixels. This study is, to our knowledge, the first to use experimental data on this subject and was done in view of the SMOS mission, in order to contribute to calibration/validation studies and the analysis of heterogeneous surfaces. Because the multi-angle observations were contained in swaths, swaths were used instead of pixels as the basic surface unit in this study. Simultaneous retrievals of soil moisture (SM) and vegetation optical depth (τNAD) were undertaken by inversion of the L-MEB zero-order radiative transfer model. This was done for two different retrieval configurations, the first consisting of swath-effective values of SM and τNAD and the second consisting of values of SM and τNAD for the non-forested (i.e. grass) fraction of the swath, with forest emission known from forward modelling. Model inputs for non-retrieved parameters were either default values taken from the literature or site- and time-specific values obtained from observations of nearby homogeneous swaths gathered during the same flight. The main focus of this study was on retrieval behaviour for various soil moisture conditions and forest fractions. Area-averaged retrieval results were generally very reasonable for both retrieval configurations. When retrieving swath-effective values of SM and τNAD, τNAD showed an increased overestimation with increased forest fraction. The results show the difficulty in flagging upper limits of pixel forest fraction during soil moisture retrievals, besides the fact that erroneous parameter values can lead to high errors in retrieved SM, especially in wet conditions. This study is the first to give a realistic idea of the errors and uncertainties involved in soil moisture retrievals from partly forested swaths, and as such will contribute to a better understanding of SMOS calibration/validation issues.

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1. Introduction

ESA’s Soil Moisture and Ocean Salinity (SMOS) mission, launched in November 2009, carries a multi-angle interferometric L-band (1.4 GHz) radiometer for monitoring soil moisture and ocean salinity at global scale (Kerr et al., 2001). Spatial resolution of the instrument is around 40 km at nadir view, which means that most pixels of the earth’s surface will be heterogeneous, consisting of a mixture of forest, crops, grass and bare soil. The target error for SMOS is below 0.04 m³m⁻³ volumetric soil moisture. Studies involving soil moisture retrievals from crops and grassland have indicated that this target error can be achieved (e.g. Pardé et al., 2004; Wigneron et al., 2007; Saleh et al., 2007). However, soil moisture retrievals over forested areas are expected to give poorer results, due to the higher attenuating effect of the denser vegetation cover. Previously, soil moisture retrievals over homogeneous forested areas using experimental observations at L-band have been attempted in several small-scale studies (e.g. Chauhan et al., 1999; Lang et al., 2001; Lang et al., 2006). The results of these studies showed some sensitivity to soil moisture, depending on forest biomass and ground conditions. However, Lang et al. (2001) indicated the need for accurate measurement of ground temperature in order to achieve these results. A modelling study by Della Vecchia, Saleh, et al. (2006) also found an appreciable sensitivity to soil moisture over forests. Although temperate deciduous and coniferous forests have been found to have a reasonably high transmissivity, ranging from 0.4–0.6 (Grant et al., 2008; Guglielmetti et al., 2008; Guglielmetti et al., 2007;
Della Vecchia, Ferrazzoli, et al., 2006; Hallikainen et al., 2000), above-canopy L-band observations can show only a small sensitivity to changes in soil moisture content due to the obscuring effect of the litter and understory layers, if these are present (e.g. Grant et al., 2007 and 2009). A relatively invariable forest emission could actually be an asset in soil moisture retrievals over heterogeneous pixels containing forest, as the soil moisture of the non-forested part of the pixel might still be retrieved with the required accuracy if the emission of the forested part of the pixel is modelled correctly. The current study investigates these issues for heterogeneous pixels containing a mix of grassland and open Eucalypt forest. This type of forest has not been previously studied and differs from the temperate forests mentioned above due to (among other things) its open character and low litter cover.

To date, all known studies concerning soil moisture retrievals from heterogeneous forest pixels have been based on model simulations (Van de Griend et al., 2003; Van de Griend et al., 2004; Loew, 2008), rather than experimental data. The first two of these studies concluded that ignoring the a priori knowledge of the forest cover fraction α results in large errors in soil moisture retrieval if α<10%, but if α is known and ≤50%, soil moisture in the non-forested area can be determined with a precision better than the 0.04 m3m-3 target error for SMOS. The third study found a similar result, but again stressed the importance of knowing the surface temperature to within 4 K. That study also indicated that soil moisture retrievals over mixed forest pixels can show a good temporal evolution of soil moisture although the retrieval results themselves are biased. Retrieval accuracy was also found to depend on scale, increasing with decreasing spatial resolution until levelling out above a 10 km resolution.

While the above modelling studies present rather optimistic results, the studies are restricted to a limited range of moisture and land cover conditions, and, importantly, the results have not been verified with experimental data. Moreover, significant assumptions are made concerning parameter values. Especially, forest optical depth was assumed to be much higher than values found from recent field experiments (1–1.5 compared to 0.4–0.6).

In view of the SMOS mission, the current study seeks to validate the results of previous modelling studies using large-scale experimental data which include both homogeneous and heterogeneous pixels, different land cover fractions, and different soil moisture conditions. The National Airborne Field Experiment 2005 (NAFE ’05) field campaign (Panciera et al., 2008) is well suited to this task. The main objective of the current study is thus to better understand and quantify the influence of forested areas on the soil moisture retrieval from heterogeneous pixels.

2. Materials

2.1. Site description

The area of study (lat/lon (32° 8′ S, 150° 6′ E) to (32° 11′ 6″ S, 150° 9′ 7.1994″ E)) covered part of the ‘Roscommon’ farm. This area was part of the larger ‘Kru’ study area covering the Krui River subcatchment, which lies within the Goulburn River catchment in southeast Australia. The location of Roscommon within the catchment is outlined in (Panciera et al., 2008), while Fig. 1 shows the farm boundaries, forest areas and flight lines in more detail.

The study area has an average elevation of 300 masl and is characterised by native grassland and relatively open Eucalypt forest areas. The forested surfaces were generally found on the more steep and rocky parts of the landscape (gently rolling with elevation differences up to ~15 m), whereas the flatter parts had been cleared for grazing.

The grassland areas consisted of native grass spp., with an average vegetation height estimated to be ~30 cm. Average grass Normalized Difference Vegetation Index (NDVI) during the experiment was 0.60. This was calculated using a handheld Model 100BX Radiometer with 4 channels (450–520, 520–600, 630–690 and 760–900 nm). NDVI readings were taken at sixteen 50 m spaced locations across a 150 m by 150 m area (the so-called ‘high resolution area’, cf. Panciera et al., 2008). At each location, three readings were taken of each spectral band. Estimates of leaf area index (LAI) derived from MODIS data at 250 m resolution were around 1.8 m2m-2 for the entire campaign. Grass water content was estimated to be around 0.5 ± 0.2 kg based on destructive measurements of the weight difference between wet and dry biomass.

The forest areas consisted mainly of Box (Eucalyptus spp.), Ironbark (Eucalyptus spp.) and some Black Cypress-pine (Callitris endlicheri). Fish-eye photographs were taken of the Eucalypt vegetation, from which the fraction cover was determined to be ~39% and the LAI was estimated at 2.5. MODIS images showed that forest LAI did not noticeably change during the experiment. The understory was an open-heath formation consisting mainly of Sifton bush (Cassinia quinquefolia). Some litter was present on the ground and formed a generally very thin (~ 0.5 cm) layer. Litter dry bulk density was 0.15 ± 0.03 g cm-3. It is estimated that around 10–15% of the forest floor consisted of bed rock, with the remainder covered by sandy soil (67% sand, 15% clay) with a bulk density of 1.22 g cm-3 and a porosity of 0.437. Field observations found the thickness of the soil layer to be highly variable, however, more detailed information on this parameter is unavailable.

2.2. Data

The airborne L-band measurements used in the current study were made using the dual-polarised Polarmetric L-band Multibeam Radiometer (PLMR) on 1st, 8th, 10th, 15th, and 22nd November 2005. Rather heavy precipitation occurred at the very beginning of the experiment, followed by a long drying-up period and finally some scattered rainfall at the end of the experiment. Precipitation data recorded at the Stanley station (approx. 8 km northwest of Roscommon) were available from the Goulburn River experimental data set (Rüdiger et al., 2007). Table 1 shows an overview of meteorological conditions over the study area on the relevant flight days and times.

PLMR observations were made in a pushbroom configuration at four different altitudes; however, the current study used only the lowest (approximately 190 m above ground level) altitude data in order to obtain a sufficient number of swaths. At this altitude the nominal ground resolution (~3 dB footprint) was 62.5 m at nadir. Observations were made every second at incidence angles of +/-7°, +/-21.5° and +/-38.5°, with the six footprints covering a total swath of approximately 375 m. Observations where the aircraft pitch/roll angle was >5° were filtered out. More detailed information on PLMR and the flight characteristics can be found in (Panciera et al., 2008).

Thermal infrared emissions TIR were obtained with a FLIR ThermaCam S60 thermal imager (spectral range 7.5–13 μm), which was also on board the aircraft carrying PLMR. The FLIR had a ~1 m resolution at the lowest altitude flight and obtained TIR using an overall scene emissivity of 0.98, which is a value often used for vegetation in the thermal infrared range. One FLIR image covered approximately the same area as the PLMR swath. For each PLMR swath, only minimum, maximum and average TIR values for the whole swath were used.

A Landsat 5 TM image from October 2005 (spatial resolution 25 m) was used to define seven land cover types (dense forest, open woodland, native grass, bare soil/low LAI, crops, cloud and cloud shadow), based on a combination of supervised and unsupervised classification methods. In the current study, the ‘dense forest’ and ‘open woodland’ classes were joined together to define forest areas, while the ‘native grass’ class was used to define the grassland areas (cf. Fig. 1).

Ground measurements of the top 5 cm soil moisture content were taken using a portable Stevens Water Hyd probe® sensor. A site-specific calibration of this sensor against gravimetric samples in the field and laboratory has indicated that the data are accurate to within
\[ \pm 0.033 \text{ m}^3\text{m}^{-3} \] (Merlin et al., 2007). Approximately 10–15 measurements were taken at random throughout the forest area per day and approximately 60–100 throughout the grassland areas, although these were concentrated in the south-west part of the farm. These measurements were part of the ‘farm-scale’ sampling (cf. Panciera et al., 2008) done at Roscommon. All available data points within the current study area (Section 2.1) were taken into account, irrespective of the resolution grid they belonged to.

Finally, field measurements of temperature were made at two fixed locations on Roscommon farm: one in a grassland area and one in the forest. Soil temperatures at the grassland location were obtained at 1 cm depth with Unidata 6507A/10 sensor, and (for 22nd Nov. only) at 2.5 cm depth with a T107 sensor, every 20 min. At the fixed forest location, temperatures were obtained every 10 min from thermocouples installed at 2 cm depth in the soil, on the soil surface, 2 cm within the tree trunk at breast height, and at 5 m and 7.5 m in the canopy.

### 3. Methods

#### 3.1. L-MEB

The radiative transfer model used was the L-band Microwave Emission of the Biosphere (L-MEB) model (Wigneron et al., 2007), which forms the base of the SMOS Level 2 Soil Moisture Algorithm. The main L-MEB equation for a vegetation-covered soil is based on a simplified zero-order radiative transfer approach of the \( \tau\omega \) type (Kirdyashev et al., 1979; Mo et al., 1982), as shown in Eq. (1):

\[
T_D = T_s \cdot \left(1 - R_D \right) \cdot \gamma_D + \left(1 - \omega_D \right) \cdot T_c \cdot \left(1 + R_D \right) \cdot \gamma_D \cdot \left( \tilde{y}^D \right)^2
\]

The respective terms describe the upwelling ground radiation, the combination of up- and downwelling canopy radiation, and the sky.

#### Table 1

Overview of meteorological conditions for the Roscommon farm study area on the relevant flight days. \( \text{SM} = \) area-averaged soil moisture ± standard deviation, \( T_{\text{IR,av}} = \) area-averaged swath-average infrared temperature ± standard deviation. Subscripts ‘G’ and ‘F’ denote grass and forest, respectively.

<table>
<thead>
<tr>
<th>Day</th>
<th>Local time [h]</th>
<th>SM ( \text{G} ) [m(^3)m(^{-3})]</th>
<th>SM ( \text{F} ) [m(^3)m(^{-3})]</th>
<th>( T_{\text{IR,av,G}} ) [K]</th>
<th>( T_{\text{IR,av,F}} ) [K]</th>
<th>Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/11</td>
<td>14.35–14.45</td>
<td>0.283 ± 0.028</td>
<td>0.184 ± 0.019</td>
<td>301.88 ± 1.03</td>
<td>302.06 ± 1.20</td>
<td>± 16.5 mm on previous 2 days; 0.4 mm on this day</td>
</tr>
<tr>
<td>8/11</td>
<td>10.30–10.40</td>
<td>0.217 ± 0.011</td>
<td>0.127 ± 0.059</td>
<td>300.24 ± 1.56</td>
<td>300.72 ± 1.90</td>
<td>Rain just before flights; previous 2 days dry</td>
</tr>
<tr>
<td>10/11</td>
<td>10.10–10.20</td>
<td>0.097 ± 0.002</td>
<td>0.055 ± 0.030</td>
<td>304.73 ± 1.65</td>
<td>305.37 ± 2.08</td>
<td>0.2 mm previous day; 8.8 mm 2 days ago</td>
</tr>
<tr>
<td>15/11</td>
<td>10.05–10.15</td>
<td>0.068 ± 0.011</td>
<td>0.035 ± 0.019</td>
<td>312.04 ± 1.59</td>
<td>312.91 ± 1.84</td>
<td>Dry</td>
</tr>
<tr>
<td>22/11</td>
<td>10.00–10.10</td>
<td>0.031 ± 0.008</td>
<td>0.014 ± 0.003</td>
<td>313.57 ± 3.11</td>
<td>317.66 ± 2.51</td>
<td>Dry</td>
</tr>
</tbody>
</table>
radiation reflected by the ground surface. The sky radiation reflected by the canopy is neglected, as is multiple scattering between the ground and the canopy. The parameters \( T_s \) and \( T_c \) are the temporal temperatures of the soil and vegetation canopy, respectively. The vegetation canopy can consist of either grass or forest, indicated by the respective subscripts ‘G’ and ‘F’ from here onwards. The sky brightness temperature \( T_{sky} \) is calculated according to the method outlined in (Pellin et al., 2003). The variable \( \alpha^T (P=H \text{ or } V \text{ polarization}) \) is the single scattering albedo of the vegetation layer and the variable \( \gamma^p \) (\( \theta = \text{observation angle} \)) describes the transmissivity of the vegetation layer, which is related to vegetation optical depth \( \tau^p \) according to:

\[
\gamma^p = \exp(-\tau^p / \cos \theta)
\]  
(2)

dividing the optical depth by the cosine corrects for the difference in physical pathway length through the canopy layer at different angles. However, it should be noted that the variables \( \tau \) and \( \alpha \) in L-MEB are effective parameters resulting from the use of the Delta-Edington approximation (Joseph et al., 1976), which assumes that scattering is in the forward direction only. Thus, \( \tau^p \) in Eq. (2) must account for the fact that in reality the incident radiation comes from a range of directions within the canopy. While in Eq. (2) the cosine is taken of a single angle, in fact the aperture of the radiometer and the structure of directions within the canopy determine the real range of incidence angles.

In order to take into account the effects of canopy anisotropy, an extra parameter (\( \theta_T \)) has been introduced in the L-MEB model to account for such remaining angular effects. The relation between the canopy determine the real range of incidence angles.

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### Table 2

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default value</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t^f_{G} )</td>
<td>1</td>
<td>Kerr et al., 2007</td>
</tr>
<tr>
<td>( t^c_{G} )</td>
<td>1</td>
<td>Kerr et al., 2007</td>
</tr>
<tr>
<td>( H^f )</td>
<td>0.5</td>
<td>Kerr et al., 2007</td>
</tr>
<tr>
<td>( H^c )</td>
<td>0.4</td>
<td>Saleh et al., 2007</td>
</tr>
<tr>
<td>( N^f )</td>
<td>1</td>
<td>Wigneron et al., 2007</td>
</tr>
<tr>
<td>( N^c )</td>
<td>0</td>
<td>Wigneron et al., 2007</td>
</tr>
<tr>
<td>( SM )</td>
<td>0.15</td>
<td>—</td>
</tr>
</tbody>
</table>

The error computed by this cost function represents the sum of the squared differences in observed and simulated brightness temperatures \( (T_b - T_b)^2 \) plus the squared differences in retrieved and initial parameter values \( (p_i - p_{ini})^2 \) for \( N \) observations and \( n \) parameters. The parameters \( \sigma^f_{p_i} \) and \( \sigma^c_{p_i} \) are the corresponding variances, and allow for the possibility of constraining parameters. However, no constraints were used in the current study (i.e. large values of \( \sigma^f_{p_i} \) were used) and all retrievals were tested for model convergence. Initial values for retrieved parameters are given together with the relevant references in Table 2.

3.2.2. Homogeneous swaths

The retrievals over homogeneous swaths were performed per observation day, per flight line. Homogeneous forest and grass swaths within a given flight line were selected and the assumption was made that all areas of a particular vegetation type (grass or forest) within a given flight line were identical. Then, single retrieval was performed using all the homogeneous forest swaths of a given flight line, and one using all the homogeneous grass swaths. Note that only four of the six flight lines covered forest areas (cf. Fig. 1). The choice to
do the retrievals per flight line rather than for the whole area at once was made in order to obtain a better insight into the spatial variability of the parameters and the errors in their retrieval.

Input values of SM were taken from the available field measurements. Swath SM was calculated as follows: if a PLMR swath contained Hydraprobe point measurements, the SM value for that swath was calculated by taking the average of the ground measurements. However, a majority of the swaths, especially in the forest areas, did not contain any Hydraprobe measurements. In these cases, an ‘observed’ soil moisture for the swath was calculated as

\[ SM_{\text{swath}} = \alpha \cdot SM_G + (1 - \alpha) \cdot SM_F, \]

with \( SM_F \) and \( SM_G \) indicating average forest and grassland soil moisture, respectively. These averages (cf. Table 1) were calculated from all Hydraprobe SM measurements in the relevant homogeneous swaths (forest or grassland). An estimate of the errors involved in using the area-averages rather than having exact swath values of SM is given by the standard deviations of \( SM_F \) and \( SM_G \) in Table 1, which are rather low.

Each of the parameters \( H_F, H_G \) and \( r^2 \) was fixed rather than included in the retrievals because the latter option systematically resulted in model instability, i.e. bad convergence, when tested for each parameter separately. Therefore, the actually retrieved parameters over homogeneous swaths were \( \gamma_{NAD}, \alpha^3, \beta^2 \) and \( \beta \).

By introducing the parameter \( \beta \) in the model (Section 3.1), all errors related to soil emission which can influence retrieval results will be taken into account by \( \beta \) rather than by \( H_F \), which would be the case if the retrievals were performed without \( \beta \) and including \( H_F \). The advantage of this approach becomes apparent in the next step when SM is retrieved. Although a date-specific relationship remains between SM and \( \beta \), the retrieved values of SM are at least not directly influenced by erroneous values of \( H_F \). The errors in the retrieved values of SM will therefore give a better idea of the actual retrieval errors involved, rather than merely being a reflection of errors in the previously retrieved \( H_F \). In other words, the inclusion of the correction parameter \( \beta \) allows the assumption of a correct roughness value in the SM retrievals. Indirectly, the parameter \( \beta \) might also partly correct for errors in soil temperature.

### 3.2.3. Heterogeneous swaths

Retrievals over heterogeneous swaths were performed using the a priori information on land cover fractions obtained from the land use map (Section 2.2). In the case of heterogeneous swaths, two modelling approaches were tested: 1) simultaneous retrieval of swath-effective values of soil moisture and optical depth (\( SM_{\text{swath}} \) and \( \gamma_{NAD}, \alpha^3, \beta^2 \)), and 2) simultaneous retrieval of grassland soil moisture and optical depth values (\( SM_G \) and \( \gamma_{NAD,G}, \beta^2 \)). These two methods were chosen in order to show two extremes in the range of possible retrieval configurations consisting of combinations of SM and \( \gamma_{NAD} \).

In the first modelling approach, it was assumed that the soil moisture content under grassland and forest areas was equal, i.e.

\[ SM_{\text{swath}} = SM_G = SM_F. \]

While this assumption is incorrect in reality, it should be kept in mind that the soil emission from forested surfaces is believed to make only a minor contribution to the observed brightness temperature, with the majority of the forest signal coming from the vegetation itself. The errors involved in this approach are therefore less extreme than might be thought.

In this approach, footprint temperature \( T_{\text{ footprint}} \) was approximated by

\[ T_{\text{ footprint}} = \alpha \cdot T_F + (1 - \alpha) \cdot T_C. \]

Further model inputs were the default parameters given in Table 2 and the daily area-averages of \( \alpha^3, \beta^2 \) and \( \beta \) taken from the retrievals over homogeneous swaths (previous section).

Model inputs for the second approach differed from those for the first approach in the following ways: \( SM_G \) was fixed to the area-average value, \( \gamma_{NAD,G} \) was fixed to the average daily value resulting from the retrievals over homogeneous swaths (previous section), and \( T_F \) and \( T_C \) were separate input values. Although this approach is not likely to be implemented operationally due to the unavailability of initial information on the above parameters, the results are included in this study as a theoretical exploration of the hypothesis that the soil moisture of the non-forested part of the pixel might still be retrieved with the required accuracy if the emission of the forested part of the pixel is modelled correctly enough. In theory, the first (swath-effective SM retrievals) and second (grassland SM retrievals) approaches respectively represent worst- and best-case scenario’s in terms of the amount of initial available model input.

It should be specifically noted that model convergence for this second approach was only achieved if a given swath contained at least two angular footprints containing 100% grass cover. The reason for this is, of course, the fact that in order to retrieve two (here: grassland) parameters, at least two independent (grassland) observations are needed. This fact should be kept in mind for any future studies dealing with within-pixel retrievals. As a result of this restriction, there were less heterogeneous swaths available for analysis in the second approach than in the first.

It should be noted that the antenna pattern was not taken into account during the retrievals over heterogeneous swaths, i.e. simulated \( T_F \) values were not weighted by the distribution of intensity within the PLMR footprint. However, the resulting errors were negligible; as an indication, a comparison of weighted and non-weighted values of \( \alpha \) on 1st Nov. (\( N = 1552 \)) resulted in a correlation coefficient of 0.999 and a root mean square error (RMSE) in \( \alpha \) of 0.0268. In other words, at most 2.7% of the swath emission was incorrectly calculated by not taking the antenna pattern into account, while a considerable reduction in computing time was won.

### 4. Results and discussion

#### 4.1. Footprint temperature and emissivity

##### 4.1.1. Thermodynamic temperatures

Field measurements of temperature were made at one fixed location in the forest and one fixed location in the grassland area (Section 2.2). The field measurements, together with the average \( T_{IR} \) value for the corresponding swath, are shown in Table 3. \( T_F \) was approximated by taking the average of soil (2 cm depth), bole and canopy temperatures at the forest location, whereas \( T_C \) was approximated by soil temperature at 1 cm depth at the grass location. These approximations were justified by the fact that the field measurements of soil and canopy temperatures were very similar (differences in the order of 1.5–3 K). In theory, soil temperatures at depth could also be important in the case of a dry, sandy soil. However, in the NAFE '05 data set the temperature and moisture data necessary for a correct calculation of effective soil temperature were lacking. Given the high spatial variability in temperature, besides the presence of a vegetation cover, neglecting the soil temperature at depth in the overall temperature calculations is not expected to introduce large errors in the resulting patterns of soil moisture retrieval found in this study.

The bias for forest and grassland in Table 3 gives the difference between the thermodynamic temperatures derived from thermal infrared observations (\( T_{IR,F} \) and \( T_{IR,G} \)) and those derived from field measurements (\( T_F \) and \( T_C \)). It can be seen that in the wettest conditions (1st Nov.), \( T_F \) and

<table>
<thead>
<tr>
<th>Date</th>
<th>( T_{IR,F} )</th>
<th>( T_F )</th>
<th>Bias (F)</th>
<th>( T_{IR,G} )</th>
<th>( T_C )</th>
<th>Bias (G)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Nov.</td>
<td>302.11</td>
<td>300.85</td>
<td>1.26</td>
<td>302.93</td>
<td>301.05</td>
<td>1.88</td>
</tr>
<tr>
<td>8th Nov.</td>
<td>299.57</td>
<td>292.83</td>
<td>6.74</td>
<td>299.28</td>
<td>296.14</td>
<td>3.14</td>
</tr>
<tr>
<td>10th Nov.</td>
<td>306.91</td>
<td>296.44</td>
<td>10.47</td>
<td>305.76</td>
<td>299.05</td>
<td>6.71</td>
</tr>
<tr>
<td>15th Nov.</td>
<td>309.62</td>
<td>294.25</td>
<td>15.37</td>
<td>313.02</td>
<td>299.05</td>
<td>13.97</td>
</tr>
<tr>
<td>22nd Nov.</td>
<td>315.17</td>
<td>294.40</td>
<td>20.77</td>
<td>320.28</td>
<td>301.93</td>
<td>18.35</td>
</tr>
</tbody>
</table>
were very similar at the time of flight. In drier conditions, $T_C$ was generally higher than $T_F$. Furthermore, in drier conditions the $T_K$-derived values clearly start to overestimate those derived from field measurements quite substantially, mainly due to the difference in sampling depth between the two methods. Table 3 shows that, for both vegetation types, this overestimation (i.e. the bias) increases almost linearly with time. Besides resulting from the difference in sampling depth, the discrepancies are also partly instrumental in origin. In order to correct for both effects, the thermodynamic temperature ($T_{\text{footprint}}$) of a footprint with a given forest fraction $\alpha$ was calculated as in Eq. (7), using the bias $(F)$ and bias $(G)$ of the observation day in question.

$$T_{\text{footprint}} = \alpha \cdot (T_{R,F} - \text{bias}(F)) + (1-\alpha) \cdot (T_{R,G} - \text{bias}(G))$$

(7)

4.1.2. Emissivity

Fig. 2 gives examples of the angular emissivities of homogeneous grassland and forest footprints, respectively, using observations made on 1st and 22nd November, under ‘wet’ and ‘dry’ conditions respectively.

Grass and forest emissivities $e_G$ and $e_F$ were calculated according to the Rayleigh–Jeans approximation $(T_R - T_{\text{sky}})/(T_{\text{footprint}} - T_{\text{sky}})$ (Ulaby et al., 1986) and plotted against incidence angle $\theta$. The patterns seen in Fig. 2 are in agreement with theory, showing increasing and decreasing emissivities with $\theta$ for $V$ and $H$ polarization, respectively. This implies that the (polarised) soil emission is only partly attenuated by the vegetation layer. The figures show that, as expected, $e_G$ is slightly lower than $e_F$, and $e_G$ shows greater angular variation than $e_F$. The fact that emissivity is higher and the signal is flatter over forested areas indicates a higher vegetation emissivity and a stronger attenuation of the soil signal, and therefore a lower sensitivity to soil moisture changes than in grassland areas.

The difference in emissivity between wet and dry conditions shows that there is a certain sensitivity of above-canopy brightness temperature to changing moisture conditions for open Eucalypt forests. The fact that there is less scatter present in the ‘dry’ data is most probably due to the inherently high emission from a dry soil, in which case the relative influence of vegetation and surface roughness on the signal becomes smaller, as suggested earlier by (Crosson et al., 2005). Also, soil moisture usually becomes more homogeneous in dry conditions. The few outliers in the data are assumed to be the result of wrongly classified landuse for those footprints.

It was found that in wet conditions the range in brightness temperature was much larger than the range in thermodynamic temperature, indicating a large spatial variation and large effect of non-temperature variables such as canopy parameters, soil moisture and/or effective surface roughness. For dry conditions, the variation in these surface characteristics is clearly smaller and thermodynamic temperature may play a more important role. These conclusions were found to be valid for any given $\alpha$, i.e. for both homogeneous and heterogeneous footprints.

4.2. Retrievals

4.2.1. Retrievals from homogeneous swaths

The parameter values retrieved from homogeneous swaths are shown in Table 4A (forest) and B (grass). There are differences in parameter values between flight lines, owing to the fact that in reality the vegetation cover is of course not homogeneous, however, although the large spatial variability is visible, the general orders of magnitude remain fairly consistent. The single scattering albedo for $H$-pol is systematically somewhat higher than for $V$-pol, while $\beta$ varies somewhat between flight days, as expected. The negative values of forest single scattering albedo on 8th November could be due to the fact that rainfall occurred just before the flights. This effect is, however, not seen in the grass swaths, where the shorter vegetation might have resulted in the precipitation already having dried up. In further analyses, daily averages of $e_{H,F}$ and $e_{V,F}$ for 8th

Fig. 2. Example of angular emissivities of (top) 100% grassland footprints ($e_G$) and (bottom) 100% forest footprints ($e_F$) under ‘wet’ (left) and ‘dry’ (right) conditions on 1st and 22nd Nov. respectively. Corresponding area-average soil moisture values are $SM_G \approx 0.28$ m$^3$m$^{-3}$ and $SM_F \approx 0.18$ m$^3$m$^{-3}$ (wet) and $SM_G \approx 0.03$ m$^3$m$^{-3}$ and $SM_F \approx 0.01$ m$^3$m$^{-3}$ (dry).
November were therefore estimated by taking the averages of the 1st and 10th November, i.e. the observation days before and after Nov. 8th. Both forests and grass show high retrieved values of either \( \tau_{\text{NAD}} \) (especially) or \( \phi^\beta \) on 22nd of November, the reason for which is not well understood. The values of \( \beta \) are reasonable given the low reflectivity of a sandy soil and the physical condition 0.01 \( \leq \alpha \leq \alpha \leq 0.99 \) of the studies by Loew (2008). On the other hand, the high standard deviation of the retrievals seems to reflect the actual spatial variability, which is much higher than that of the observations. The field observed standard deviation, however, is based on only a few measurements, insufficient to characterize the actual spatial variability. It should also be realized that, in this case, the retrieved values refer to ‘swath-effective’ values of which the exact physical meaning is difficult to identify because of non-linear mixing effects, and because the soil properties between the forest and the grass soils are different.

As indicated in the study by Loew (2008), it is important to observe the bias in \( SM \) together with the RMSE, as a low RMSE can still be coupled to a high bias. In the current study it should be kept in mind that, due to the limited number of field observations, many of the observed values of \( SM \) are based on \( \alpha \)-weighted area-averages and great caution should thus be taken with the interpretation of RMSE(\( SM \)) and bias (\( SM \)).

The retrieved values of \( \tau_{\text{NAD,swath}} \) are slightly higher than expectations based on Table 4A,B, an effect which will be discussed later in more detail in the context of Fig. 4. Finally, the values of RMSE (\( T_\alpha \)) indicate that, overall, the model is able to match \( T_\alpha \) simulations to observations reasonably well, although this of course becomes more difficult with increasing wetness, when soil and vegetation emission show increasingly opposed behaviour (i.e. soil emission decreases while vegetation emission increases).

The results for 1st November (wet) and 22nd November (dry) are shown in more detail in Fig. 4 (note that y-axis scales differ) using the first retrieval approach, i.e. simultaneous retrieval of \( SM \) and \( \tau_{\text{NAD,swath}} \). The results for the first retrieval approach, i.e. simultaneous retrieval of \( SM \) and \( \tau_{\text{NAD,swath}} \), indicate that, overall, the model is able to match \( T_\alpha \) simulations to observations reasonably well, although this of course becomes more difficult with increasing wetness, when soil and vegetation emission show increasingly opposed behaviour (i.e. soil emission decreases while vegetation emission increases).

4.2.2. Retrievals from heterogeneous swaths

In order to give an idea of the distribution of forest fraction \( \alpha \) per swath, the histogram in Fig. 3 shows an example for the 1st November. Note that only heterogeneous swaths (0.01 \( \leq \alpha \leq 0.99 \)) have been included in the figure. The distribution varies slightly per observation day, but the overall pattern is very similar in all cases. The total number of 87 heterogeneous swaths was relatively small, as the forested parts of Roscommon were not very extensive. In comparison, there were 185 homogeneous grass swaths (\( \alpha \approx 0.01 \)) and 98 homogeneous forest swaths for this day. The results of the retrievals from heterogeneous swaths (0.01 \( \leq \alpha \leq 0.99 \)) are shown in Table 5A,B, and Fig. 4. Table 5A shows the results for the first retrieval approach, i.e. simultaneous retrieval of \( SM \) and \( \tau_{\text{NAD,swath}} \). It can be seen that, except on the driest day, the average retrieved \( SM \) slightly overestimates the average observed value, which was an effect also found for pixels in (Loew, 2008). On the other hand, the high standard deviation of the retrievals seems to reflect the actual spatial variability, which is much higher than that of the observations. The field observed standard deviation, however, is based on only a few measurements, insufficient to characterize the actual spatial variability. It should also be realized that, in this case, the retrieved values refer to ‘swath-effective’ values of which the exact physical meaning is difficult to identify because of non-linear mixing effects, and because the soil properties between the forest and the grass soils are different.

As indicated in the study by Loew (2008), it is important to observe the bias in \( SM \) together with the RMSE, as a low RMSE can still be coupled to a high bias. In the current study it should be kept in mind that, due to the limited number of field observations, many of the observed values of \( SM \) are based on \( \alpha \)-weighted area-averages and great caution should thus be taken with the interpretation of RMSE(\( SM \)) and bias (\( SM \)).

The retrieved values of \( \tau_{\text{NAD,swath}} \) are slightly higher than expectations based on Table 4A,B, an effect which will be discussed later in more detail in the context of Fig. 4. Finally, the values of RMSE (\( T_\alpha \)) indicate that, overall, the model is able to match \( T_\alpha \) simulations to observations reasonably well, although this of course becomes more difficult with increasing wetness, when soil and vegetation emission show increasingly opposed behaviour (i.e. soil emission decreases while vegetation emission increases).

The results for 1st November (wet) and 22nd November (dry) are shown in more detail in Fig. 4 (note that y-axis scales differ) using the first retrieval approach, i.e. simultaneous retrieval of \( SM \) and
The retrieved values of $\tau_{\text{NAD,swath}}$ show, as expected, a generally increasing pattern with increasing forest fraction $\alpha$. Excepting the outlier on 22nd Nov., the values of $\tau_{\text{NAD,swath}}$ for low $\alpha$ are of the same order of magnitude as those found for grassland areas in Table 4B. However, the values of $\tau_{\text{NAD,swath}}$ for higher $\alpha$ are higher than would be expected according to Table 4A and it thus appears that increased forest fraction does influence retrievals of optical depth by resulting in an increased overestimation.

The retrieved values of $\tau_{\text{NAD,swath}}$ in the right-hand images show maximum values of retrieved $\tau_{\text{NAD,swath}}$ at intermediate $\alpha$. Even though these plots do not show the actual errors in retrieved SM (because, as said previously, values of RMSE($\tau_{\text{NAD,swath}}$) are not completely reliable), an idea of the errors involved can be derived from subtracting the area-average observed SM (the middle of the two solid lines) from the retrieved values. In this case, an approximately convex curve remains.

**Table 5**

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<th>Date</th>
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<th>SMswath (obs)</th>
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<th>Bias (SMswath)</th>
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**Table 5**

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<td>0.73±0.29</td>
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**Fig. 4.** Retrieved 'swath-effective' values of soil moisture ($\text{SM}_{\text{swath}}$ [m$^3$m$^{-2}$]) and optical depth ($\tau_{\text{NAD,swath}}$ [−]) plotted against forest fraction $\alpha$ for heterogeneous swaths (0.01 ≤ $\alpha$ ≤ 0.99) on (top) 1st November (wet) and (bottom) 22nd November (dry). Left: average and 75th percentile of retrieved $\tau_{\text{NAD,swath}}$. Right: average and 75th percentile of retrieved $\text{SM}_{\text{swath}}$. Solid lines indicate area-average $\text{SM} = \alpha \cdot \text{SM}_{\text{G}} + (1−\alpha) \cdot \text{SM}_{\text{F}}$ ± 0.04 m$^3$m$^{-2}$ (with $\text{SM}_{\text{F}}$ and $\text{SM}_{\text{G}}$ from Table 1). NB. Note different ranges of $y$-axes in right-hand plots.
Such a shape was also found in a modelling study by Van de Griend et al. (2003) for retrievals over pixels containing a mix of bare soil ($\tau = 0$) and vegetation with $\tau = 0.4$. That study also found a flatter curve in drier conditions, as seen here in Fig. 4. However, contrary to the current study, the modelling study assumed that no a priori knowledge of $\alpha$ was available. Another modelling study by Loew (2008) which did assume a priori knowledge of $\alpha$ to be available, shows a result for mixed forest/grassland pixels which could be interpreted as a similar curved shape, although it is not conclusive as forest fractions above 65% are sparse. However, that study assumed higher values of forest optical depth ($\tau = 0.8 – 1$) than the current study does. It seems that the mix of optical depth values, i.e. the contrast present between forested and non-forested areas, determines the shape of the curve, whereas the un-/availability of a priori knowledge of $\alpha$ mainly influences the absolute error values.

Modelling studies by Van de Griend et al. (2003, 2004) both with and without a priori knowledge of $\alpha$, show that when higher values of $\tau$ are introduced in the mixed pixel, the maximum of the error curve shifts towards higher values of $\alpha$. It is therefore too general a statement to simply say that if $\alpha$ is known a priori, all pixels containing more than 50% forest fraction will give errors in retrieved $\text{SM}$ greater than 0.04 m$^3$m$^{-3}$. The value of $\alpha$ at which this 0.04 m$^3$m$^{-3}$ boundary will be crossed (if it is crossed) will differ according to the different land use optical depths within the pixel and their values relative to each other. This makes sense, as optical depth and soil moisture are indirectly linked in the tau–omega model. Unfortunately, the consequence for SMOS is that it will be extremely difficult to find reliable flags for the maximum allowed forest fraction in mixed pixels.

Table 5B shows the results for the second retrieval approach, i.e. simultaneous retrieval of $\text{SM}_G$ and $\tau_{\text{NAD},G}$ while the emission of the forested part of the swath is modelled with parameter values as retrieved from the homogenous forest parts. The table shows that in dry conditions the results are generally very reasonable. The results will, at least partly, reflect a compensation for the forward modelled emission of the forested part of the swath. Retrieved values of $\tau_{\text{NAD},G}$ are generally close to observed values (taken from Table 4B), except for 22nd Nov. which had very high values of ‘observed’ $\tau_{\text{NAD},G}$ (Table 4B). No relationship can be seen between moisture conditions and the degree of over- or underestimation in $\tau_{\text{NAD},G}$. As also said for Table 5A, the values of RMSE($\text{SM}_G$) and bias($\text{SM}_G$) should be taken with extreme caution. The study by Loew (2008) found that the bias ($\text{SM}$) increases with increasing dryness, therefore the low error values for dry conditions found in the current study should not lead straight to the conclusion that $\text{SM}$ retrievals over forested areas are reliable enough as long as the moisture content is low. This issue is important for SMOS and deserves further attention in future.

Values and patterns of RMSE($\text{To}$) are very similar to those in Table 5A, therefore it can be concluded that the model does not have more difficulty in fitting simulations to observations when the forest part of the swath emission is known from forward modelling.

It should be noted here that, as explained in §3.2, this second approach only works for swaths with more than 2 angular footprints containing 100% grass. As in this study a maximum of 6 angles was observed for each swath, the consequence of this requirement is that at least 33% of the swath will cover grassland. Therefore, this analysis only includes swaths with $\alpha$ < 0.66 and a possible heightened influence of high forest fraction is thus not taken into account. Due to this limited range of $\alpha$ and, as a result, the low number of suitable swaths, a figure similar to Fig. 4 was not drawn up for this retrieval approach (retrieval of $\text{SM}_G$ and $\tau_{\text{NAD},G}$).

### 4.3. Effects of errors in L-MEB parameter values

In order to determine the effect of each fixed model parameter on RMSE($\text{SM}$), a sensitivity analysis was performed. Simultaneous retrievals of $\text{SM}_{\text{swath}}$ and $\tau_{\text{NAD,swath}}$ were performed for heterogeneous swaths (0.01 $\leq \alpha \leq 0.99$), each time with errors superimposed on one of the fixed L-MEB parameters, for 1st November (wet) and 22nd November (dry).

The resulting difference $\delta$ (RMSE($\text{SM}_{\text{swath}}$)) between the mean RMSE($\tau_{\text{NAD,swath}}$) values found for the ‘error’ and the ‘default’ situations is plotted vs. $\alpha$ for each parameter in Figs. 5 (wet) and 6 (dry), with values of RMSE($\text{SM}_{\text{swath}}$) averaged per 0.2 increment in $\alpha$. Note that the scales on the y-axis can differ per parameter. The specific values of each superimposed error are shown in the figure caption. It should be specifically noted here that the goal of this analysis is not to compare the relative effects of the different model parameters. This is impossible as the effect of each parameter is dependent on the given model configuration. The main focus of this analysis is on the difference in patterns between dry and wet conditions, for different forest fractions ($0 \leq \alpha \leq 1$). The superimposed errors were based on realistic ranges in parameter values, known from the literature and various SMOS-related studies (e.g. Wigneron et al., 2007 and Kerr et al., 2007).

Figs. 5 and 6 show that the effects of superimposed errors are much more obvious in wet conditions than in dry. In each plot, the difference between two markers indicates, for a given $\alpha$, the sensitivity of the model to the parameter concerned. In wet conditions (Fig. 5), it can be seen that the effects of temperature $T$ ($T = T_h = T_c$) and the roughness parameters $H_k$ and $N_{\text{UV}}$ are greatest in the case of the most highly mixed swaths (i.e. intermediate values of $\alpha$). The parameters $\alpha^H$ and $\alpha^V$ also show the greatest effect on $\text{SM}$ retrievals in the case of highly mixed swaths, whereas $\alpha^D$ shows the most effect in more homogeneous grass or forest areas and $\alpha^D$ shows no clear relationship with $\alpha$. It is thus quite possible that the greater errors in retrieved $\text{SM}_{\text{swath}}$ at intermediate $\alpha$ are caused by non-linear mixing effects of (most of) the model parameters. However, in dry conditions (Fig. 6) the effects of superimposed errors are less clearly concentrated at intermediate values of $\alpha$. As said previously (Section 4.1.), in dry conditions the difference between vegetation and soil emission is smaller, therefore it is not surprising that in this case the influence of $\alpha$ on the overall results is also smaller.

Besides the dependence on $\alpha$, it is obvious that erroneous values of the default L-MEB parameters can lead to high errors in retrieved $\text{SM}$, especially in wet conditions. Given the difficulty of determining several of the L-MEB parameters (e.g. $\alpha^H$, $H_k$ and $N_{\text{UV}}$) independently, this issue will need attention from the very operational start of SMOS. Ideally, these parameters should be determined at the satellite scale by model inversion using actual SMOS data where possible.

### 5. Summary and conclusions

The NAFE ‘05 experimental data set was used to investigate L-MEB soil moisture retrievals over mixed Eucalypt forest/grassland swaths. Airborne L-band observations were selected over swaths with varying fractions of forest cover (0–1), on five separate days with different moisture conditions. The data set was used to study the retrieval of soil moisture from heterogeneous swaths using two different approaches, both based on a priori knowledge of forest fraction ($\alpha$). Model inputs for non-retrieved parameters were either default values taken from the literature or site- and time-specific values obtained from observations of nearby homogeneous swaths gathered during the same flight. Because of the experiment–specific configuration, the swath was used as the basic calculation unit.

In the first retrieval approach, swath-effective values of soil moisture (SM) and swath-effective vegetation optical depth ($\tau_{\text{NAD}}$) were simultaneously retrieved using the L-MEB model. In the second approach, soil moisture and optical depth retrievals of the non-forested (i.e. grass) fraction of the swath were performed, while the forest contribution to swath emission was known from forward modelling. This is, to our knowledge, the first study to use experimental data rather
than model simulations to specifically investigate the effect of forest cover fraction on soil moisture retrievals.

Because of the large spatial variation within the NAFE '05 experimental site, and the (375 m) resolution of the airborne swaths, a large amount of variation was present in the observed brightness temperatures. Although the amount of ground measurements was limited and the data set showed a few systematic inconsistencies, some additional calibration steps were performed to limit the consequences of these issues, resulting in a consistent data set suitable for the anticipated study. Given the obvious and well known difficulties and limitations of airborne campaigns, the retrieval results were generally very reasonable.

Concerning the swath-effective retrievals, values of swath-effective soil moisture ($SM_{\text{swath}}$) were slightly overestimated compared to area-averaged SM values resulting from field measurements. Retrieved values of $T_{\text{NAD,swath}}$ showed a general increase with increasing forest fraction ($\alpha$), as expected, but also an increasing overestimation with increasing forest fraction. Maximum retrieved values of $SM_{\text{swath}}$ and maximum errors in the retrieved values were found at intermediate values of forest fraction. These results are important for the SMOS mission as they indicate the difficulty in flagging upper limits of pixel forest fraction during soil moisture retrievals. The upper limit is expected to differ depending on forest type and density.

A subsequent sensitivity analysis for all L-MEB parameters showed that, especially in wet conditions, the errors superimposed on the parameter values often also had the greatest effect on retrieved $SM_{\text{swath}}$ at intermediate values of forest fraction. Besides this, it was shown that erroneous values of the default L-MEB parameters can lead to high errors in retrieved SM, especially in wet conditions. At the SMOS scale, it will therefore be necessary to determine correct parameter values with actual SMOS data and model inversion.

Concerning the retrievals for the non-forested (in this case: grass) swath fractions, $SM_G$ and $T_{\text{NAD,G}}$ were retrieved simultaneously, with a known forest emission derived from the homogeneous forest swaths in the area. Although these analyses were only valid for the range $0 \leq \alpha \leq 0.6$, retrieved values of $SM_G$ and $T_{\text{NAD,G}}$ were generally

Fig. 5. Results of superimposing errors on each of the fixed L-MEB parameters for 1/11 (wet conditions), then simultaneously retrieving $SM_{\text{swath}}$ and $T_{\text{NAD,swath}}$ for heterogeneous swaths ($0.01 \leq \alpha \leq 0.99$) only. The vertical axis shows the difference ($\delta$ [m$^3$m$^{-3}$]) between the mean RMSE($SM_{\text{swath}}$) found with and without (cf. Table 5A) superimposed errors. Legend per focus parameter: $T$: $\omega' = \text{default} - 5$ K, $\omega'' = \text{default} + 5$ K, $HP'; \omega' = \omega'' = \text{default} + 0.5; N_{\text{HR}}$: $\omega' = \text{default} - 1$, $\omega'' = \text{default} + 1; \omega', \omega'' = \omega' = \omega'' = 0$, $\omega'' = \text{default} + 0.1$; and 1$: $\omega' = \text{default} - 0.5$, $\omega'' = \text{default} + 0.5$. All non-focus parameters were fixed to default values during the retrievals. NB. Y-axes differ in range.
reasonable and close to observed values. The procedure used in this study, which involves retrievals of canopy parameters over homogeneous swaths, followed by retrievals of SM and $\tau_{\text{HAD}}$ over heterogeneous swaths, can also be used when SMOS is operational.

Due to the use of experimental data focussed specifically on forests, the current study is the first to give a realistic idea of the errors and uncertainties involved in soil moisture retrievals from partly forested swaths. This is a relevant contribution to the analysis of heterogeneous pixels in future studies in general, and to studies concerning SMOS calibration and validation in particular. However, it should be kept in mind that the field experiment on which this study is based was conducted over a rather open Eucalypt forest, and the results presented in this study are therefore site-specific. Of course Eucalypt forest is dominant in Australia but much less so in other parts of the world. An interesting follow-up to this study would therefore be to perform similar analyses over a variety of forest structures (i.e. types) and densities, in order to obtain a better idea of the differences in results involved on a global scale. Such a study could also offer more information on the relative influences of forest structure and forest density on soil moisture retrievals. For example, it may turn out that knowledge of the type of forest present in a SMOS pixel is less important for accurate soil moisture retrievals than information on the forest density. This remains to be investigated.

**Acknowledgements**

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