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A Multi-Sensor Approach for High Resolution Airborne Soil Moisture Mapping

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Abstract: Airborne remote sensing provides a viable option for high resolution mapping of near-surface soil moisture that allows larger areas to be covered in greater spatial and temporal detail than has hereto been possible from traditional ground based techniques. However, the current retrieval algorithms require information on near-surface soil temperature and vegetation water content in order to estimate the soil moisture from well calibrated horizontally polarised passive microwave data. This paper presents a methodology for retrieving this ancillary data, through relationships with other remote sensing data. Near-surface soil temperature is estimated from land cover specific relationships with thermal infrared data, and vegetation water content is estimated from land cover specific relationships with near- and shortwave-infrared data. The methodology is tested with data from the National Airborne Field Experiment (NAFE) conducted in the Goulburn River catchment in New South Wales Australia, during November 2005. This intensive month-long field campaign involved daily airborne flights with a Polarimetric L-band Multibeam Radiometer (PLMR) and thermal imager flown onboard a small environmental aircraft at altitudes ranging from 150m to 3000m AGL, yielding passive microwave data at resolutions from 62.5m across entire farms to 1km across entire regions. This study presents a preliminary analysis of the PLMR derived soil moisture product at 250m resolution across a 2000ha farm. This is the first airborne remote sensing study to both provide such high resolution soil moisture data and to take this multi-sensor approach to soil moisture retrieval. The remotely sensed soil moisture data is compared against ground near-surface soil moisture measurements taken at resolutions ranging from 250m to 500m across the same farm on the same days. These preliminary results indicate a good agreement of the retrieved and measured soil moisture spatial distribution, with an overall absolute retrieval error of around 6% v/v.

Keywords: Passive microwave, high resolution, soil moisture, remote sensing, airborne

1. INTRODUCTION

A new airborne system for environmental sensing has provided the capacity to economically map near-surface soil moisture at resolutions as high as 50m across large areas. Near-surface soil moisture at medium to high resolution is important information for agricultural management such as irrigation planning and crop productivity forecasting. Using remote sensing systems, crucial limitations of traditional in-situ soil moisture measurements are overcome by providing better spatial information. This paper presents some first results from such a soil moisture mapping system, and is demonstrated using ground and airborne data collected during the National Airborne Field Experiment (NAFE'05), conducted in New South Wales, Australia in November 2005. The airborne component of the campaign made use of a small environmental aircraft equipped with passive microwave, infrared and visible sensors to map the study area. Ground measurements included near-surface soil moisture, as well as ancillary data such as vegetation water content, land cover information and soil temperature. This study has mapped the top 5cm soil moisture at 250m resolution using this new airborne system, and evaluated the results with ground measurements across a 2000ha farm.

Brightness temperature measurements by the airborne Polarametric L-band Multibeam Radiometer (PLMR), together with ancillary information on soil temperature and vegetation water content, represent the input required for soil moisture retrieval. A significant part of this paper deals with establishing a methodology for estimating the soil temperature and vegetation water content information required. Ground-based thermal infrared radiometers were used to develop relationships between skin and top 5cm soil temperature, which are subsequently used to map the spatial variation in soil temperature from aircraft thermal imager observations. Likewise, relationships for estimating vegetation water content have been developed from ground measurements of vegetation water content, and visible, near-infrared (NIR) and short-wave infrared (SWIR) reflectance's. The Moderate Resolution Imaging Spectro-radiometer (MODIS) on Aqua was subsequently used to map spatial variation in vegetation water content, using vegetation type dependent relationships with a remotely sensed vegetation index.

Using this approach, maps of soil moisture, together with soil temperature and vegetation water content, have been produced. The retrieved soil moisture is compared to the ground measurements for coherence in both spatial and temporal variability. A very good agreement was found between the retrieved and measured soil moisture, particularly considering the preliminary nature of this study, with no systematic over- or under-estimation. Therefore the results are encouraging towards further use of this airborne system for soil moisture mapping studies.

2. SOIL MOISTURE

The theory behind microwave remote sensing of soil moisture is based on the large contrast between the dielectric properties of liquid water and dry soil. In this study, soil moisture is retrieved using the brightness temperature (T_b) equation of Ulaby et al. (1986), which treats the surface as a two-layer incoherent medium by

$$T_b = \left[1+(1-e)\gamma_{veg}\right](1-\gamma_{veg})(1+\alpha)T_{veg} + (e\gamma_{veg}T_{soil}) \quad (1)$$

where e is the surface emissivity calculated by the Fresnel equations as a function of the dielectric constant and sensor look angle, adjusted for surface roughness (Choudbury et al., 1979), γ_{veg} is the transmissivity of the vegetation layer, which is dependant on the vegetation opacity, α is the single scattering albedo which can be assumed as zero for L-band (Jackson and Schmugge, 1991), T_{veg} is the vegetation skin temperature and T_{soil} is the effective soil temperature. In this study, T_{veg} is assumed to be equivalent to T_{soil}, which is interpreted as the temperature of the top 5cm of soil, and estimated from thermal infrared observation of the ground surface.

3. SOIL TEMPERATURE

A relationship between near-surface soil temperature (T_{soil}) and thermal infrared observations (T_{TIR}) was developed from ground data collected during the NAFE'05 campaign. Ground T_{TIR} data were collected by four tower mounted TIR radiometers at sites with different vegetation cover (bare soil, native grasses, lucerne and wheat). Additionally, duplicate soil temperature sensors were installed at three different depths (1, 2.5 and 4cm) for each site, which provided T_{soil}. This relationship was subsequently applied to thermal infrared data collected by the aircraft, in order to obtain soil temperature estimates across the study area at the same time as passive microwave observations.

The top 5cm soil temperature was estimated as a weighted average of the measured temperature data, based on the thickness of the layer represented by the data. Subsequently it was found that the 2.5cm measurement was a good approximation to the top 5cm soil temperature, and was used to represent T_{soil} in this analysis.

While the relationship between T_{soil} and T_{TIR} is influenced by soil type, vegetation coverage and soil moisture, the primary influencing factor was found to be the time of day. Consequently, a single linear empirical relationship was developed for the campaign period (Figure 1), with slope and offset depending on the aircraft observing time

$$T_{soil} = slope(t) \times T_{TIR} + offset(t). \quad (2)$$

This relationship has been applied to the infrared temperature detected by the airborne thermal imager to obtain maps of soil temperature for the entire study area (see Figure 3). Table 1 contains the coefficients associated with the plots in Figure 1.

In order to achieve a 4% v/v accuracy in soil moisture retrieval (the goal for the future SMOS mission), soil temperature must be estimated with an error lower then 4 Kelvin (very dry soil) and 7 Kelvin (very wet soil). Analysis of the regression equations proposed here for soil temperature estimation suggests an error in derived soil temperature of less than 3K, which is well below the required accuracy.

Table 1. Slope and offset coefficients used by equation (2) to estimate soil temperature from TIR data as a function of time.

Time	Slope	Offset
7am	0.496	10.22
10am	0.372	13.22
1pm	0.452	14.12
4pm	0.636	10.13

4. VEGETATION EFFECT

The vegetation layer absorbs and scatters the microwave radiation emitted by the ground surface, as well as being a source of microwave radiation itself. The vegetation effect is therefore an important factor to be considered in passive microwave soil moisture retrieval, and is usually quantified through a parameter called vegetation optical depth or vegetation opacity, τ. The transmissivity of the vegetation layer depends on the vegetation opacity, according to

$$\gamma_{veg} = \exp\left[-\tau \sec \vartheta\right]. \qquad (3)$$

The value of τ depends on the vegetation type, the vegetation water content (VWC) and the wavelength of the radiation. The model used in this study is from a previously developed relationship between τ and VWC of the form $\tau = b*VWC$ (Jackson and Schmugge, 1991), where b is an experimentally derived parameter dependent on the vegetation type and the wavelength. Estimates of VWC and observations of vegetation type are therefore required in order to apply this model to the soil moisture retrieval algorithm. This was achieved by building relationships between ground measured VWC and reflectance's in the visible, NIR (near-infrared) and SWIR (short-wave infrared) bands, and subsequently upscaling the VWC to the whole study area using satellite imagery acquired using the same bands.

4.1 Vegetation Indices

A vegetation index that can provide estimates of VWC is typically a ratio between the difference and the sum of radiances in two different bands: a reference wavelength where the water absorption coefficient is low and a measurement wavelength where water absorption is moderate or high and the penetration into the canopy is maximised. The most common vegetation index is the Normalised Difference Vegetation Index (NDVI), based on the NIR and red bands. However, several studies have indicated that NDVI has a reduced sensitivity to changes in VWC in the case of dense vegetation coverage. In order to capture the wide range of canopy

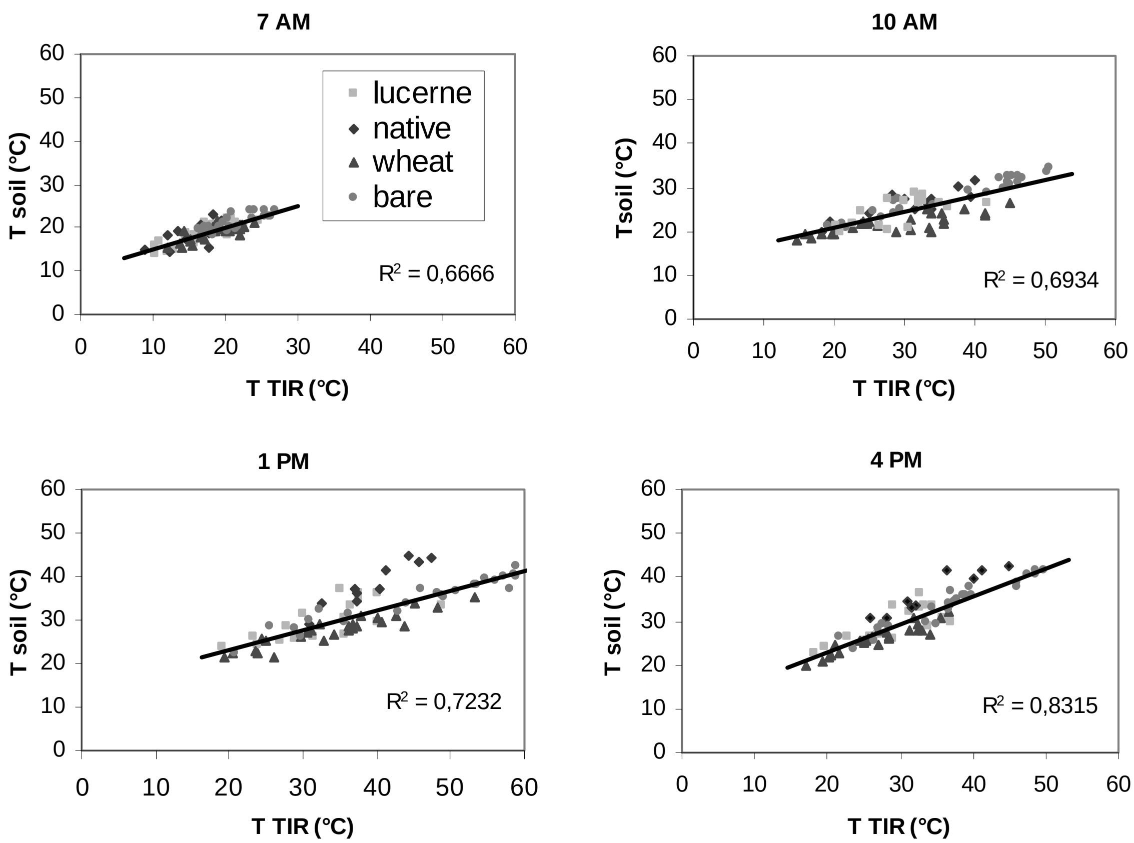

Figure 1. Examples of the linear regression between soil temperature and thermal infrared measurements at four different hours of the day. The relationships are based on data collected for four different land cover types.

conditions present at the Goulburn study area, an additional index was investigated, the Normalized Difference Water Index (NDWI), based on the water absorption dominated SWIR bands which are more sensitive to VWC changes (Jackson et al., 2004)

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR}. \quad (4)$$

In order to develop relationships between MODIS-based vegetation indices and VWC, and to assess the performance of these relationships, ground VWC data collected during NAFE’05 and MODIS daily reflectance (bands 1-7, 500m resolution) were used. The VWC data was obtained by weighing vegetation samples before and after drying for seven days in an oven at 40°C, physically defined as the mass of water per ground unit area (kg/m²). Both the NDWI indices used by Jackson et al. (2004), $NDWI_{1640}$ (using SWIR 1640nm) and $NDWI_{2130}$ (SWIR 2130nm), have been evaluated from daily MODIS 500m reflectance data in bands 6 and 7, to find a relationship between VWC and a vegetation index that is representative of a wide range of canopy conditions (Figure 2). It was found that $NDWI_{1640}$ gave the best relationship for estimating crop (wheat and barley) VWC (R^2=0.79, RMSE=0.39kg/m²)

$$VWC = 13.2 \mathrm{x} (NDWI_{1640})^2 + 1.62 \mathrm{x} NDWI_{1640}, \quad (5)$$

while $NDWI_{2130}$ gave the best relationship for estimating native vegetation (R^2=0.90, RMSE=0.02kg/m²)

$$VWC = 0.78 \mathrm{x} NDWI_{2130} + 0.01. \quad (6)$$

4.2 Land Cover

To estimate VWC across the study area, a map of the land cover was required to distinguish between areas of crop and native vegetation. A supervised land cover classification was performed on a Landsat image using information about vegetation type collected during the field campaign, in order to derive this map. The resulting classes include urban, crop and native vegetation.

4.3 VWC Estimates

Using daily MODIS reflectance data and the land cover classification, VWC was estimated at 500m spatial resolution across the study area for cloud-free days, applying the relationships given in equations (5) and (6) for crop and native grass respectively (see Figure 3).

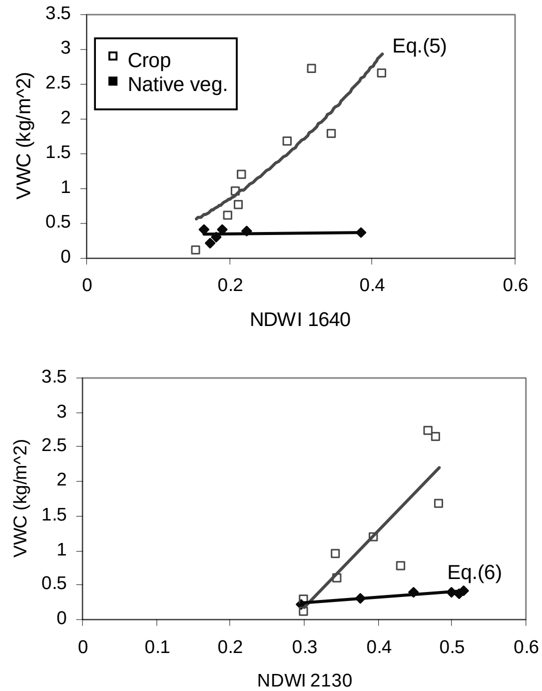

Figure 2. Vegetation water content as function of MODIS derived NDWI. The symbols represent individual ground data while the continuous lines are the fitted relationships.

5. SOIL MOISTURE ESTIMATION

While the NAFE’05 data set includes flights across an entire 40km x 40km area at 1km, and a total of 8 farms at 62.5m, 250m, 500m, and 1km resolutions, only results for the Midlothian farm at 250m and 500m spatial resolution are presented here. The algorithm developed processes input data in the form of grids, where each grid cell corresponds to the value of the input variable for a location in space. These grids correspond to raster representations of the variable spatial distribution.

As the three input data came from different sensors, pre-processing was necessary to provide the data on a consistent grid specification. Therefore the brightness temperature, vegetation water content and soil temperature data were georeferenced in the same coordinate system (Universal Transverse Mercator, UTM) and interpolated to the same spatial resolution and grid orientation.

Two regular grids (250m and 500m) covering the Midlothian farm were created as reference grids for all the input data, corresponding with two of the PLMR brightness temperature resolutions. Soil temperature data were aggregated to the appropriate resolution, and 500m VWC data applied directly at 500m and

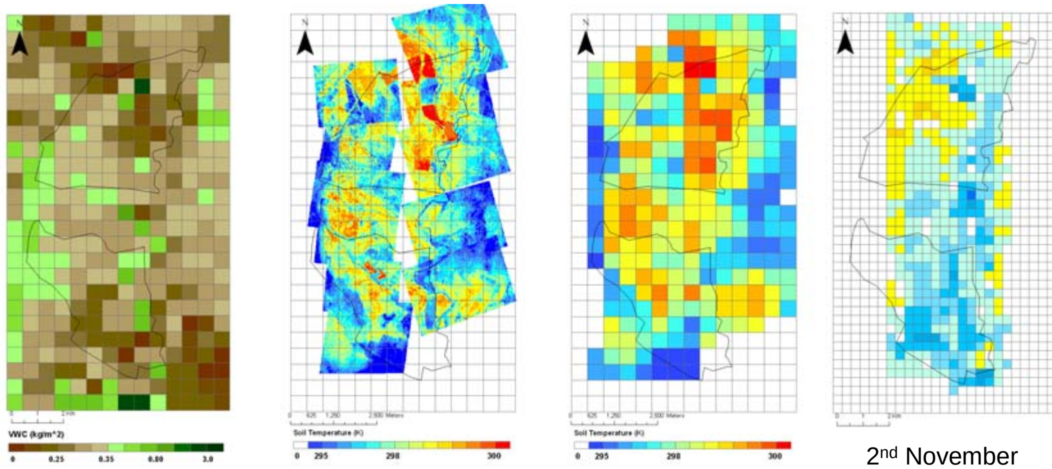

Figure 3. From left to right, maps of derived VWC from 500m MODIS data and a land cover classification, derived soil temperature from aircraft measurements of thermal infrared and subsequently processed to 500m resolution, and retrieved soil moisture at 250m resolution.

nested 250m resolutions. Soil moisture retrieval was then estimated from equation (1); see Figure 3.

The soil moisture retrieval performance was evaluated by making comparison with the ground data collected during the NAFE'05 campaign. This ground data includes soil moisture measurements across parts of the Midlothian farm on the four dates that aircraft data were processed and continuous measurement of rainfall and soil moisture at a permanent recording station on the same farm (Figure 4).

6. RESULTS

The absolute error was calculated in each pixel containing both ground observations and retrieved soil moisture. Ground sampling was performed at the Midlothian farm once a week during the month-long field campaign. Mean absolute error (MAE) and error variance are summarised for each of the four days and two resolutions in Table 2.

Table 2. Mean absolute error (MAE) and variance of the error (% v/v) across Midlothian farm for the two resolutions and four dates.

	MAE		Error Variance	
	250m	500m	250m	500m
2-Nov	5.9	6.3	0.6	0.6
11-Nov	5.1	6.6	0.4	0.6
16-Nov	7.9	9.3	0.6	0.5
23-Nov	3.1	2.7	0.2	0.0
Average	5.7	6.8	0.4	0.4

A satisfactory error in soil moisture estimation is considered as 4% v/v; the target for the future SMOS mission. This aim was achieved on November 23 when the soil moisture variation was low and the soil moisture content was dry, with both resolutions having a MAE of about 3% v/v. In all the other cases the MAE was lower than 9% v/v, with an average MAE of 5.7% v/v for the 250m resolution and 6.8% v/v for the 500m resolution. While these are somewhat larger than the target accuracy, one must remember that a single point measurement is being compared with an areal average, and these point measurements may not always be representative of a larger area. Moreover, these are preliminary results that are relying upon a preliminary calibration of the point measurement device.

It was also found that there was no systematic over- or under-estimation for three out of four days of data processed. Only on November 16 was there evidence of an underestimation in the value of soil moisture. This is likely to be due to the drying process the soil was experiencing on that day, as a result of earlier rainfall.

The temporal trend of the soil moisture variation during the month of the campaign was well predicted by the model, since there is consistency between the retrieved soil moisture, ground measured soil moisture, and rainfall observations (Figure 4). The whole range of conditions for soil moisture has been successfully retrieved, from the first week of the campaign when the soil water content was close to saturation, through to the last week of

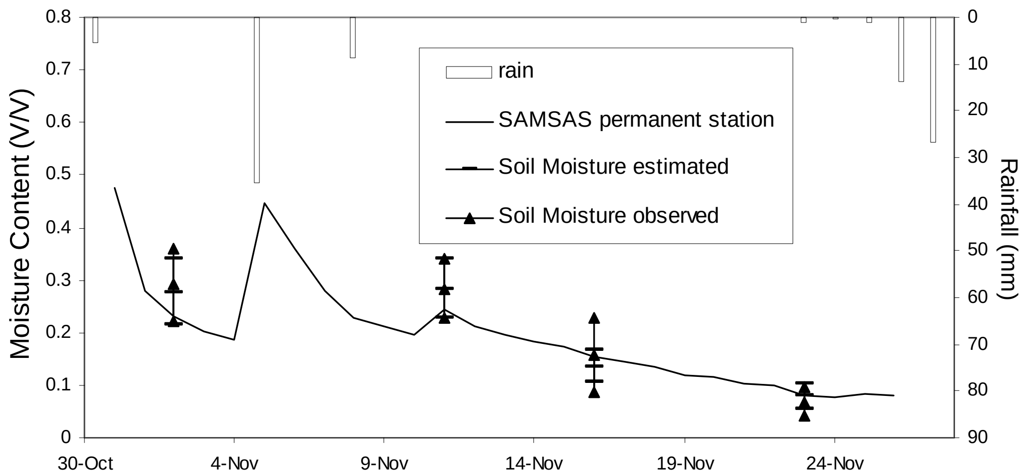

Figure 4. Comparison of continuous soil moisture measurement at one location on the Midlothian farm, with spatial (min/mean/max) soil moisture from ground measurements and estimates from concurrent aircraft observations. Also shown is daily rainfall observed at the monitoring station.

the campaign when soil moisture was close to the residual moisture content across the entire farm.

7. CONLUSIONS

The results from this preliminary study are encouraging. Consequently the methodology presented here will be refined and applied to further data sets of NAFE for ongoing improvement and verification. An ability to efficiently and economically map soil moisture content across entire farms and/or regions at resolutions as high as 50m will be a powerful tool for many environmental applications.

8. ACKNOWLEDGEMENTS

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