

Validating Soil Moisture Estimates from Polarimetric Radar Using GIS Models : further results from the 1993 AIRSAR mission to Australia.

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Abstract

The capability of active microwave remote sensing to measure soil moisture was validated via the use of GIS techniques incorporating soil landscape unit assessment and terrain wetness. The work was carried out over an 80 km² region in the Mount lofty Ranges in South Australia. Search for atypically wet sites (ie. wet areas in a dry landscape, which were non-irrigated) was completed using analysis of co-registered visible - infra-red imagery from Landsat.

Soil dielectric constant (a surrogate for volumetric soil moisture) was derived from L Band polarimetric AIRSAR data acquired in the 1993 mission to Australia. Results from this dielectric modelling, which have been previously reported by Bruce (1996), showed areas of wet soil in the landscape. At the sub-catchment scale (2 km²) reasonable correlation with ground measurements of soil moisture was observable and, moreover, correlation with other data sets indicating soil wetness was encouraging. These data sets, reported in more detail by Fitzpatrick *et al* (1999), consisted of a Topographic Index (TI), derived from contributing surface area and slope, a Discharge Index, derived from EM31 ground measurements, a Vegetation Colour Index, derived from multi season aerial photography and a potential waterlogging attribute, extracted from a Soil Landscape Units (SLU) GIS data set derived from mapping at 1 : 50,000 scale. The strength of the spatial correlation between these data sets led to a comparison, at the regional scale, of the soil moisture as inferred from polarimetric radar, with the SLU and TI. This comparison showed that indeed L band Polarimetric radar can be processed to estimate broad categories of soil wetness and, when combined with co-registered Landsat TM data, can be used to locate unusually wet sites where ground water discharges at the surface.

In a related component of the research, it was found that soil dielectric/wetness derived from the polarimetric SAR assisted the prediction of soil salinity at both the catchment and regional scales. At the latter scale soil dielectric was combined with geology, TI and SLU to create a best estimate of potential salinity.

Soil Moisture Estimation Using AIRSAR

Soil dielectric constant has been derived from the use of Synthetic Aperture Radar (SAR) multi-polarisation C-, L- and P- band data from the NASA/JPL airborne synthetic aperture radar (AIRSAR) instrument which acquired imagery over the study area for early spring, 1993. The processed data for the site was received from JPL as a 12 band composite image with pixel size of approximately 6.7 m × 8.3 m. The characteristic effects associated with data of this type, ie. near-range compression, brightness fall-off and radar speckle were all present in the image and it was necessary to correct for some of these geometric and radiometric errors prior to processing for soil moisture determination. In addition the image was re-sampled to a 10 m pixel size for effective comparison with the other data sets.

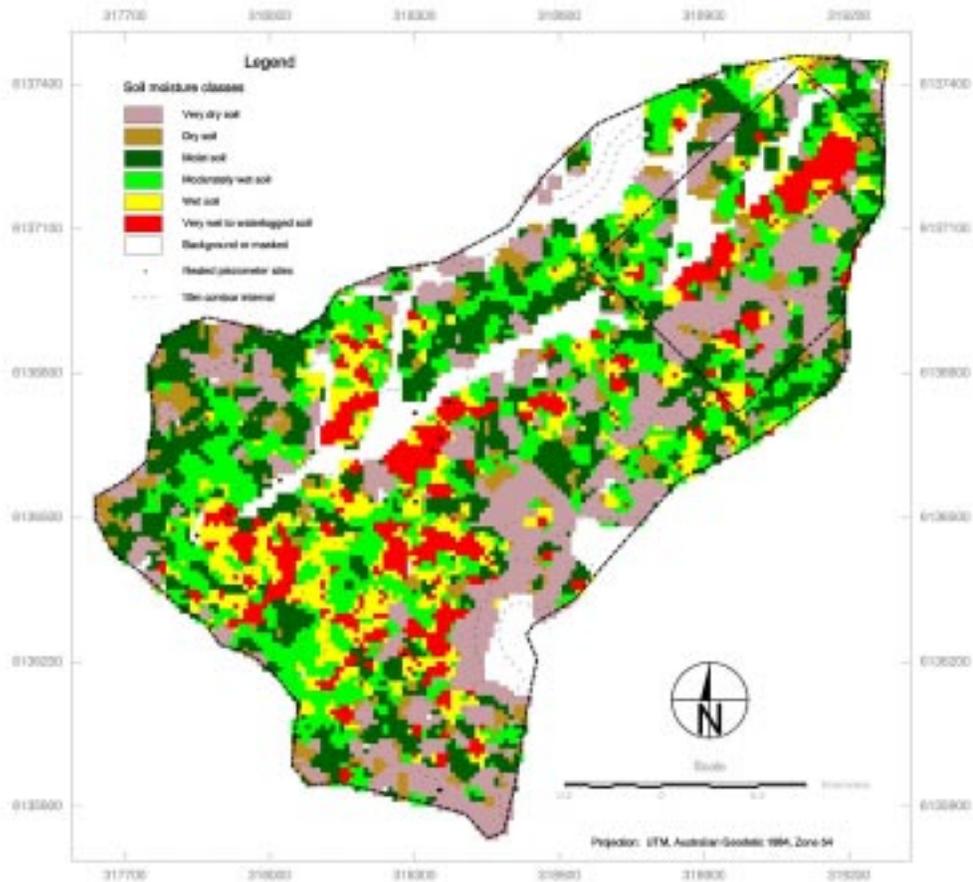
Dubois *et al.* (1995) suggested an empirical approach for the modelling of radar backscatter (σ^0) from the variables of incidence angle (θ), soil dielectric constant (ϵ), wave number (k), surface roughness (s) and wavelength (λ). The model, which utilises co-polarised data and is expressed in the following relationships:

$$\sigma_{hh}^0 = 10^{-2.75} \frac{\cos^{1.5} \theta}{\sin^5 \theta} 10^{0.028\epsilon \tan \theta} (ks \sin \theta)^{1.4} \lambda^{0.7} \quad \sigma_{vv}^0 = 10^{-2.35} \frac{\cos^3 \theta}{\sin^3 \theta} 10^{0.046\epsilon \tan \theta} (ks \sin \theta)^{1.1} \lambda^{0.7}$$

was implemented for the L-band of the AIRSAR data. The inversion model, which is described in more detail by Bruce (1996), utilises three input raster data sources and produces two output raster images. The first input consisted of the corrected AIRSAR image, which had been despeckled and geometrically corrected. The second input consisted of an image of local incidence angle deduced from the radar geometry combined with the DEM described above. This derivation computes the slope and aspect of each DEM cell and uses this as input to a trigonometric solution for the local incidence angle in the direction of the SAR pulse. The final input to the model is a binary mask image in which all objects with large backscatters, particularly in the VV polarisation, are identified so as to not be used in the output calculations. These objects, which are usually stands of native trees, buildings, etc., are masked out of the output data as they are not bare soil (or soil covered by grass). The two outputs of the model are maps of soil dielectric/wetness and roughness.

Results of the work conducted by Bruce (1996) have been compared with ground measurements and GIS data at the catchment scale (2 km²). The variation in the raw values of the soil dielectric constant is considerable with some values even being less than 1 ! This shows weakness in the model and/or unsuitability in the application of the model to this terrain type. Some poor results (approximately 1 % of the input) can be attributed to backscatter from terrain objects such as wire fence lines within +/- 25^o parallel orientation to the radar antenna. In order to make this estimate of dielectric constant more useful, the output was processed such that error values were rejected and the remaining values re-coded to six classes of soil wetness/drainage. A generalisation of the output was then undertaken using a majority filter. Re-coding was validated at the catchment scale by comparison with the other data sets and then applied to the majority of the area covered by the AIRSAR image (~ 80 km²) with the near range component of the image data being removed due to the extremely low incidence angles. Figure 1 illustrates this final dielectric/wetness product.

RADAR derived soil moisture: Herrmann's catchment study area, Mt Lofty Ranges



**Mt Torrens 80 km² study area
(RADAR derived soil moisture)**



Produced by: CSIRO Land & Water, Adelaide
 Date: July 1999
 Data Source: Compiled by D.A. Braco from polarimetric analysis of airborne RADAR (AIRSAR) data acquired September 1995 by MAGA/PL and resampled to 10 m pixel size



RADAR derived soil moisture: Mt Torrens study area, Mt Lofty Ranges

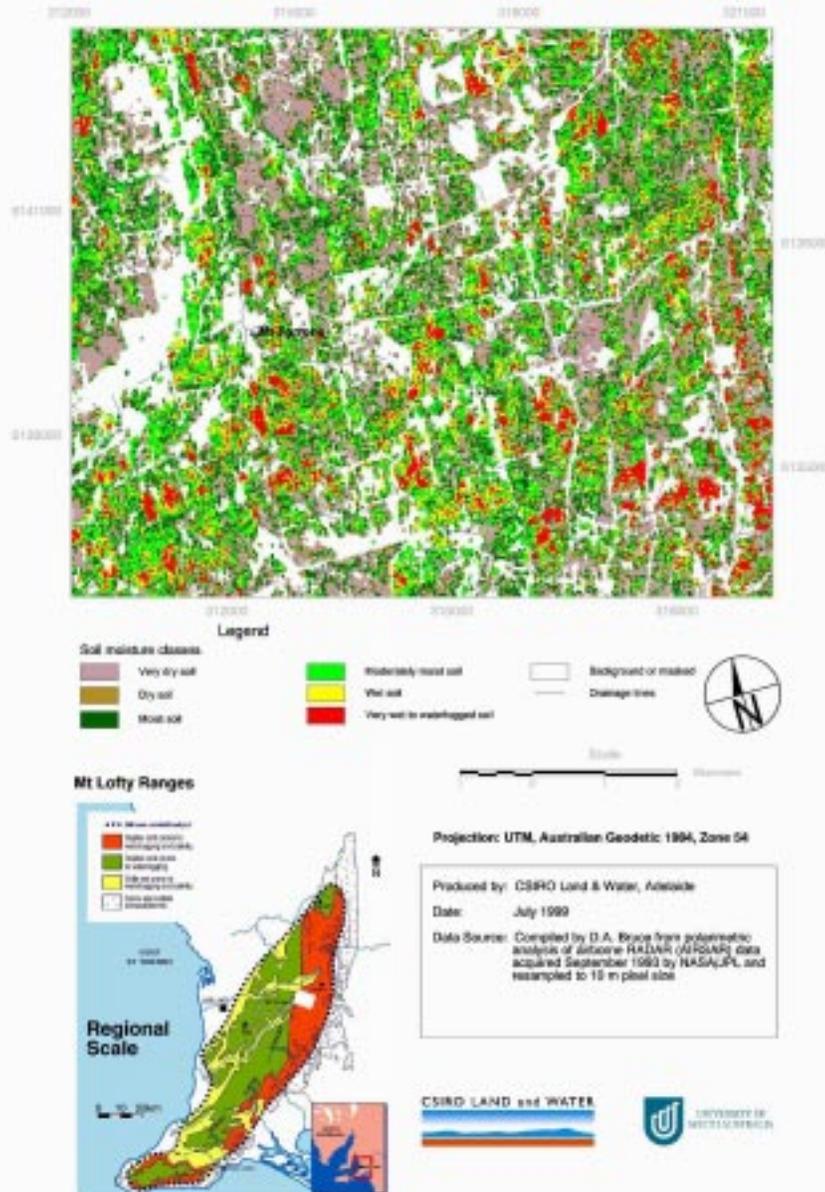


Figure 1 : Soil dielectric constant/wetness at the catchment scale (2km²) –top and the regional scale (80 km²) bottom.

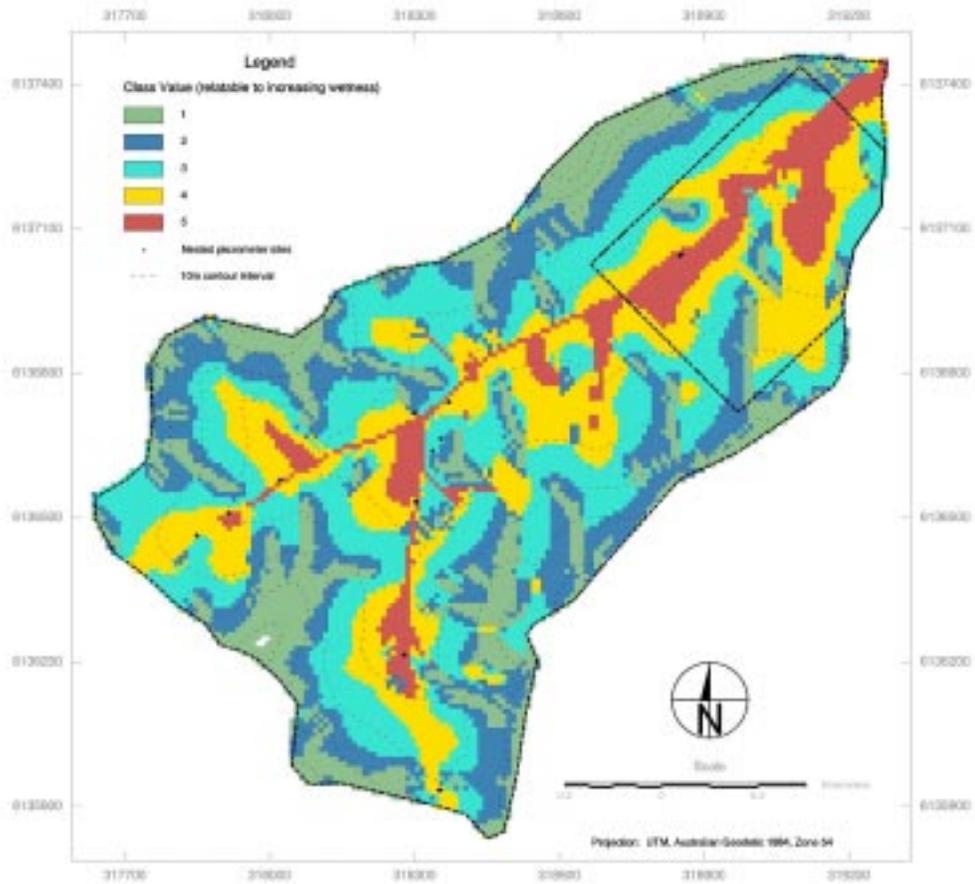
In Figure 1 colours range from white (masked), through brown (dry soils), to yellow and red (wet, poorly drained soils). In order to validate the use of the dielectric/wetness mapping reported above, a second predictive indicator of soil wetness was developed : this was the Topographic Index.

Topographic Index (TI)

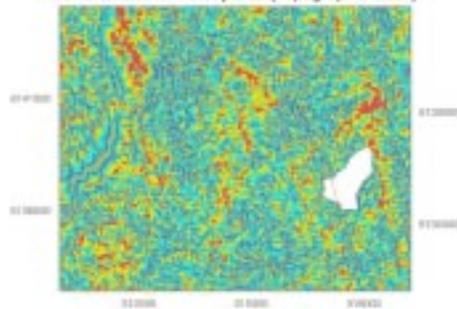
The Topographic Index was derived from analysis of the shape of the land surface by Davies *et al* (1998). The primary modelling structure used in this analysis of catchment topography is the DEM, of which there are three fundamental representations: grids, triangular irregular networks and digital contours (see Weibel and Heller, 1991 for a detailed review of elevation model structures). To determine the spatial distribution of a topographic index for the study area a hydrologically correct, grid DEM was created using the method of Hutchinson (1989). The interpolation technique imposes morphological constraints on the DEM using existing drainage, such that elevations decrease monotonically down each stream line and ridges and streams are represented more accurately (Hutchinson, 1993). The inputs to the interpolation are essentially drainage and elevation data and prior to input, the required inputs were edited and cleaned to remove any errors of logical consistency.

For this study a DEM with cell size of $10\text{ m} \times 10\text{ m}$ was created as the most suitable for simulating geomorphic and hydrological processes (Zhang and Montgomery, 1994), while reducing the bias towards large topographic index values associated with coarser grid sizes (Quinn *et al.*, 1995). The topographic index, $\ln(A_s/\tan\beta)$ was calculated for the study area to represent the geomorphic processes associated with soil moisture and its spatial distribution in the landscape. The variables of the index (A_s = specific catchment area; $\tan\beta$ = local slope angle) were evaluated on a cell by cell basis from the DEM, using the procedure of Hutchinson and Dowling (1992). This index was computed for both a 10m resolution DEM for the entire area and a 5m resolution DEM available for just the small focus catchment area. Results showed that the 10m resolution DEM provided a better macro view of the catchment surface hydrology than the 5m DEM, which gave a view of the micro patterns of potential surface water distribution. Consequently, the Topographic Index from the 10m DEM was used in further analysis, which consisted of majority filtering and a re-coding to 5 drainage/wetness classes. The final result of the topographic analysis can be viewed in Figure 2 where colour ranges from green (low Topographic Index) to red (high Topographic Index). This range can be viewed to represent a potential variation in soil wetness condition.

Topographic Index for Herrmann's catchment study area, Mt Lofty Ranges



Mt Torrens 80 km² study area (Topographic Index)



Produced by: CSIRO Land & Water, Adelaide
 Date: July 1999
 Data Source: Compiled by P.J. Davies from a 10 m grid DEM using ARC/INFO TOPOGRID
 Topographic Index = ln(Astariff)



Topographic Index distribution: Mt Torrens study area, Mt Lofty Ranges

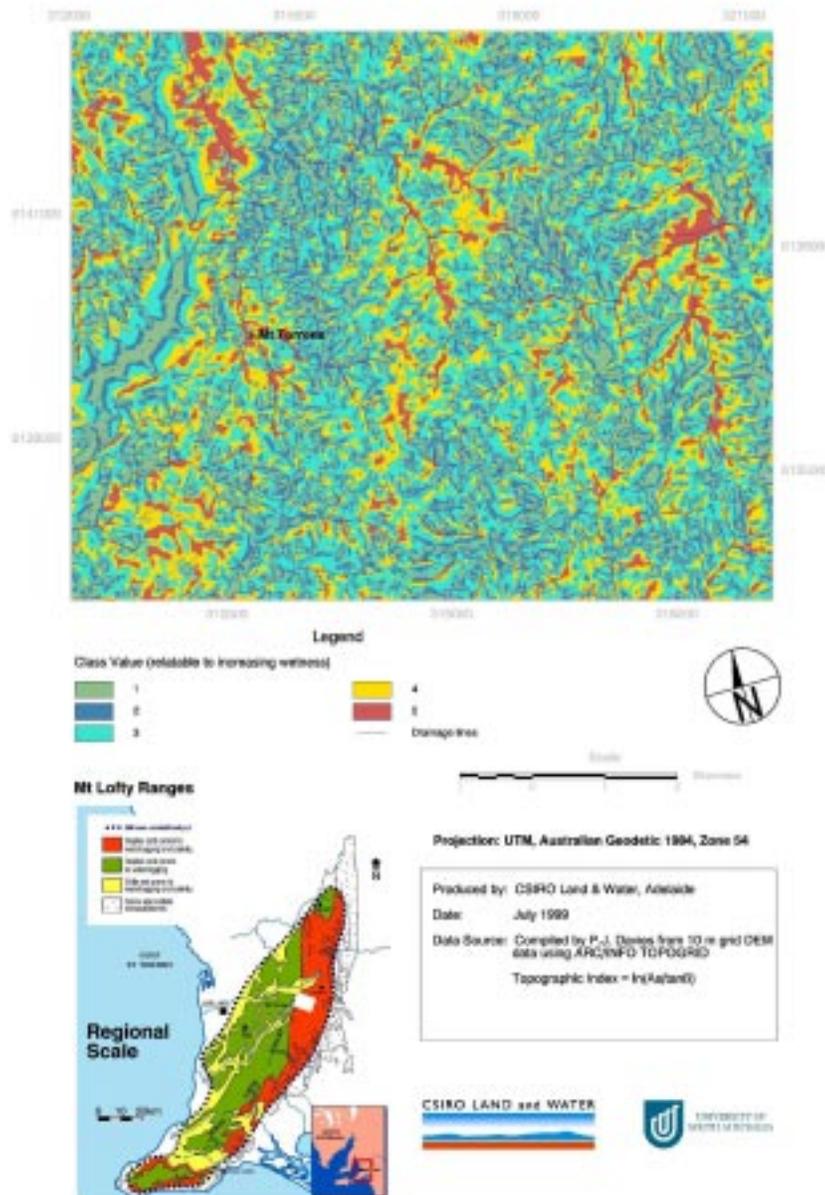


Figure 2 : Topographic index (TI) at the catchment scale (top) and at the regional scale (bottom)

Soil Waterlogging from Soil Landscape Units (SLU)

Soil Landscape Units (SLU) data are produced for the whole of the state of South Australia with 1:50,000 mapping by the Department for Primary Industries and Resources, SA (PIRSA). The land classification tables associated with the digital SLU data summarise a range of key attributes for each mapping unit. These attributes, or land qualities include: drainage, water erosion potential, scalding, salinity and recharge potential. The classification ranks each of these land qualities on a

numeric scale, according to eight, generically defined class limits. Each successive class implies an increasing level of management input to overcome any limitation(s) identified by the classification from Class I (very low level of limitation) to Class VIII (extreme level of limitation).

For this study, two attributes (salinity and drainage) were identified as being indicative of aquic conditions (i.e. soil landscape units prone to waterlogging). These were selected as inputs to a weighted index model with salinity given a greater weighting as it was considered an indicator of more permanent wetness in the landscape (Cox *et al.*, 1996). The results of this model are visible in Figure 3 and are shown at the regional scale only, as the original PIRSA mapping was not intended to be used at large scales. Colours in Figure 3 vary from brown (minor susceptibility to waterlogging) through beige, green, gray and blue (severe susceptibility to waterlogging). This aquic Index is a predictor of soil wetness as is the Topographic Index discussed above.

Aquic Soil Index: Mt Torrens study area, Mt Lofty Ranges

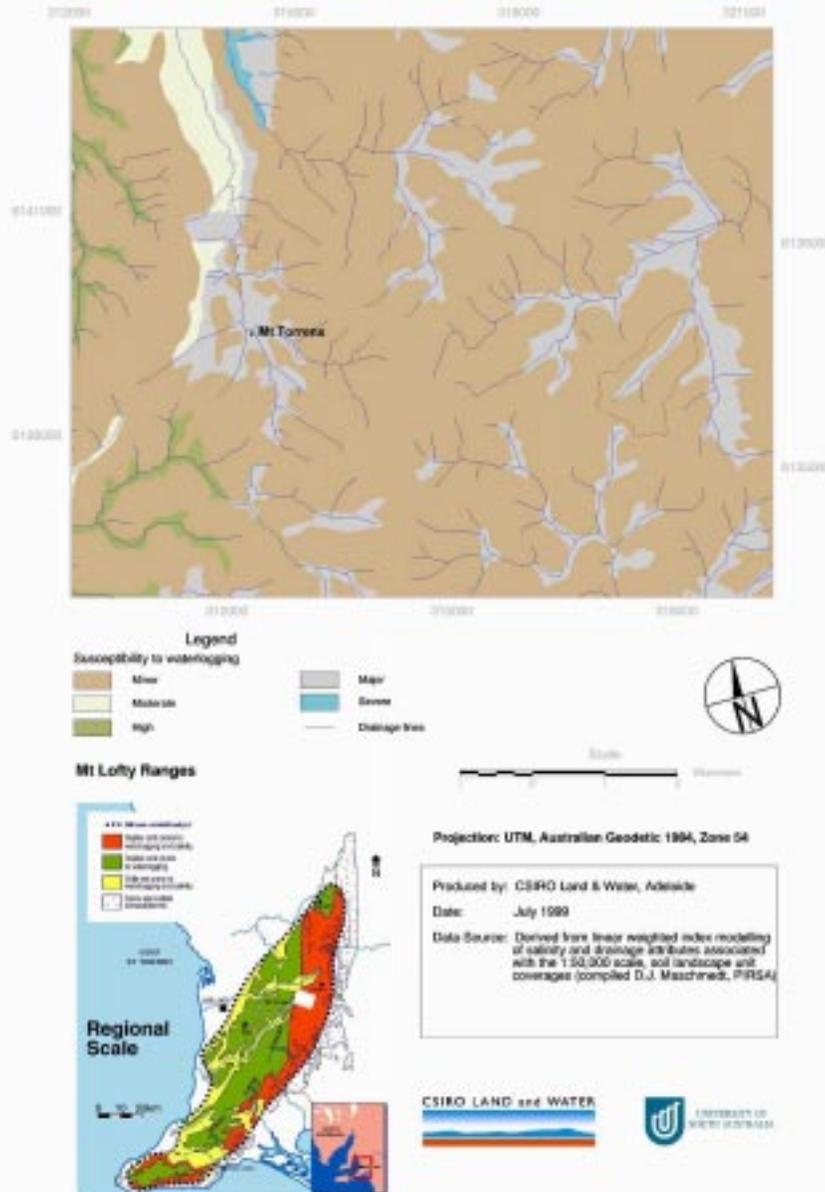


Figure 3 : Aquic soil index from SLU data at the regional scale.

Multi data set Comparison.

Comparison of the three models of soil wetness at the regional scale was carried by overlay techniques in GIS. Figure 4 provides the reader with a view of a section of the region showing all three soil wetness models. Consultation of Figure 4 shows strong agreement between the critical classes in the Topographic Index (yellow and red) and the aquic index (blue), with the Topographic Index providing greater detail than the Aquic Index. Critical soil dielectric/wetness classes (yellow

and red) show some agreement with the other two indicators in the valleys, but also show disagreement in some of the up slopes. The most noticeable difference is the linear grouping of high soil dielectric/wetness running from south to north along the eastern edge of Figure 4 left. This corresponds to a fault system known as Fendler Hill fault and represents areas of terrain with relatively steep slopes facing away from the radar antenna. Furthermore, this fault is one of the areas in the region where north – south rock lineaments feature at or near the surface.

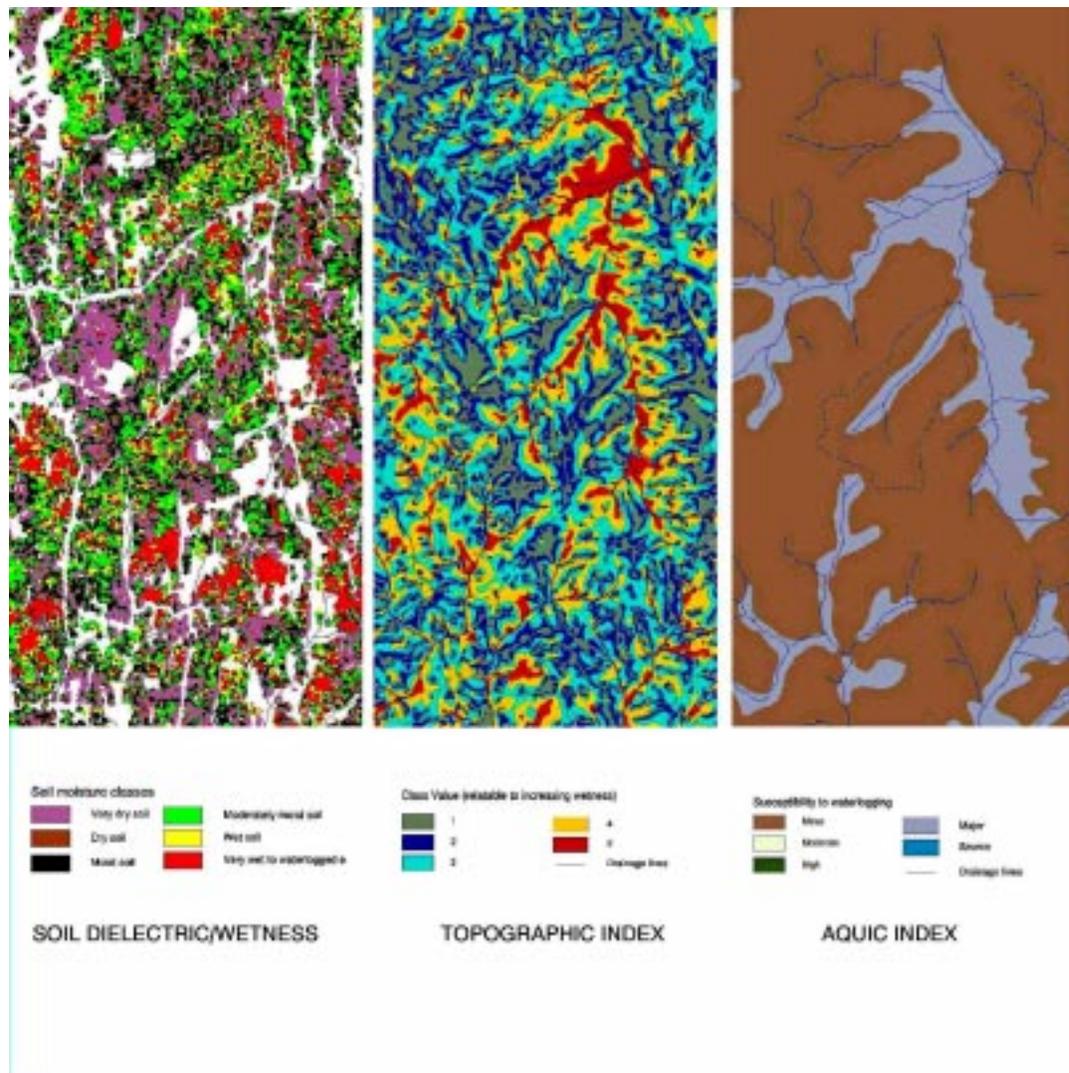


Figure 4 : Comparison of soil wetness from AIRSAR (left), Topographic Index (middle) and Aquic Index (right) for the same section of the regional area.

A “best estimate” of drainage/waterlogging at the regional scale has been constructed from the experience gained at the catchment scale. Up-scaling of processes using all data sets at the catchment scale was not possible, as detailed vegetation index and discharge index data were not available at the regional scale. Previous work by Bruce has shown that single date Landsat TM imagery does not provide sufficient differentiation of vegetation classes and multi-season imagery was not available. However, it is believed that future research (late 1999) utilising hyper-spectral data will provide sufficient discrimination of vegetation units to allow its incorporation into the model. Soil Landscape Units (SLU) data was used to derive the aquic index as described above and this was utilised in conjunction with the soil dielectric/wetness and topographic index to generate the best estimate of water logging at the regional scale. This estimate is derived from the following raster GIS model :

$$BEWL_R = 2*TI + DC + AI$$

Where $BEWL_R$ = Best Estimate of drainage/waterlogging at the regional scale.

TI = Topographic Index

DC = Soil Dielectric/wetness

AI = Aquic Index.

This model carries the same weights for the Topographic Index and soil dielectric as was applied at the catchment scale and results in the information presented in Figure 5. This estimate is predominantly a drainage/waterlogging prediction, but does carry some measurement bias through the soil dielectric determination. The areas masked out in the soil dielectric/wetness modelling due to large backscatter are now overridden by the other two data sets. Colours vary from brown (rarely waterlogged – freely drained), through beige, green, grey to blue (very poorly drained – strongly waterlogged).

Best estimate of drainage/waterlogging: Mt Torrens study area, Mt Lofty Ranges

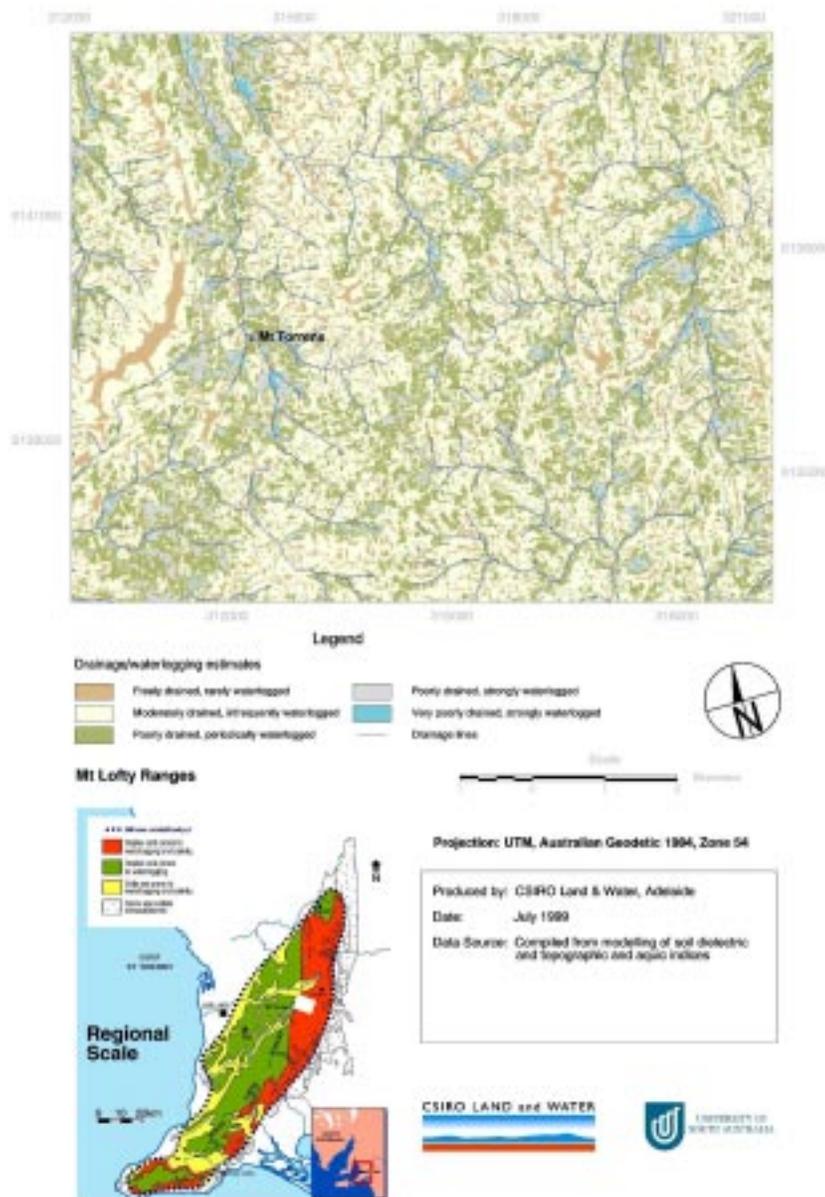


Figure 5 : Best estimate of soil waterlogging at the regional scale.

Combining Soil Dielectric and Landsat Data

Landsat Thematic Mapper data was acquired together with the 1993 radar data and at subsequent dates. This was used in conjunction with the backscatter data to classify large objects (buildings, trees, etc) for non inclusion in the soil dielectric/wetness modelling. Further information from the red and infra-red bands (3,4 and 5) of the Landsat TM enabled easy identification of crops

used in irrigation. It is most likely that these areas would have exhibited moist soils due to the irrigation practice and thus it is possible to differentiate between those areas in the landscape at which moist soil is due to waterlogging and those areas which are moist due to irrigation. Figure 6 illustrates a subset of the region with Landsat TM 5 on the left and the dielectric/wetness map on the right.

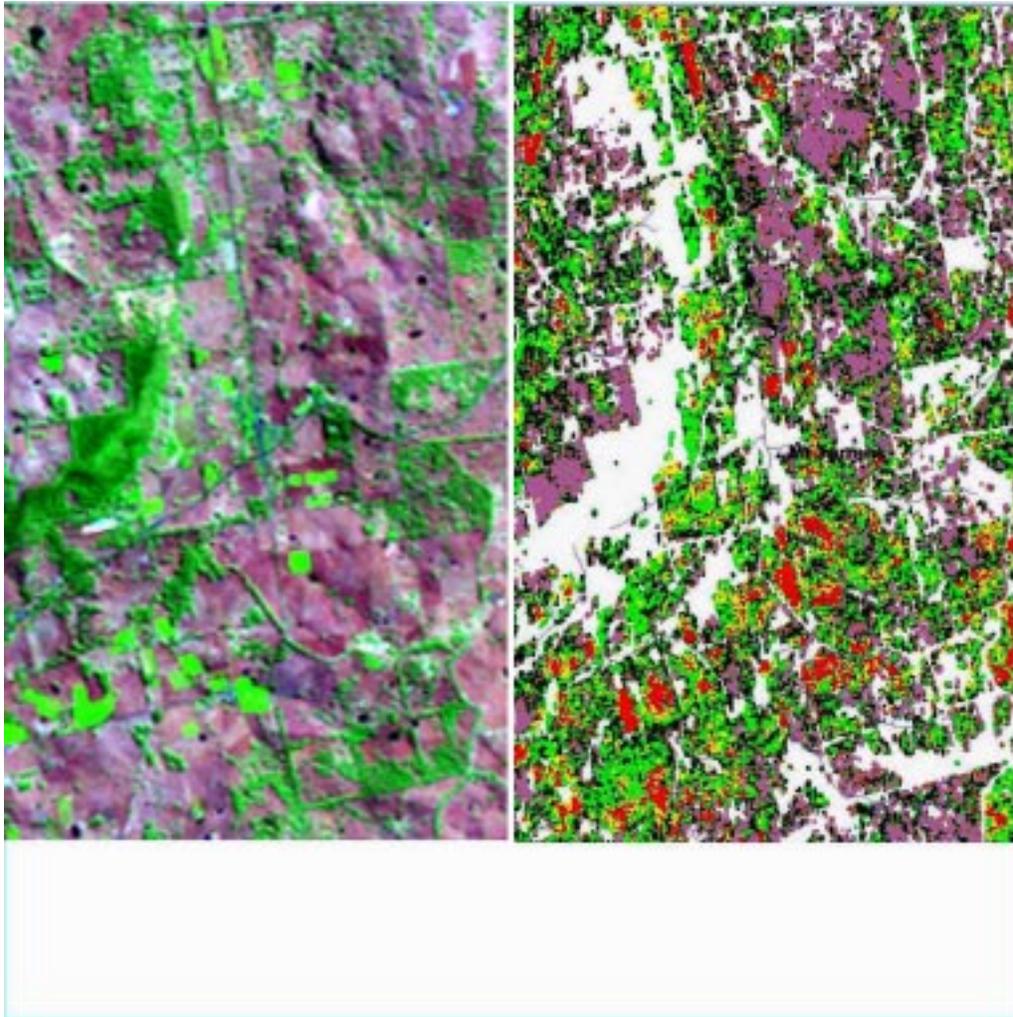


Figure 6 : Comparison of Landsat TM (5,4,3) and Dielectric/wetness

It is relatively easy to recognize irrigated crops in the left hand image by the small, smooth bright green patches. Many of these correspond to areas of high dielectric/wetness (yellow and red) in the right hand map. This kind of analysis shows the power of the combination of polarimetric SAR with visible, infra-red imagery and suggests many other possibilities such as in the areas of surface salinity.

Polarimetric Radar and Salinity

The relationship between the complex component of the soil dielectric constant and soil salinity has been alluded to by Dobson (1993). Whilst the intention of the dielectric constant work described above was to estimate soil moisture (using the real component of the dielectric constant) a slightly unexpected outcome of related work was that, when constructing the “best estimate” of soil salinity at the regional scale, Fitzpatrick *et al* (1999) found that incorporation of the soil dielectric/wetness produced a better estimate than other combinations of data. Soil dielectric/wetness was used in conjunction with digital geology, TI and SLU to predict the existence of surface salinity in the landscape. This was validated by field verification at a number of sites across the region.

Conclusions

The results of the 1993 AIRSAR data acquisition over the central Mount Lofty ranges in South Australia are encouraging from the perspective that extreme values of soil moisture can be qualitatively measured. When results from the early spring acquisition are compared with predictive models using soil landscape units and topography, reasonable agreement is apparent. However, differences do exist between these models, with such differences possibly attributable to extreme incidence angle effects, or to the existence of rock structures in fault zones. A new acquisition of the same area simultaneously with extensive ground truthing is planned for PACRIM 2 in April 2000. This timing will be very advantageous as it represents the end of the long dry summer season : a time when moist soils are either irrigated or are experiencing ground water discharge. The latter is a strong indicator of surface salinity in this geographic area and tests will be undertaken to examine the relationship between this phenomenon and the complex component of the dielectric constant inferred from the polarimetric SAR.

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