2011

ACLEP-Tasmanian Digital Soil Mapping Project – (a component of the Wealth from Water Land Suitability Project)

Darren Kidd & Raphael Viscarra Rossel

aclep Australian Collaborative Land Evaluation Program

tiar

UTAS

THE UNIVERSITY OF SYDNEY

Tasmania Explore the possibilities

Darren Kidd[1], Raphael Viscarra Rossel[3], Chris Grose[1], Rob Moreton[1], Mathew Webb[1], Zhuo Wang[1], Regan Parkinson[1], Rhys Stickler[1], Brendan Malone[2], Alex McBratney[2], Budiman Minasny[2], Bill Cotching[4], Leigh Sparrow[4], Rowan Smith[4], Fiona Kerslake[4]

[1] Department of Primary Industries, Parks, Water & Environment, Tasmania, 7250, Australia

[2] University of Sydney, Faculty of Agriculture, Food and Natural Resources

[3] CSIRO Land & Water / ACLEP

[4] Tasmanian Institute of Agriculture (TIA)

Wealth from Water Pilot Program – Land Suitability Using Digital Soil Mapping

The Wealth from Water Pilot Program commenced in November 2010 as a partnership between the:

- Department of Primary Industries, Parks, Water and Environment
- ACLEP (Australian Collaborative Land Evaluation Program)
- Department of Economic Development, Tourism and the Arts
- Tasmanian Institute of Agriculture
- University of Sydney (ARC Linkage Project)

The Program's goal is to classify land according to its suitability for various agricultural enterprises, (initially as a 20,000 pilot area), to enhance the uptake of irrigation water in the newly established irrigation areas of the State. It will potentially be rolled out across all new Tasmanian irrigation districts (340,000 ha) if deemed successful, and adequately funded. The project aims to provide comprehensive soil, climate and crop enterprise data to farmers and investors, specifically to assist farmers to move or diversify into higher-valued enterprises, and improve productivity.

Land Resource Assessment Project Aims:

1. Generation of soil and climate surfaces to fit land suitability parameters.
2. Land Suitability modelling for a range of agricultural enterprises, at a required nominal scale of 1:50,000, (or 30m resolution).

ACLEP Project Components:

1. MiR/ vis-IR predictions of soil properties.
2. Gamma Radiometric Mapping of the Meander West Area (Earth-Rover).

Area:

Meander East and Meander West Irrigation Districts – Total: 20,000ha (Approximately 10,000ha each).

Figure 1. Meander East and West Pilot Areas

Methodology:

Crop Suitability Rules were developed by TIA (Tas Institute of Agriculture), based on research and industry workshops (Appendix 1). Required soil parameters:

- pH ($CaCl_2$)
- ECe (Saturated Extract)
- Clay %
- Depth to Sodic Layer
- Depth to Impeding Layer
- Stone %
- Drainage (Soil Drainage Classes, as per McDonald et al 1998)

Soils:

The TIA Land Suitability input parameters require soil property surfaces; consequently, soil property mapping rather than soil type mapping was considered the most efficient approach, considering the time and resources available. There are a large number of scientific publications available that describe the successful generation or prediction of soil property surfaces using various digital soil mapping (DSM) techniques, (McBratney et al. 2003). In many cases, these outputs can be superior to traditionally developed polygonal soil property surfaces alone, and provide good enhancement to existing polygonal mapping. DSM is the computer-aided development of predictive maps of soil properties or attributes (e.g. soil pH). It uses traditionally developed soil data (both maps and site based data), newly available remotely or proximally sensed data (e.g. terrain analysis), as well as a range of geo-statistical techniques to predict the soil attributes of spatial entities (usually in the form of geographic grid cells). (From Recommendations for the Advancement of Digital Soil Assessment in Australia – Robinson et al. 2010, p.4). The pilot soil mapping process was developed around such principles (DSM).

<u>Soil Mapping:</u>

<u>Process Summary:</u>

Use soil sampling and available covariates to develop predicted soil attribute surfaces for land suitability modelling (for individual enterprises).

1. Review existing soil mapping and database site locations.
2. Compile covariates and generate all necessary derivatives. (Including existing soil mapping to provide soil-expert input, and a check that modelled outputs are in agreement with described soil-landscape processes). Also included ground-based gamma radiometric mapping for Meander West – ACLEP Project.
3. Develop statistically robust sampling design.
4. Undertake Soil Sampling – training and validation sampling (Australian "Yellow Book" morphology and landscape descriptions, full chemical and partial physical analysis, CSBP, MIR/ NIR analyses – CSIRO Land & Water – ACLEP Project).
5. Fit depth-spline functions to soil chemistry results to allow depth-queries for suitability modelling.

6. Apply various statistical/ geo-statistical modelling approaches to produce best soil property surfaces, 30 resolution, based on sample sites and all covariates (ie. Models with best "fit" and validation).
7. Determine "uncertainty" values for each soil property surface.
8. Apply generated soil property and climate surfaces to Land Suitability Model for each enterprise (rules generated by TIA).
9. Produce and Review Suitability surfaces for each enterprise.

Review of Available Soil Mapping

All existing and available soil mapping was obtained for the Meander East and West pilot areas. (1:00,000 Meander Soils Map, (Spanswick and Zund 1999). It was determined that the mapping was not of the scale or quality to produce soil property surfaces at a scale of 1:50,000.

Assembled all available spatial covariates (soil predictors).

Covariates:

a) 1:00,000 Soil Maps
b) 1:100,00 Land Capability Maps
c) SRTM DEM 30m (from CSIRO/ Geosciences Australia).
d) Airborne Radiometrics (40m grids, based on 200m flight lines, (Mineral Resources Tasmania), Radioactive Potassium, Thorium, Potassium and Dose. (Only partial coverage in some areas).
e) 1:25,000 Surface Geology Mapping, (Mineral Resources Tasmania).
f) Satellite Imagery: SPOT multipsectral 2009, RapideEye multipsectral 2010, LandSat multipsectral 2010.
g) All available Climate Data, (BoM, Landscape Logic).
h) Land Use, 1:50,000 (DPIPWE, 2010).
i) Vegetation Mapping, TASVEG, 1:25,000, (DPIPWE 2010).

Derivative Covariate Processing:

a. Terrain Derivates based on the 30m SRTM DEM (SAGA GIS)
    i. Analytical Hillshade
    ii. Slope/ Mid-slope Position/ Slope Height
    iii. Aspect
    iv. Curvature/ Plan Curvature
    v. Topographic Wetness Index, SAGA Wetness Index
    vi. Distance to Channel Network, Channel Network
    vii. MrVBF (Multi-resolution Valley Bottom Flatness Index
    viii. MrRTF (Multi-resolution Ridge-top Flatness Index)
    ix. Valley Depth
    x. Protection Index
b. Satellite Imagery (ARCGis Spatial Analyst)
    i. NDVI
    ii. FVC

Soils Covariate Processing:

The existing 1:100,000 soil map only partially covered the pilot area (approximately 80%); it was therefore necessary to extrapolate the mapping into the un-mapped areas, so that the soils layer (and associated soil expert knowledge of the soil-landscape processes) could be incorporated into the soil property prediction process as a complete covariate layer. The soil association map was partially disaggregated into minor soil components (types) to provide better prediction capabilities as a covariate layer, and as a means to extrapolate the soil type extents into the un-mapped areas (by modelling the soil surveyor soil-landscape relationship).

A desktop process using satellite RGB imagery (SPOT and RapidEye) using over-laid soil mapping, TASVEG 1:25,000 vegetation mapping, geology, radiometrics and terrain derivatives was undertaken to visually identify points in the landscape where there was a high chance that soil association components would occur (based on soil survey knowledge). This was determined by indicators such as visible imagery soil colour, vegetation type, landscape position, and land use. Existing soils database sites identifying soil type were added to the desktop sites, combining to produce a total of 162 training sites. These soil types were modelled/ predicted using all available covariate data as a discrete-variable discriminant analysis using "See 5" software (© RULEQUEST RESEARCH). R-squared values for training and validation (using a one-third random holdback) were around 0.76. The resulting "disaggregated" 30m resolution soil map (classed as a "pre-map" in DSM terms) was accepted as an additional suitable covariate data via desktop assessment, with limited visual field validation. It also was considered a means to apply soil survey and soil scientist landscape knowledge to the attribute prediction process.

ACLEP Project Component - Radiometrics (Meander West):

Radiometrics were considered an important covariate for the Meander West area due to large and complex alluvial units previously mapped as "Miscellaneous" soils, which was also observed during initial field scoping. The Meander West project area has only partial radiometrics coverage (approximately 15%), with full coverage for Meander East. This was considered too great an area to model the radiometric covariate "gaps" based on terrain and geology; therefore radiometrics were mapped using the ground-based CSIRO "Earth Rover", (E-Rover), with differential GPS and radiometer (Tasmanian ACLEP DSM Project, 2011).

Sixty points were created as a uniform grid pattern across the area; from these points, 600m transects (randomised directions, based on 15° increments) were travelled at a uniform speed, recording the radiometric spectrum at 1 second intervals, (Figure 2). The radiometric data was processed (R. Viscarra-Rossel, ACLEP/ CSIRO), to 30m resolution, which was compared as an "overlap" with the existing 15% coverage. Surfaces were generated using Random-Forests and Regression Kriging techniques, (Figure 3). The new surfaces were adjusted after determining the mathematical relationship between the new and existing surfaces, which will allow combining both the Meander East and West areas as a single covariate-sample set for attribute predictions. An R-squared of 0.60 was obtained after comparing the total radiometric count overlap area. The newly created gamma surfaces were then mathematically adjusted, to fit the entire Meander area.

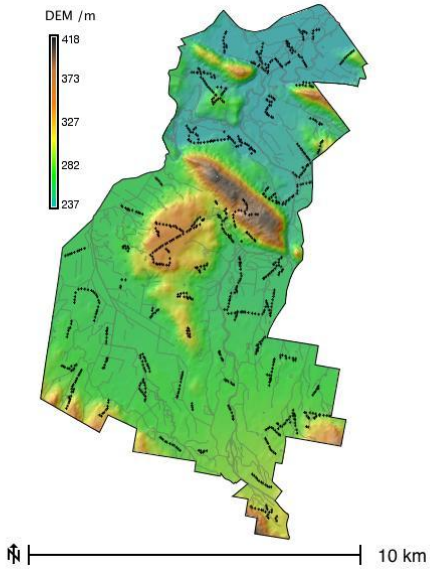

Figure 2. Earth Rover Gamma Radiometric Transects

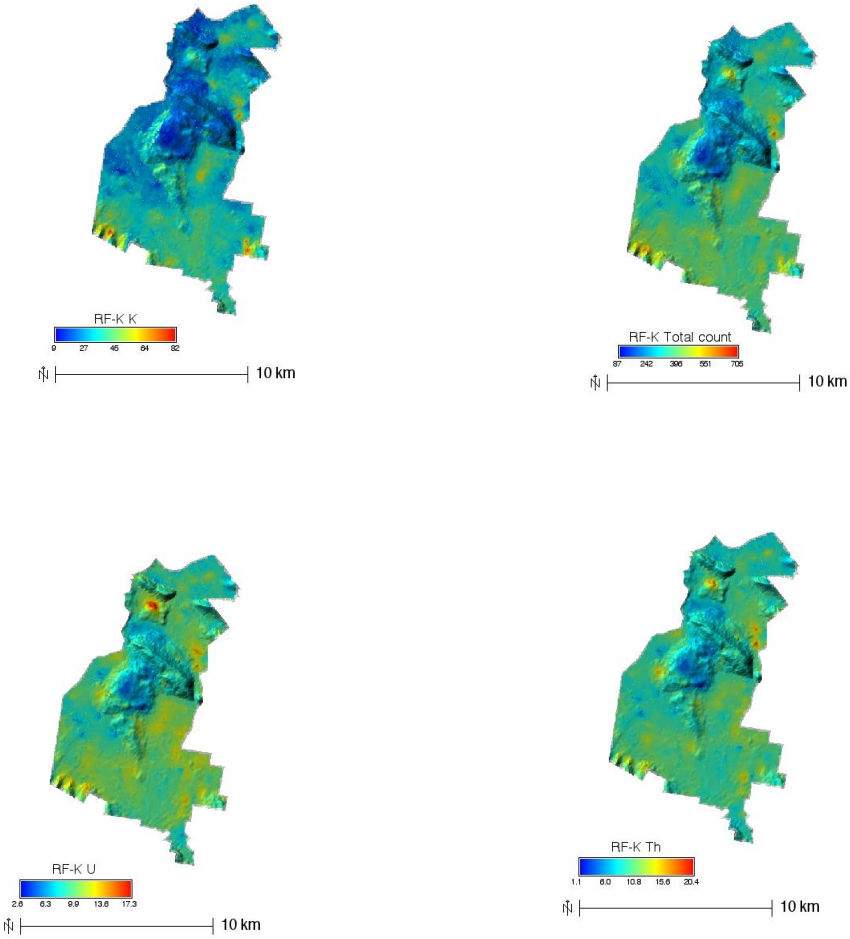

Figure 3. Gamma Radiometric Surfaces, (Total Count, Potassium, Thorium, Uranium)

Soil Sampling Design (Training):

Two-hundred training sites were required to adequately predict soil properties based on the available covariates and existing soils data in the total Meander Area at 30m resolution. This is consistent with literature sample density (Brungard and Boettinger 2010), and Sydney University experience (McBratney pers. comm. 2010). The site density is also the minimum required for 1:50,000 soil mapping according to the Australian Guidelines for Surveying Soil and Land Resources, (McKenzie et al. 2008). Site locations were chosen according to a "conditioned Latin Hypercube" design, (Minasny and McBratney 2006a; Minasny and McBratney 2006b), (a random-stratified sampling approach based on all available covariates). An extra 25 sites were added to the design as "emergency" sites, in cases where sampling was not possible due to access and sampling constraints, for example, physical access (land use/ tenure, terrain, permissions) and site contamination (cattle camps, infrastructure). In the case where a sample location was deemed unsuitable/ inaccessible, the next available "emergency" site was used in its place. A 30m error-margin was allowed for each location where exact proximity was not possible (using GPS locations). This accounted for a single pixel variation, and therefore little variation to covariate values, and overall sample distribution. The sample design was considered difficult to implement due to physical and land use constraints.

Close-range Variation:

Five percent of sites were identified as "close-range variation sites", where an additional site was sampled within 10m of the initial site (randomly selected). Close-range sampling will allow evaluation of paddock-scaled soil property variation (within a single 30m pixel), and how successfully this can be modelled.

Soil Sampling Design (Validation):

An additional 60 sites were added for surface validation purposes, for a total of 260 sites (a 30% validation rate). Validation sites are being used as part of the overall modelling development for each soil property, as an immediate test to its validity. The sites may alternatively be used to independently spatially assess non-validated models. Ideally, validation sites would be best undertaken with a design based on all modelled soil property prediction surfaces, (a relatively complex undertaking), however, project time constraints could not allow the time-lag between these processes. Consequently, a validation design based on the covariates was used, using a "clustered" approach by fuzzy k-means analyses. Ten clusters were generated for the total area using the software "Fuzme", (Minasny and McBratney 2002), with six software-generated random samples taken form each cluster (totalling 60 samples). A ten cluster-design was settled upon (the number of major soil types mapped for the area) after trialling and visually assessing the complexity of mapped clusters. The Fuzme fuzzy exponent was also reduced from 1.30, to 1.20 to reduce complexity, and ensure a "harder fit" of covariate partial membership. The fuzzy-clusters covariate sample distribution was compared to the overall covariate sample distribution, which demonstrated a good sample design, (i.e. Distribution, mean, median and standard deviation values were very close). A comparison was also made to a conditioned Latin Hypercube design, and while not quite as close to the overall distribution as the hypercube, the fuzzy-cluster approach was still deemed adequate, (Figures 2 & 3).

Field Sampling/ Validation:

Samples were taken using a 50mm percussion soil corer, to a depth of 1.5m where possible. Three cores were taken within 50cm of each other, to allow sufficient sample volume for analyses. Samples were taken from each core, according to soil horizon, with a maximum depth of 30cm across each horizon. If a horizon was deeper than 30cm in total, separate samples were taken from that horizon. Samples were bagged and labelled accordingly, bulking like-horizons from each soil core. Cores and surrounding landscape position were described according to the Australian Soil and Land Survey guidelines, (NCST 2009).

Sample Preparation:

Samples were air-dried at 35°C, and ground to a <2mm fraction in preparation for analyses.

ACLEP Project Component - Sample Analyses:

Spectral-scanning (MIR/ NIR) of all soil samples (training and validation) was undertaken at CSIRO Land & Water in Canberra, in order to predict required soil properties (approximately 1400 samples in total). The substantial time and costs involved in undertaking wet-chemistry analysis of all samples was not possible within pilot resources. Scanning allowed a greater number of site predictions for the soil property surface generation than wet-chemistry analyses alone would allow. The spectral analyses of soils is a genuine alternative to traditional chemical and physical analyses for many soil properties, especially for programs constrained by time and resources, (Minasny et al. 2009; Pirie et al. 2005). Twenty percent of scanned samples were chosen and analysed for "wet" chemistry at CSBP Laboratories in Western Australia, (approximately 280 samples from a total of 1400), to provide calibration data for soil property predictions form the spectra scanning. Samples were chosen as a random stratified design based on all complete spectral ranges. Full analyses of each sample included pH (water and CaCl2), EC (1:5, and saturated extract), exchangeable cations (with Al and H for ECEC), N, P, K, and particle size analysis.

Mid-IR and v-IR predictions for each soil property were made using the wet chemistry results, and separately using the National vis-NIR spectroscopic models. Spectroscopic predictions ranged from good to poor, with Clay % predictions having the best correlation. This will improve once spectral-prediction libraries a generated for Tasmanian soils. The Tasmanian DPIPWE purchased a MiR spectrometer during this period, and will scan these samples for comparisons against the CSIRO (Canberra) machine. The department's capacity was increased to undertake its own MiR analyses, using the recommended methodology from CSIRO, as another project output.

Depth-Splines:

Depths splines were fitted to all sites and sample values for each soil property, once all results are available, (Malone et al. 2011; Malone et al. 2009). The splines allow depth specific queries and surface generation, in accordance with individual land suitability model parameters for each enterprise.

Soil Attribute Prediction:

pH (CaCl2) (0 to 15cm)

Modelled/ validated as a continuous variable, using various software and approaches, eg. Cubist (© RULEQUEST RESEARCH), Artificial Neural Networks*, Random Forests, standard multiple-regression kriging. Based on depth-spline calculations in the top 15cm.

ECe (Saturated Extract) (0 to 15cm)

Modelled/ validated as a continuous variable, using various software and approaches, eg. Cubist (© RULEQUEST RESEARCH), Artificial Neural Networks*, Random Forests, standard multiple-regression kriging. Based on depth-spline calculations in the top 15cm.

Depth to Sodic Layer

Calculated from either MIR/ NIR calibration of exchangeable Sodium, or directly from ESP calibration. This might require use of pedotransfer functions/ surrogate values if calibration values are substantially lower than 70%.

Depth to Impeding Layer

Modelled as a depth to physical limitation based on physical profile descriptions, eg. Stone Content, Clay%, Structure, Water Table.

Stone %

Modelled using physical profile descriptions, either as a discrete variable, (stone content class), or median stone % as a continuous variable, using See5/ Cubist. To be determined – initial modelling showing promising predictions.

Drainage (Soil Drainage Classes, as per McDonald et al 1998)

Modelled using physical profile descriptions, either as a discrete variable, (soil drainage class), or soil drainage index, using See5/ Cubist, artificial neural networks*. To be determined – initial modelling showing promising predictions. Soil Drainage Classes 1 to 6, modelled as a continuous variable to produce a "soil drainage index" map (where the index corresponds to drainage class number), is looking promising (R-squared training/ validation 0.76/0.67 respectively). This is showing better results than See 5 class modelling, and eliminates the need to define the drainage class as an ordinal variable. This index surface can then be re-classified to fit the suitability model requirements. (There was insufficient time and resources to measure soil drainage by physical field means).

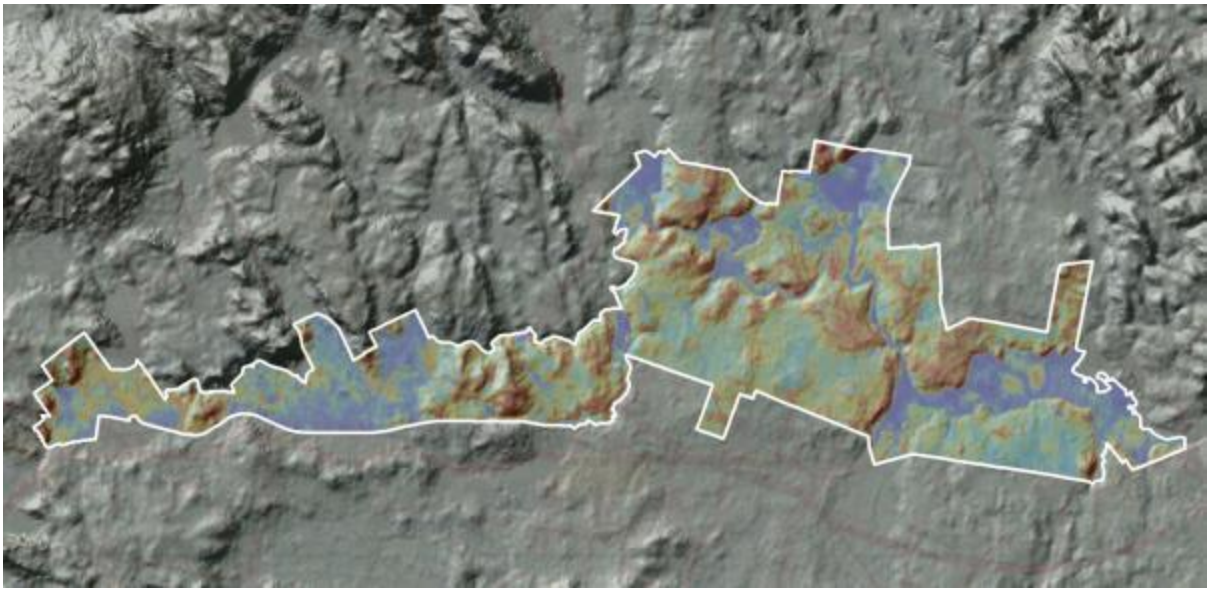

Figure 3. Drainage "Index Map" (Unclassified).

Clay % (0 to 15cm), depth to maximum %

Modelled/ validated as a continuous variable, using various software and approaches, eg. Cubist (© RULEQUEST RESEARCH), Artificial Neural Networks*, Random Forests, standard multiple-regression kriging. Based on depth-spline calculations in the top 15cm, or depth to maximum clay%.

Clay percentage (0-15cm) was modelled, validated and compared using Cubist® (Rulequest Research), artificial neural networks, (ANN using JMP®), and regression kriging (SAGA GIS). The two-hundred training sites were used for both training and validation, (as MIR scanning of validation sites was incomplete at the time of publication), with a stratified random hold-back of sixty training sites for validation. Using step-wise linear regression, the best clay predictors were determined to be the SRTM DEM; topographic wetness index; radiometric dose; height above channel network; valley depth; slope height; MrVBF; and MrRTF. The best preliminary clay predictions were achieved using standard regression kriging, (Hengl et al. 2007). Global universal kriging (SAGA GIS) produced a model training R-squared of 0.73 and RMSE of 4.1, with a validation R-squared of 0.57, and RMSE of 5.4 (after adding model residuals). Cubist® produced an R-squared of 0.61 and 0.43, and ANN 0.43 and 0.32 for training and validation respectively. Remaining soil property predictions were tested using comparable techniques, which should improve during 2012 as more training and validation sites are sampled in adjacent areas.

Spatial clay predictions were greatly enhanced by the Earth Rover Gamma Radiometric surfaces. Statistical validation improvements improved from 0.3 to 0.6 (with Regression Kriging), while the output surfaces in Meander West appeared more “realistic”, and were not as heavily influenced by the terrain derivatives (which showed little variation).

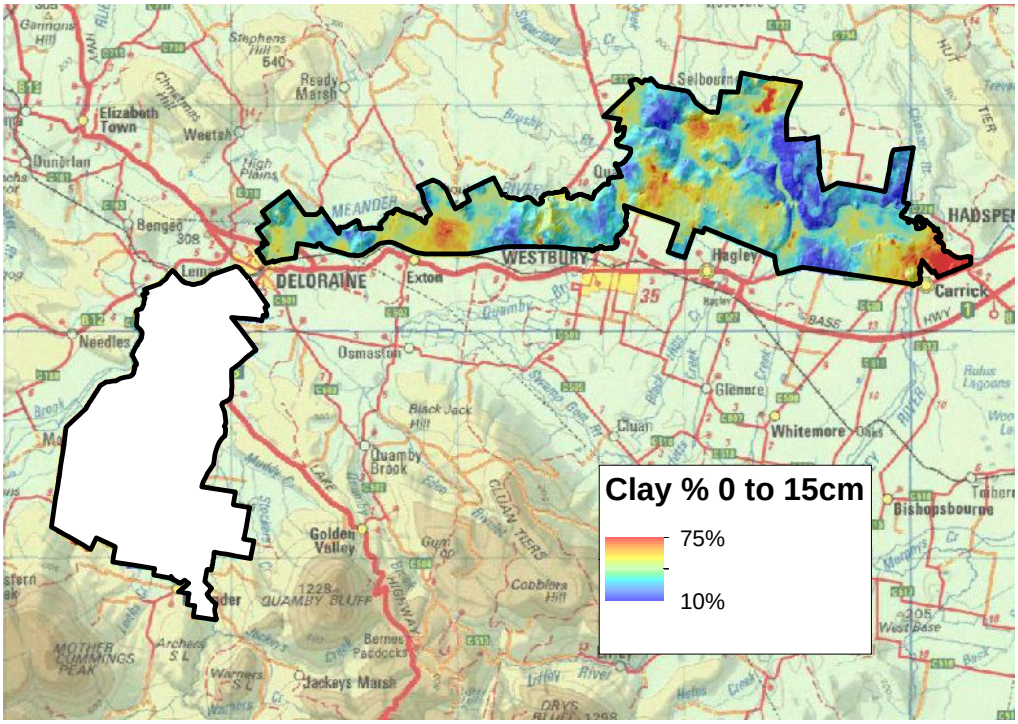

Figure 4. Clay % - Regression Kriging

<u>Climate Modelling: (For Separate and More Detailed Review)</u>

Summary:

A similar process to the above has been used for the collection of relevant data for development of land suitability model climate parameters. Required parameters (which are enterprise specific) are:

a. Frost (Mean number of "frost" days (temperature based) expected at certain times of the year, eg. Crop flowering)
b. Mean Maximum Monthly Temperature (for key months of the year)
c. Mean Rainfall Totals (by month)
d. Chill Hours (eg. Total number of hours within a defined temperature range, over a key period)

Methodology:

Available climate data was not at sufficient resolution or sample density to reliably inform the suitability mapping at the desired scale. Production of more detailed climate surfaces was facilitated by installing temperature sensors at a rate of 0.4 /km^2, (80 loggers in 20,000ha). Sensors were located using the previous fuzzy k-means clustered sampling approach, derived from a range of temperature-related terrain derivatives (from the SRTM 30m DEM). A further six climate stations were installed to measure rainfall. Three months of data had been processed at time of publication; with climate surfaces generated using this data and terrain covariates by regression-kriging. The terrain and climate suitability parameters developed for each enterprise are; slope %; frost risk (risk

of frost events in a % of years (eg. September to October for blueberries)); mean monthly maximum temperature (eg. October to march for blueberries); and chill hours. Following a full year's data collection, various modelling processes, (eg. regression kriging, Cubist®, and ANUSPLIN®), will be evaluated to explain the variation between temperature loggers due to terrain, and adjusted to long-term averages using historical Australian Bureau of Meteorology data.

Land Suitability Model:

ESRI "Model Builder" was used to develop a decision-based model by querying the generated soil and climate surfaces, with regards to the suitability "rules' developed by TIAR. These "rules" were based on Tasmanian agricultural research trials, existing literature, expert opinion, and workshops with leading Tasmanian industry experts and agronomists.

Pilot Program enterprises are;

- Poppies,
- Barley,
- Carrots,
- Blueberries,
- Hazelnuts,
- Pyrethrum,
- Commercial Hemp.

The developed model uses a "most limiting factor" approach, such that the overall enterprise suitability rating is dependent on the lowest suitability rating of any one parameter. The model produces an overall suitability rating for each enterprise for each 30x30m pixel, and displays the suitability rank for each parameter as a spatial output.

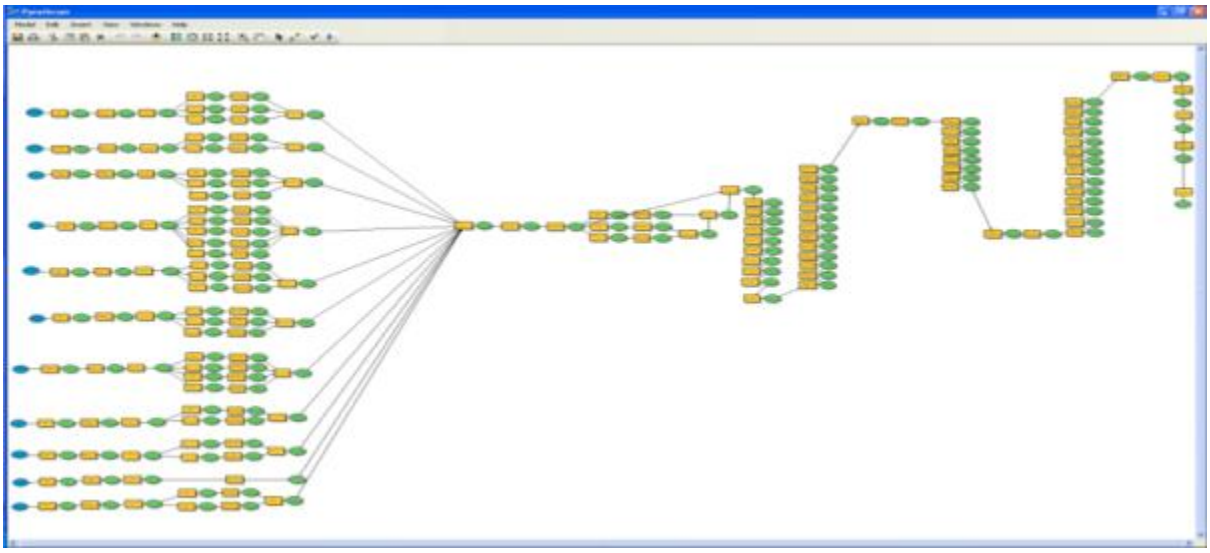

Figure 5. Land Suitability Model (Pyrethrum) – Model Builder

Final Land Suitability Outputs:

The final Land Suitability Maps are produced displaying the level of suitability for each 30x30m pixel, (Well Suited, Suitable, Marginally Suitable, and Un-Suitable). Final products are placed on the Tasmanian "The LIST" spatial web portal (Figure 8), to allow the public to overlay surfaces with other land and environmental layers, and determine limiting suitability parameters.

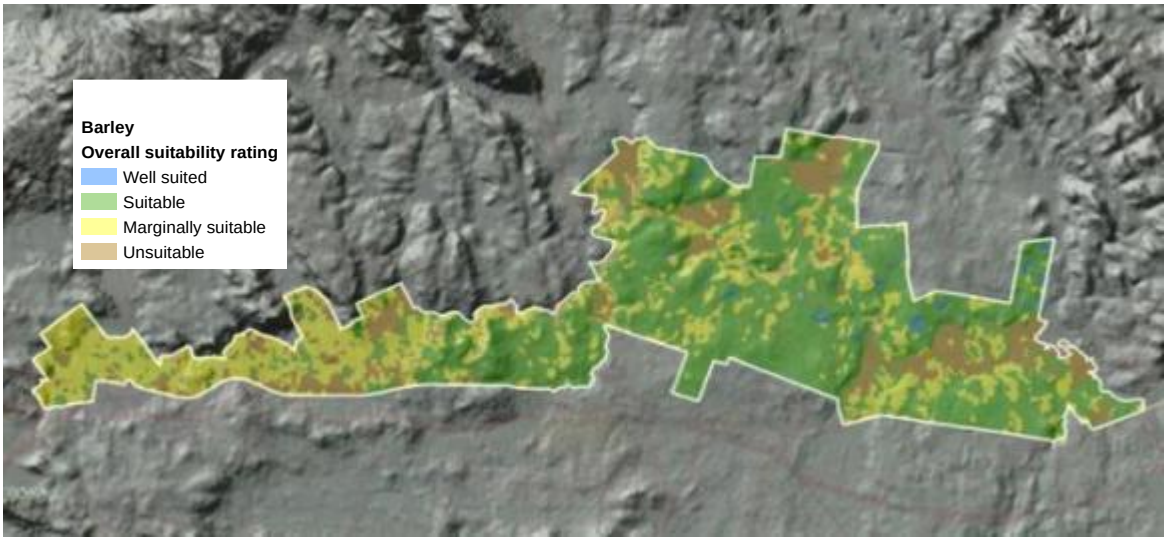

Figure 6. DRAFT Land Suitability (Barley)

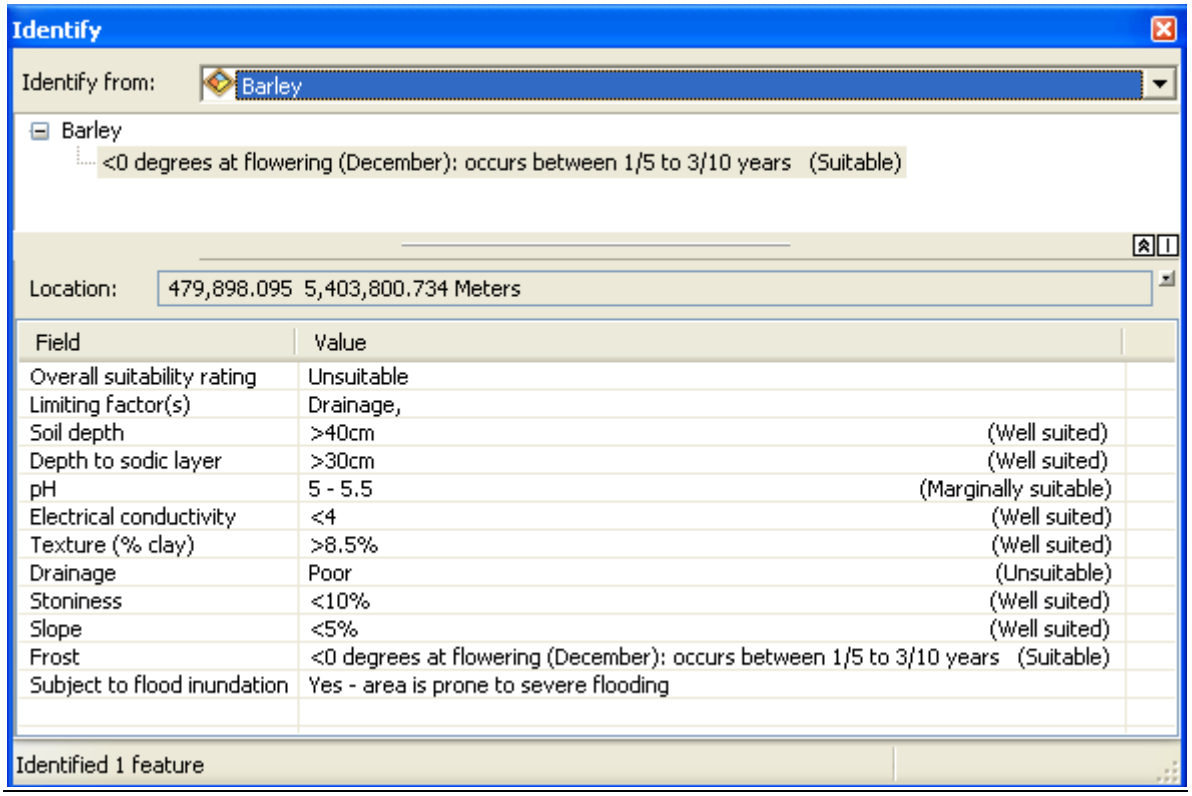

Figure 7. Sample "IDENTIFY" model output by interrogating suitability map

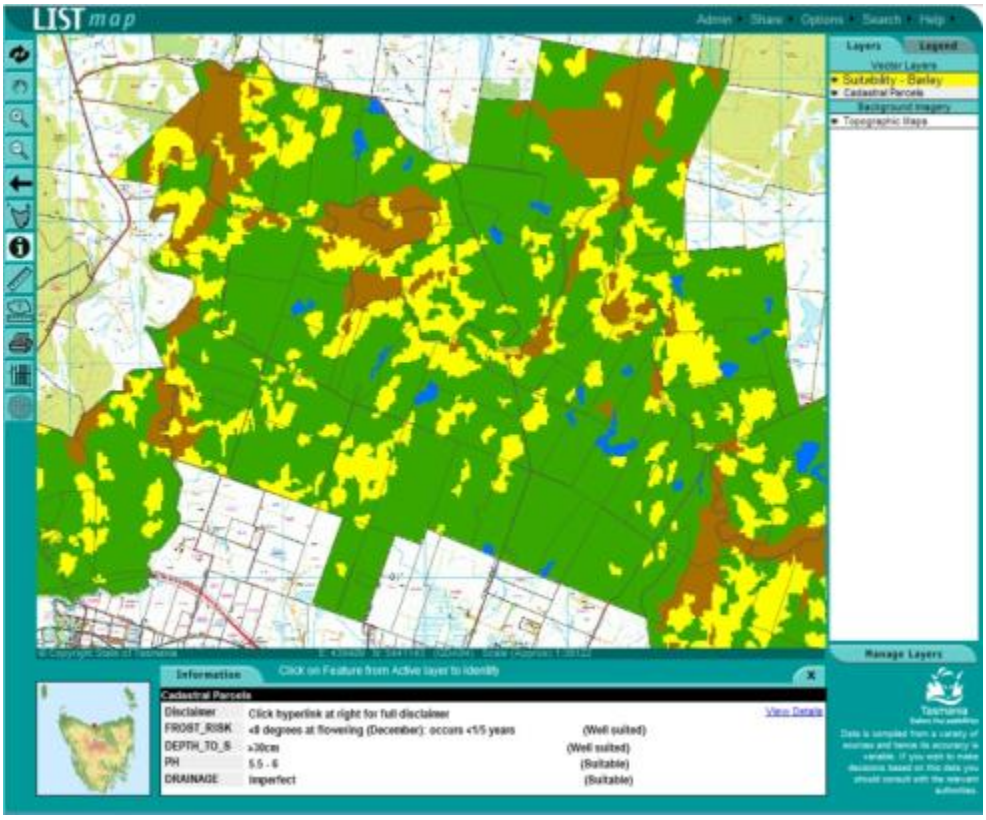

Figure 8. The LIST - Spatial Land Information Web Portal - Land Suitability (Barley)

Digital Soil Mapping ACLEP Project – Conclusions:

A digital soil assessment process such as the Wealth from Water Project has many components; the ACLEP project enabled two important processes to be completed; soil spectral predictions, and ground-based gamma radiometrics.

Gamma radiometrics have been shown to be important predictors for many DSM soil property predictions, especially in the alluvial complex areas of Meander West, which have little variation in terrain, and low relief. Existing soil and geology mapping also provided little variability in terms of explanatory variables. Without the ground-based gamma radiometric mapping undertaken through the ACLEP project, soil property predictions would not adequately explain the known variability and complexity in this area. The project has successfully demonstrated the use of the Earth Rover for DSM proximal sensing at a regional scale.

Predictive mapping of soil properties also depends on an adequate density of training and validation data points, with appropriate soil chemical data. This would also be economically unfeasible using wet chemistry techniques alone; the MiR and vis-IR spectral predictions through the ACLEP project allowed suitable sample density for 30m resolution predictions within allocated budgets. The predictions were generally poor; however, these should improve as more spectral scanning is undertaken within the State. The Tasmanian DPIPWE have purchased an MIR spectrometer, and

through the ACLEP Project, have increased their capacity to undertake independent spectral analyses, to build A Tasmanian spectral library, and contribute to the Nation Library.

Spatial predictions through digital soil mapping, such as clay%, with an R-squared 0.73 and 0.57 for training and validation respectively, show that the available spatial covariates (including the newly acquired radiometric surfaces) are good predictors of certain soil properties to certain depths. Similarly, good correlations are being achieved for predicted climate parameters using existing data, temperature loggers and digital terrain models. The suitability model uses a conventional "most limiting factor" approach, which is reliant on the soil and climate predictions, and will therefore only be as reliable as those predictions. Uncertainty of predictions will compound for each input parameter prediction, ultimately providing an overall modelled uncertainty for each pixel. As Digital Soil Assessment theory moves from academic research into operational Government business, undertakings such as the Wealth from Water Project become invaluable in assessing the practicality and applicability of emerging techniques. The Project has achieved a high level of interest within Tasmania, and has been extended to another 50,000 ha within the Central Midlands and remaining Meander Irrigation Districts during 2012, for twenty enterprises. Subject to review and available funding, the project has the potential to map the remaining 300,000ha of Tasmania's newly commissioned and proposed irrigation schemes, trialling new covariates and prediction techniques.

Key Recommendations for Future ACLEP DSM Projects

1. To continue to build on the capacity development of DSM-related undertakings with the States.
2. To continue to build a local and national soil spectral library, to improve uncertainty of predictions.
3. To continue the development and assessment of DSM proximal sensing at a regional scale, especially in areas with low relief/ low terrain complexity.
4. Support to develop ACLEP project components into published scientific papers for peer review.

Milestone Report

Milestone	Milestone Date	Payment (Excl GST)
1. Signature and return of the Letter and Attachments 1 to 2.	Following receipt of a signed Letter and invoice - complete	$20,000
2. Provision of relevant digital data sets to CSIRO including: existing soil mapping, soil site data and existing covariate data such as DEM, radiometrics, remote sensing, etc.	15th Nov 2010 - complete	$ Nil
3. Develop a soil sampling strategy in collaboration with University of Sydney and utilising existing soil spectra analysis data provided by CSIRO	1st Dec 2010 - complete	$ Nil
4. Provide a land suitability classification framework in collaboration with University of Tasmania and identify the required soil attributes and land qualities	1st Mar 2011 - complete	$ Nil
5. Undertake soil sampling and chemical analysis for identified sites and deliver soil samples to CSIRO for spectroscopic analysis and modelling	30th Apr – June 2011 - complete	$ Nil,
6. Assist CSIRO to undertake ground based proximal sensor survey, including radiometrics, of part of the study area	30th Apr 2011 - complete	$ Nil
7. Interim report detailing activities and results to date	20th June 2011 - complete	$20,000
8. Assist CSIRO with mapping of high resolution gamma radiometrics data	30th July 2011 - complete	$ Nil
9. Assist with digital soil mapping of land suitability	30th Sept 2011 - complete	$ Nil
10. Develop final products and provide input to draft scientific paper	15th Oct 2011 - complete	$Nil
11. Final Project report including documentation of data sets and recommendations for future activity provided to CSIRO.	1st Dec 2011 - complete	$20,000
TOTAL		**$60,000**

Appendix 1 – Sample Land Suitability Rules (TIAR) for Poppies, Barley & Hazelnuts – version as at 19th October, 2011.

Crop	**Soil Depth**	**Depth to sodic layer**	**pH of top 15cm (H2O)**	**EC** (top 15 cm)	**Texture** (top 15cm - % clay))	**Drainage**	**Stoniness** (top 15cm)	**slope**	**Frost**	**Mean max monthly temp**	**rainfall**	**Growing season (GDD)**	**Chill hours**
Poppies	Flowering occurs mid November to mid December												
W	>40cm	? >30cm	>=6		? >10%	Well, Mod Well	<10% (>200mm)	<5%	None at flowering				
S	>40cm	>30cm	>=6		>10%	Excess well, Imperfect	10-20%	5-20%	? None at flowering				
MS	? >40cm	15-30cm	5.3-<6		5-10%	Excess well, Imperfect	10-20% (>200mm)	5-20%	One day with min temp of 2- -2°C during flowering				
U	<40cm	<15cm	<5.3		<5%	Poor, V poor	>20% (>200mm)	>20%	One day at <-2°C during flowering				
Carrots													
W	>40cm		>=6			Well	<2 (2-200mm)	<10%					
S	>40cm		5.8-<6			Mod Well, Excess well	2-10% (2-200mm)	10-25%					
MS	? >40cm		5.5-<5.8			Imperfect	10-20% (2-200mm)	10-25%					
U	<40		<5.5		Duplex – clay at <40cm (USYD to produce surface)	Poor, V poor	>20% (2-200mm)	>25%			Rain at harvest (TBD)		
Barley	Flowering occurs in December												
W	>40cm	>30	>=6	<4	Any (not sand) >8.5%	Well Mod Well Excess Well	<10% (>200mm)	<5%	At least 1 day where T_{min} <0°C @ flowering – ocurrs <1/5 years.				
S	>40cm	20-30	5.5-<6	4-8	>8.5%	Imperfect	10-20% (>200mm)	5-25%	At least 1 day where T_{min} <0°C @ flowering – ocurrs 1/5-3/10 years				
MS	?>40cm	<20	5-<5.5	8-16	S Sand <8.5%	Imperfect	10-20% (>200mm)	5-25%	At least 1 day where T_{min} <0°C @ flowering – ocurrs 3/10-2/5 years				
U	<40	?<20	<5	>16	<8.5%	Poor, very poor	>20% (>200mm)	>25%	At least 1 day where T_{min} <0°C @ flowering – ocurrs >2/5 years.				

Crop	**Soil Depth**	**Depth to sodic layer**	**pH of top 15cm (H2O)**	**EC** (top 15 cm)	**Texture (**top 15cm - % clay)**)**	**Drainage**	**Stoniness** (top 15cm)	**Frost**	**Mean max monthly temp**	**rainfall**	**Chill hours**
Hazelnuts											
W	>60cm		6.5	<0.15dS/m	10–30%	Well, Moderately well	<10% (>200mm)	No days < -6 deg C in June, July or Aug – occurs 4/5 years	Mean Jan or Feb max temp – 20-30°C	<50mm (mean March)	Chill hours 0-7° C (April-August inclusive): >1200
S	40-50cm		5.5-6.5	>0.15dS/m	30-50%	Imperfect	10-20% (>200mm)	No days < -6 deg C in June, July or Aug – occurs 3/5 to 4/5 years	Mean Jan or Feb max temp – 30-33°C & 18-20°C	<50mm (mean March)	Chill hours 0-7° C (April-August inclusive): 600 - 1200
MS	30-40cm		6.5-7.1	>0.15dS/m	30-50%	Imperfect	10-20% (>200mm)	No days < -6 deg C in June, July or Aug – occurs 2/5 to 3/5 years	Mean Jan or Feb max temp – 33-35°C	<50mm (mean March)	Chill hours 0-7° C (April-August inclusive): 600 - 1200
U	<30cm		<5.5 >7.1	>0.15dS/m	>50% or <10%	Poor, Very poor	>20% (>200mm)	No days < -6 deg C in June, July or Aug – occurs <2/5 years	Mean Jan or Feb max temp – >35°C & <18°C	>50mm (mean March)	Chill hours 0-7° C (April-August inclusive): <600

References:

Brungard CW, Boettinger JL (2010) Conditioned Latin Hypercube Sampling: Optimal Sample Size for Digital Soil Mapping of Arid Rangelands in Utah, USA. In 'Digital Soil Mapping'. (Eds JL Boettinger, DW Howell, AC Moore, AE Hartemink, S Kienast-Brown) pp. 67-75. (Springer Netherlands.

Hengl T, Heuvelink GBM, Rossiter DG (2007) About regression-kriging: From equations to case studies. *Computers & Geosciences* **33**, 1301-1315.

Malone BP, McBratney AB, Minasny B (2011) Empirical estimates of uncertainty for mapping continuous depth functions of soil attributes. *Geoderma* **160**, 614-626.

Malone BP, McBratney AB, Minasny B, Laslett GM (2009) Mapping continuous depth functions of soil carbon storage and available water capacity. *Geoderma* **154**, 138-152.

McBratney AB, Mendonça Santos ML, Minasny B (2003) On digital soil mapping. *Geoderma* **117**, 3-52.

McKenzie N, Grundy M, Webster R, Ringrose-Voase A (2008) Guidelines for Surveying Soil and Land Resources. *CSIRO PUBLISHING, Australia.*

Minasny B, McBratney AB (2002) FuzME version 3.0. Australian Centre for Precision Agriculture, The University of Sydney., Sydney, Australia.

Minasny B, McBratney AB (2006a) Chapter 12 Latin Hypercube Sampling as a Tool for Digital Soil Mapping. In 'Developments in Soil Science'. (Eds ABM P. Lagacherie, M Voltz) pp. 153-606. (Elsevier.

Minasny B, McBratney AB (2006b) A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Computers and Geosciences* **32**, 1378-1388.

Minasny B, McBratney AB, Pichon L, Sun W, Short MG (2009) Evaluating near infrared spectroscopy for field prediction of soil properties. *Soil Research* **47**, 664-673.

NCST (2009) 'Australian Soil and Land Survey Field Handbook - Third Edition. Australian Soil and Land Survey Handbooks Series 1.' (CSIRO PUBLISHING: Melbourne, Australia.).

Pirie A, Singh B, Islam K (2005) Ultra-violet, visible, near-infrared, and mid-infrared diffuse reflectance spectroscopic techniques to predict several soil properties. *Soil Research* **43**, 713-721.

Spanswick S, Zund P (1999) Quamby Soil Report - Reconnaissance Soil Map Series of Tasmania. A Revised Edition. Department of Primary Industries, Parks, Water and the Environment., Tasmania, Australia.