Mapping soil Available Water Capacity spatially and temporally across Wilksch's farm, Yeelanna, Eyre Peninsula

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Background

The Wilksch farm is located near Yeelanna on the Eyre Peninsula (EP) and participates in the Resilient EP Smart Farms project by contributing one of the 'focus paddocks'. This paddock had the soil moisture probe 'FrSW' installed in the ground during 2016.

Dryland farmers increasingly turn to soil moisture information to reduce decision-making uncertainty and maximise production opportunity for profit. Key decision support areas include strategic, including what to sow and when, and also tactical decisions including in-season choices such as when, or if, to apply N or for grain marketing.

To have maximum utility and reliability, soil moisture probes require sufficient time in-ground to equilibrate to soil conditions and careful calibration to convert signal to meaningful water-related measurements. However, output can only be considered reliable for soils proximal to the sensor; strictly speaking the instrument is calibrated to *that soil* and *that soil* only. This is because soils vary spatially and with depth so simple extrapolation of sensor data from one site (soil) to another is problematic; the nature and rate of change is sometimes hard to predict with any reliability - especially in landscapes that have complex soil arrangements.

Of all the soil components that contribute most to moisture retention in soils (e.g. available water capacity, AWC[1]), clay content in typical agricultural soils is the most dominant factor and so the patterns can have a very strong influence on soil-landscape variability. In practical terms this means that without advanced knowledge of the farm soils, the utility of soil moisture sensor information diminishes and devalues at an unknown rate with increasing distance from the installation. To counter this, in an ideal world the farmer would deploy an array of sensors to cover a multitude of soils that are probably present. However, because soil moisture sensors are not cheap, cost consideration shapes usage and so many farmers opt for a single on-farm installation.

The famer/advisor is then faced with the choice of where that sensor should be deployed. This decision is often built around accumulated knowledge of soil/yield patterns. Therefore the rationale

[1] The term AWC can often be used synonymously with plant available water capacity (PAWC). The PAWC estimate technically relates to the soil water availability for a crop-type for the whole rooting depth and integrates soil constraints like salinity and pH. In this pilot AWC is estimated for ≤ 1 m soil depth (depending on depth of soil core refusal and regardless of rooting depth) and does not integrate constraints.

for ‘optimal’ deployment may fall on the farmer’s interest in the consistently best-, worst- or average-performing soils – or some other criteria important to the farmer. However, the ‘optimal’ is rarely achievable because of practical constraints to installation since on the working farm sensors can rarely be positioned far from the edge of the paddock to minimise disruption to farm operations. For example, the sensor control unit and peripherals need to be outside the cropped area to not disrupt operations and to give unfettered access for checking and maintenance and deploying the sensor close to the edge of the paddock minimises disruption to crops if the senor needs to be accessed.

The purpose of this pilot study is to, firstly, test mapping AWC at a granularity (~ scale) useful for in-paddock decision making within the constraints of publicly available data using a modern soil mapping approach called digital soil mapping (DSM). Secondly, test using the soil moisture signal at various times from the FrSW probe to extrapolate to AWC soils across the farm. Apart from the probe data, the study draws only on nationally available datasets so that so that the methodology can be rolled out to other EP farms that also have soil moisture probes. That is, the study is intended as a proof-of-concept method development.

Farm soils

The Wilksch farm boundary is presented in Figure 1. The cropped area of the farm covers 2,045 Ha and is in an upland setting. The landscape is characterised by low hills featuring hillcrests, hillslopes, drainage depressions and footslopes. The soils are dominated by loams over red clay soils on slopes in the western paddocks, ironstone gravelly sandy loam over red clay soils dominate slopes in the eastern paddocks, and gradational clay loam soils dominate lower lying areas throughout. Also throughout there are less extensive areas of shallow soil on rock soils along ridges and crests.

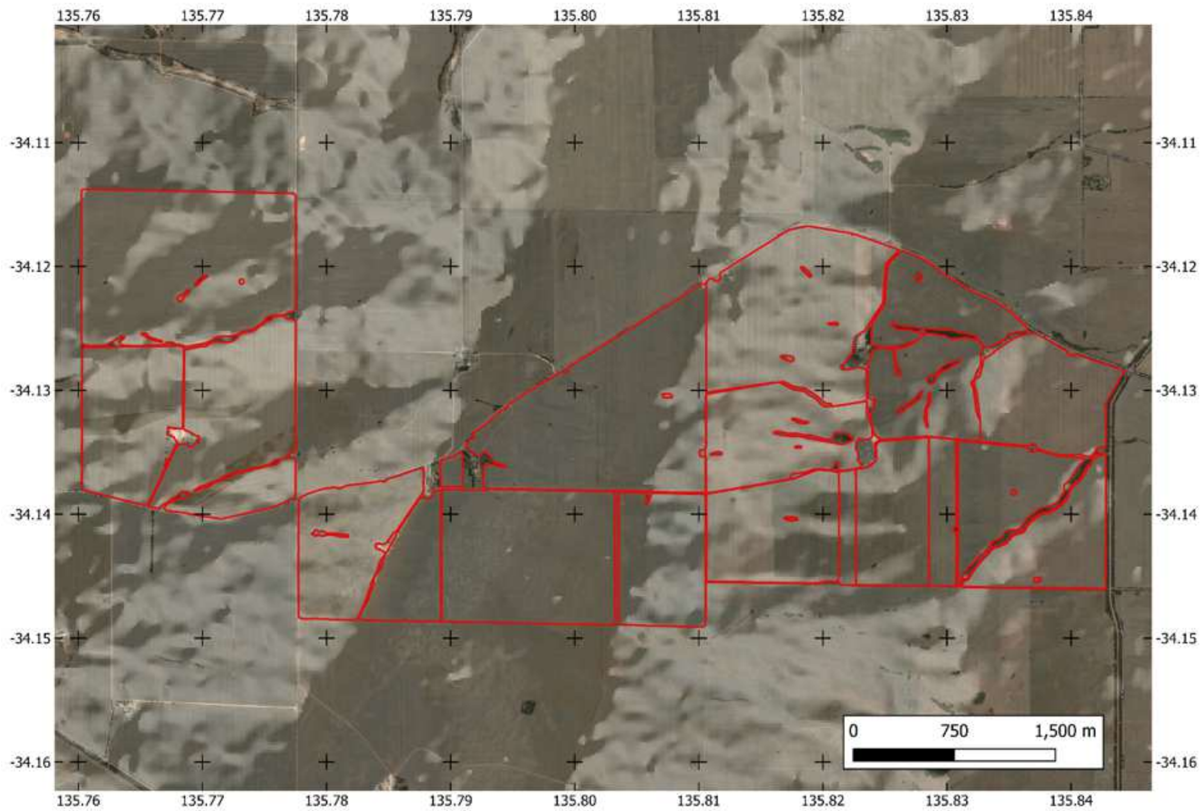

Figure 1 Wilksch farm extent including paddock boundaries (red lines) and artificial hill shading added to accentuate relief patterns

Methods

Emphasis throughout the study is to build the methodology around publicly available datasets and analytical platforms to reduce adoption barriers. The methodology follows several stages. The first stage involves devising a soil survey that is both pragmatic and efficient; efficient in terms of covering the full range of soils in the farm soil-landscape within survey constraints. In-field sampling methodology and the analytical suite of samples is described. Next, the DSM approach is discussed to map AWC. Finally, we discuss across-farm extrapolation and assessment of soil moisture signal from the FrSW probe.

Survey design and soil sampling

Conceptual background

An objective of soil survey design is to cover all soil types in a study area as best as possible and with as little bias as possible. This is because bias introduces inefficiencies because of over- or under-sampling of soils within resource constraints of the survey. Technically, bias skews surveyor (mental) and computer models by not equally covering – or even missing– important soils.

The survey planned for 25 survey points for the farm, a number arrived at because of the anticipation that 25 sites could be achieved in a working day. However, given the likelihood of attrition of sites because of access problems or running out of time, a balance of >20 sites achieved is still considered acceptable. Achieving 20 over the 2045 Ha farm gives a sampling intensity of one sample per approximately 100 Ha, equating to medium to low intensity survey, and consistent with moderately intensive uses at the farm level (Gallant et al., 2008).

There are numerous soil survey design approaches (McKenzie et al., 2008) including surveying at expertly selected sites, on a grid or at random sites. One method that 'forces' the design to cover the soil-landscape continuum applies stratification, which separates the soil-landscape based on clusters of 'similarness' and distributing the chosen number of sampling points equally within each cluster/stratum.

One effective method of clustering to define strata applies environmental correlation. This approach applies the principle that certain GIS layers relating to soils and landscapes spatially correlate to soil properties, i.e. they are soil property *covariates*. For example, the thorium (Th) gamma radiometric layer is a covariate for weathered soils; strong Th signals can therefore indicate the presence of deeper, less fertile soils (Wilford et al., 1997). Similarly, topographic wetness index (TWI) terrain analysis (Wilson and Gallant, 2000a) indicates patterns of water flows and persistence, hence is a covariate for soil thickness, water logging and soil texture. Slope can serve as a covariate for soil depth. Covariates used in the study are presented in Table 1.

Computer *k*-means analysis is an established method in soil survey for creating a map of *k-number* of statistical clusters from a stack of covariates (Burrough, 1989). The main principles of *k*-means analysis are that (i) '*k*' is an operator-determined number of clusters, and (ii) each *k*-means cluster generated is equally statistically variable – or discrete – as each of the other clusters. In practice, because clustering is based on covariates, all the user knows is that each cluster represents a coherent set of soil characteristics, although how these properties amalgamate and translate to soil types is unknown at the desktop stage. In other words, the cluster map is not a soil classification. The user-attribution of *k* is best done iteratively with expert knowledge guidance, and starts by matching a known level of soil-landscape complexity with a suitable number for *k*. For example, a non-complex landscape situation is likely to be better served by a small *k* whereas a complex situation may be better served by a larger *k* as there is more soil variability (i.e. types of soils) present.

Sources of covariates

The majority of covariates used here were collected from the Soil Landscape Grid of Australia (SLGA; Grundy et al., 2015) and the Sentinel remote sensing mission (Torres et al., 2012). The GIS rasters were unified to a 20 m ground resolution by GIS resampling, and the SLGA's digital elevation model (DEM) used to derive additional terrain attributes if not already in the suite.

Implementing *k*-means clustering

The pilot used the freely available and powerful Quantum GIS (QGIS) GIS program (https://www.qgis.org/en/site/). This GIS supports the PAT (Precision Agriculture Tool) plugin developed by CSIRO (Ratcliff et al., 2020) that is freely available; PAT preforms *k*-means clustering.

Numerous clustering iterations were implemented in PAT using combinations of covariates and numbers of *k* and assessed qualitatively. Assessment was informed by a field reconnaissance and auxiliary information, including remote sensing, soil data, publications (Hall et al., 2009) and soil mapping (Maschmedt, 2000). The output considered the best representation of soil patterns was a 3-cluster solution shown in Figure 2, achieved with the 9 covariates presented in Table 1.

Table 1. Covariates, examples of soil property proxies/covariances and usage. Tick indicates usage in the pilot.

Covariate	Examples of soil property proxies/covariances	Pilot usage Clustering	Digital soil mapping
Digital elevation model	Areas of erosion versus deposition; shallow or deeper soils; weathered or fresher soils	✓	
Radiometric K	Shallow(er) or rocky soils; rocks derived from shallow underlying geology (Wilford et al., 1997)	✓	✓
Radiometric Th	Deep(er), low fertility (leached) soils (Wilford et al., 1997)	✓	✓
Weathering Intensity Index	Separating deeply weathered, residual soils from shallow, unweathered soils (Wilford, 2012)	✓	✓
Focal Mean 300 m	Land surface relief patterns from an intermediate sized 300 m neighbourhood. Extenuates changes in slope and landform.	✓	✓
Prescott Index	Identification of soil leaching based on climate (aridity) moderated locally by slope aspect; high index values indicate poorly leached soils and possible presence of subsoil pans (Prescott, 1950)	✓	✓
Topographic Wetness Index	Areas of water accumulation and slow soil water transmission (leached,	✓	✓

Covariate	Examples of soil property proxies/covariances	Pilot usage Clustering	Digital soil mapping
	waterlogged/wet soils) and areas of water shedding (drier soils) (Gallant and Austin, 2012)		
Slope	Shallow(er) versus deep(er) soils (Wilson and Gallant, 2000b)	✓	✓
Sentinel satellite short wave infrared (VV polarisation)	Land use and near surface soil moisture		✓
Sentinel satellite short wave infrared 2 (VH polarisation	Land use and near surface soil moisture		✓
Geology	Multiple soil attributes like mineralogy, texture	✓	✓
Soil landscape mapping	Soil types at 1:100,000 scale		✓

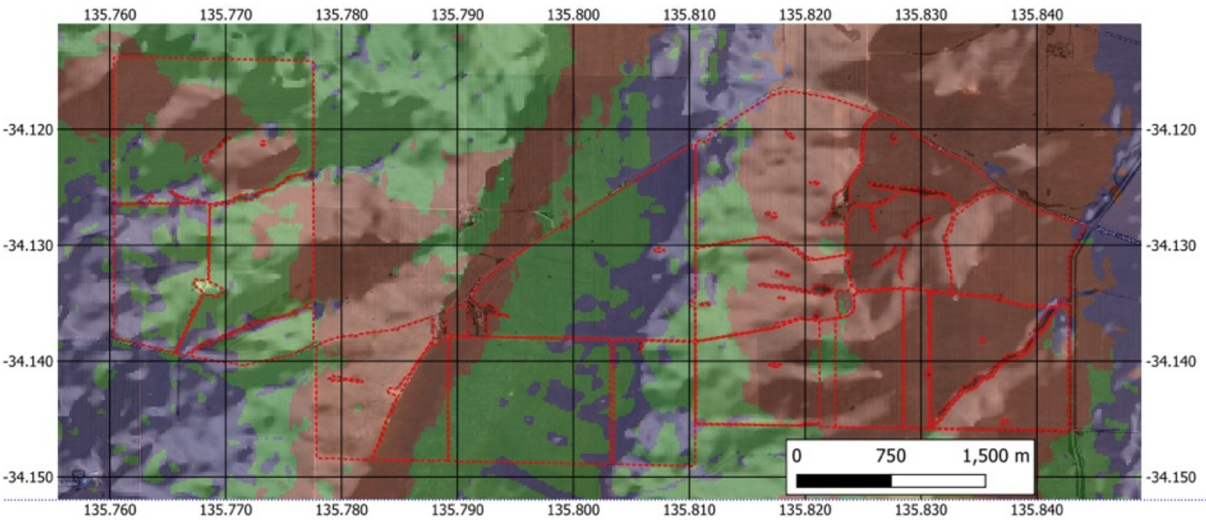

Figure 2. Wilksch farm 3-cluster k-means clustering solution.

An analysis of distribution of preliminary core AWC results sub-setted according to the 3 clusters shown in Figure 2 taken at the sampling points is shown in Figure 3. The preliminary whole profile AWC were estimated by applying soil layer properties (e.g. clay %) in the Soil Water Express app (Burk and Dalgliesh, 2012), see "Soil water retention and available water capacities" section below. Later, as the section describes, laboratory AWC data became available. Cluster 1 (green) is predominantly associated with lower hillslope zones (loams over red clay soils), cluster 2 (blue), in lower slow positions (loams over clay soils, and gradational clay loam soils) and cluster 3 (red), in upper slopes, crests and ridges where ironstone gravelly sandy loam over red clay soils and shallow soils on rocks are common soils. Figure 3 shows that cluster 2 separates well in terms of mean AWC of the cluster, whereas clusters 1 and 3 separate less well. This indicates in terms of the AWC attribute at least, the survey design appears to have adequately fulfilled the objective of covering a variety of soils on the farm; Figure 2 indicates that the survey design addresses landform and it maybe that AWC trends are not strongly linked to landform.

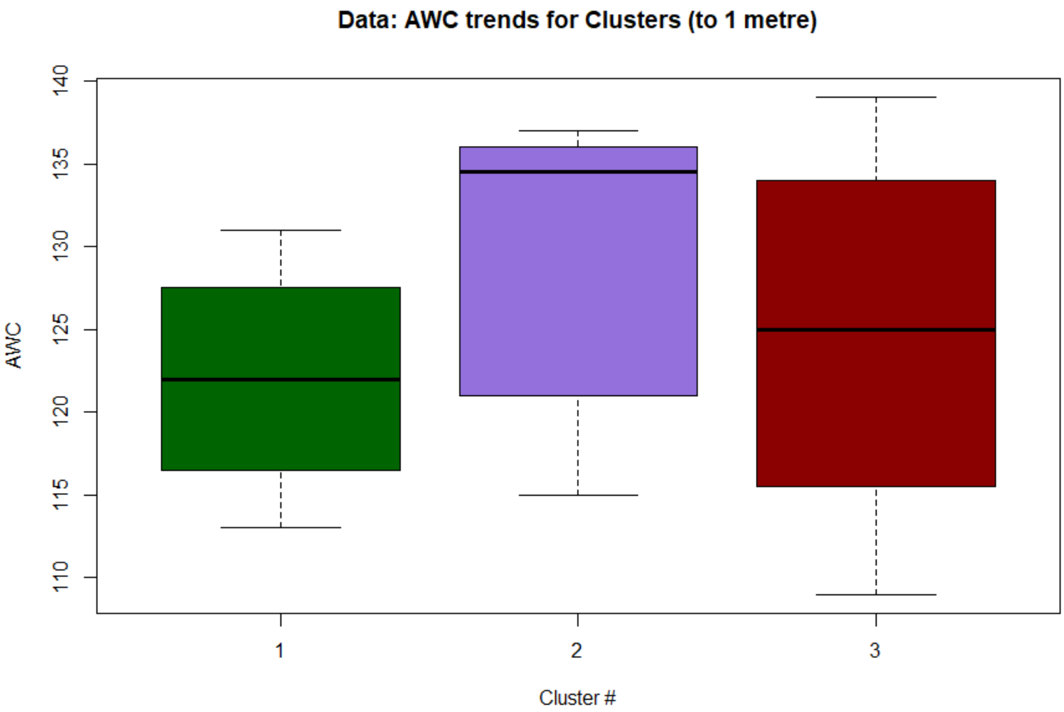

Figure 3. Boxplots of AWC size distributions at sampling points grouped by coloured cluster, as shown in Figure 2

Finding sampling sites

As discussed above, 25 candidate sampling sites were sought during the soil survey. The method to select the location of these involved distributing a proportionate amount of the 25 based on the land area of each cluster to avoid either under- or over-sampling clusters. Nine sampling sites were allocated to cluster 1, 8 to cluster 2, and 8 to cluster 3. Sites within each cluster were expertly assigned; wherever possible, sites were placed in transects down hillslopes. Transect sampling is beneficial in two ways: firstly, technical efficiencies are gained through sampling down slope because soil variability is maximised tangential to slope, thus increasing the range of soils sampled. Secondly, practical efficiencies are gained by ensuring that sites are near to one other thus helping to ensure that use of field time is maximised.

Soil sampling

A GPS was used to navigate to the sites in Figure 4. A 40-mm push tube corer was used to extract complete soil cores to a depth of 1 m. Two cores were collected for each site. The first was described at 0.2 m depth increments, each of which were bagged for physiochemical laboratory analyses. The second was divided into 0.1 m depth increments for laboratory water retention analysis (suction, pressure plate analyses). Twenty-two sites were achieved during the survey and shown in Figure 4.

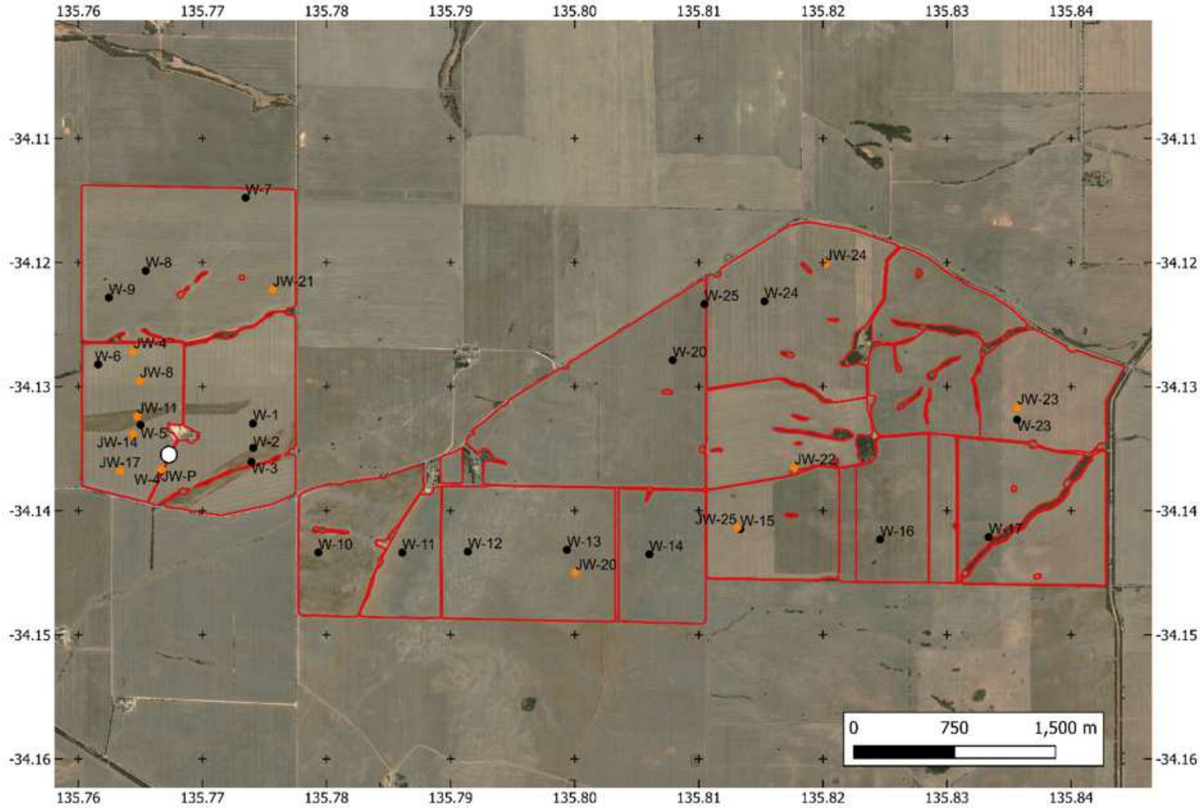

Figure 4. Distribution of the 22 sampling sites as red dots on the Wilksch farm. Black dots show sites sampled. Orange dots show location of period soil moisture sampling (see Soil moisture sampling section). The soil moisture probe FrSW is shown as the white dot.

Soil analysis

Physiochemical

The <2 mm fraction was analysed for a conventional suite of analyses on the 0.2 m depth increment samples. The analyses included pH, salinity (EC), Ca, Mg, Na, K, as well as texture. Texture was analysed using mid infra-red (MIR) scanning. MIR can often vary in accuracy depending on the strength of calibration, and in situations where prediction uncertainty was high, particle size analysis was used.

Soil water retention and available water capacities

Preliminary AWC values were estimated using the soil texture data from the physiochemical analyses (0.2 m increments). This method applied the pedotransfer function underlying the "Soil Water Express" tool (Burk and Dalgliesh, 2012) (http://apsimdev.apsim.info/swe/default.aspx).

More rigorous laboratory methods were employed to estimate soil water characteristics and AWC for each 0.1 m depth increment using methods in Cresswell (2002). The -15 bar pressure plate measurement is used to approximate the crop lower limit (CLL) and the -0.3 bar suction plate measurement is used to approximate the field drained upper limit (DUL). Conversion to volumetric water was estimated using bulk density derived from a GIS intersection of the sampling points in the SLGA bulk density data layer. Plots showing the upper (-0.3 bar) and lower (-15 bar) limits are shown in Appendix 1. The down profile AWC trends derived from the plate work are presented in Figure 8.

A whole profile AWC (to 1 m depth) for each of the 22 soils sampled was calculated by summing the 0.1 m increment AWC values and are shown in Figure 5. The mean AWC to 1 m depth for the value is 180 mm, with a standard deviation of 63 mm.

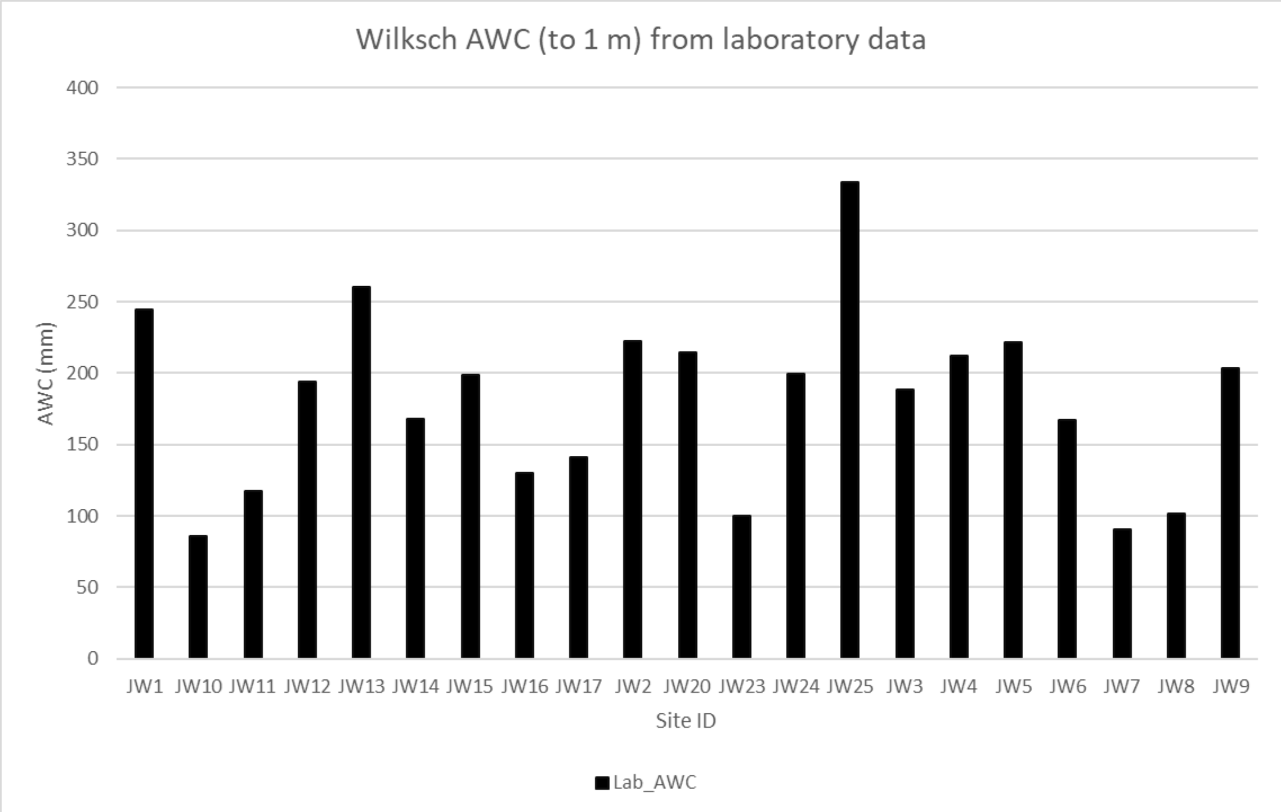

Figure 5. Whole profile (to 1 m) available water capacity for sampled soils

Digital soil mapping

The machine learning technique applies computer modelling to predict and map soil properties using DSM (McBratney et al., 2003). Many DSM approaches build and apply predictive models established from relationships between point-based soil observations (i.e. geolocated soil data) and covariates (McKenzie and Ryan, 1999), and are capable of predicting the distributions of soil properties at various depths. This pilot study applied the commonly used "Cubist" algorithm implemented in the "DSMTools" app developed by CSIRO to remove adoption barriers for non-computer programming users.

Model set-up has numerous user options. These include the suite of covariates, and the way model 'training' is supported. Training is the process by which the predictive model is iteratively built from observations (i.e. the geolocated laboratory data from the sampling sites, here AWC) intersecting with values from the stack of covariates. The model is also tested, and there are two methods to do this. One option called 'external' validation is to withhold a selection (e.g. 20 %) of the observations, build the model with the remaining 80 %, and then validate the model with the withheld 20 %. One drawback of external validation is the withheld data is 'wasted' for model building. An alternative option is to use 'internal' validation, which randomly withholds a pre-set number of data points for validation (e.g. 20 %), builds the model with the remaining 80 %, tests against the 20 %, and then finally returns the 20 % back into the set of observations. The technique repeats this multiple times, many thousands of times if desired. Statistical reliability is reported on accumulated results of each repeat. The benefit of internal validation is that all observations are used in model building as all are used in validation, ensuring all variability in the observations is used in both stages. Internal validation was used in the pilot.

The most successful model was achieved using the covariates listed in Table 1 and set to apply an 80/20 model build/validation split using all 22 site observations of whole profile AWC. The model build was repeated 50 times. In terms of mapping reliability, the model achieved an R^2 of 0.42 and a Lin's concordance correlation coefficient of 0.58. Concordance is perhaps the most informative quality metric because it reports the model quality in terms of the 1 to 1 observation/model result (Lin, 1989). A concordance value of 0.58 suggests a moderately strong model. The results for each 0.1 m depth 'slice' AWC are presented in Figure 6 and Figure 7. A whole of profile AWC (to 1 m depth) (Figure 7) was created in the GIS by combining the 0.1 m depth increment AWC layers.

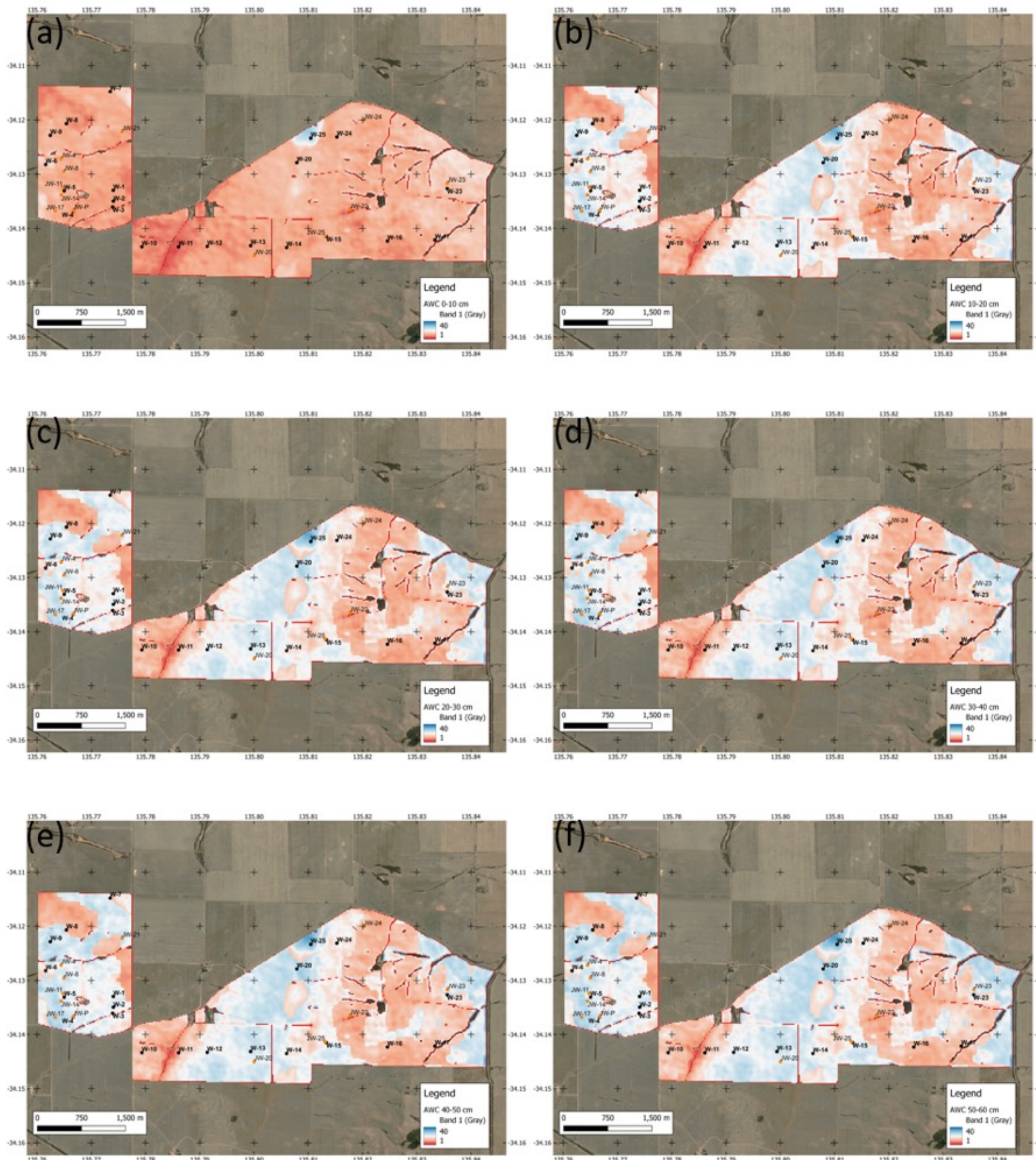

Figure 6. AWC predictions at various depth increments: (a) 0-10 cm, (b) 10-20 cm, (c) 20-30 cm, (d) 30-40 cm, (e) 40-50 cm, and (f) 50-60 cm. Soil survey sites (for lab AWC; black dots) and periodic soil moisture sampling sites (orange dots) are shown.

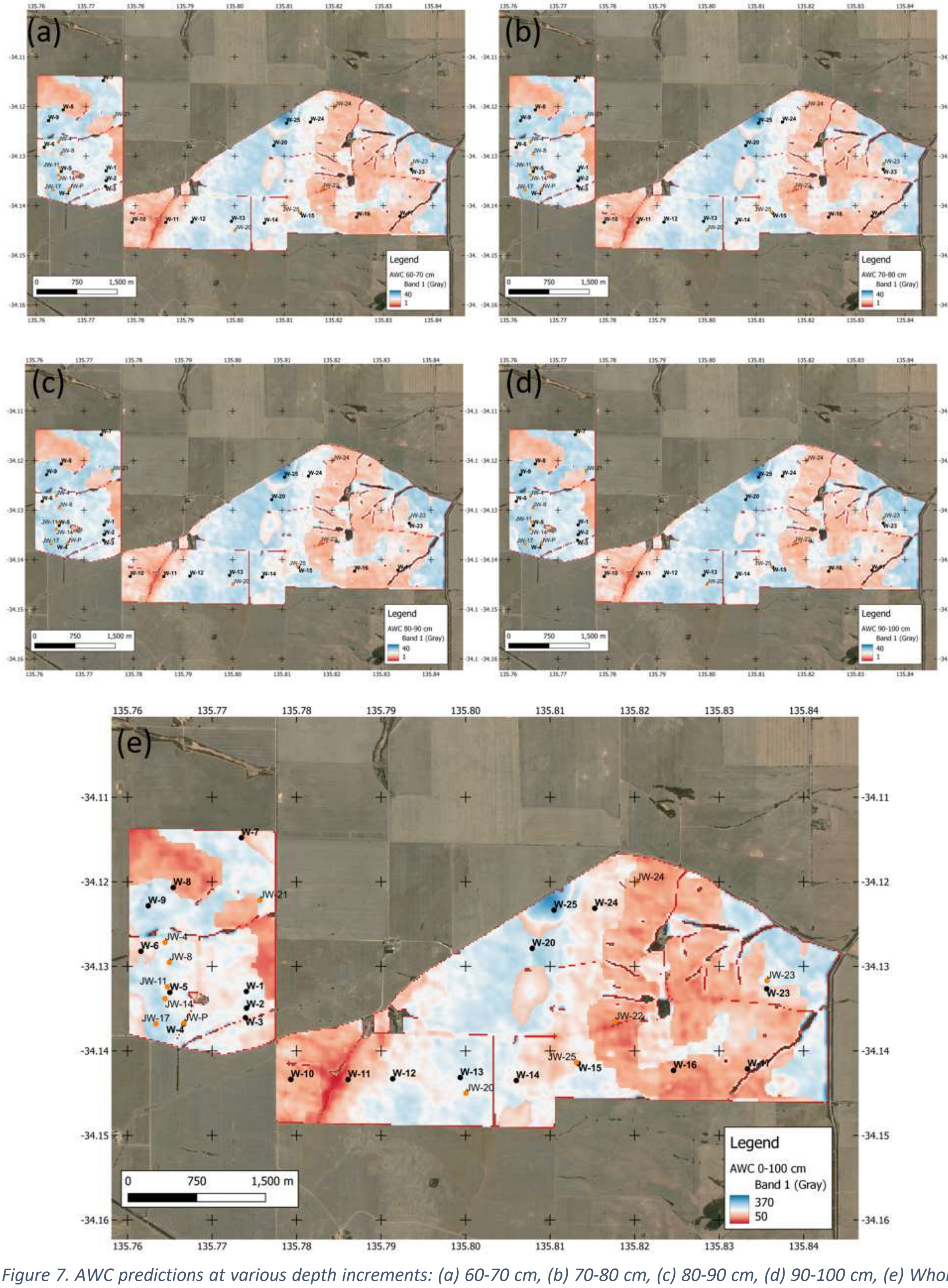

Figure 7. AWC predictions at various depth increments: (a) 60-70 cm, (b) 70-80 cm, (c) 80-90 cm, (d) 90-100 cm, (e) Whole profile to (0-100 cm). Soil survey sites (for lab AWC; black dots) and periodic soil moisture sampling sites (orange dots) are shown.

The Figures show that the depth slice predictions are in the range from approximately 0 to 40 mm AWC for each 10 cm depth slice, and for the 100 cm profile, 59 to 365 mm. Visually the figures show consistency in AWC patterns through the depth slices. The areas with the largest whole profile (0-100 cm) AWC are in the lower landscape areas in the western paddocks and the central broad valley. The smallest AWC values are in the upland areas where soils are shallower, rocker or lighter textured. Figure 8 shows the traces created from the intersection of DSM depth slices at the survey sites in

Figure 6 and Figure 7. Comparison of these down profile traces consistently shows the DSM modelling tends to generalise the down profile trend compared to the lab measured AWCs for each layer, and that DSM 'hinges' in the 10-20 cm depth range; this is typically a reliable depiction given the lighter textured topsoils generally encountered. By and large, visually the 'generalised' DSM representation of down profile AWC compared to the lab AWC indicates that in both sources, whole of profile AWC values are similar in total.

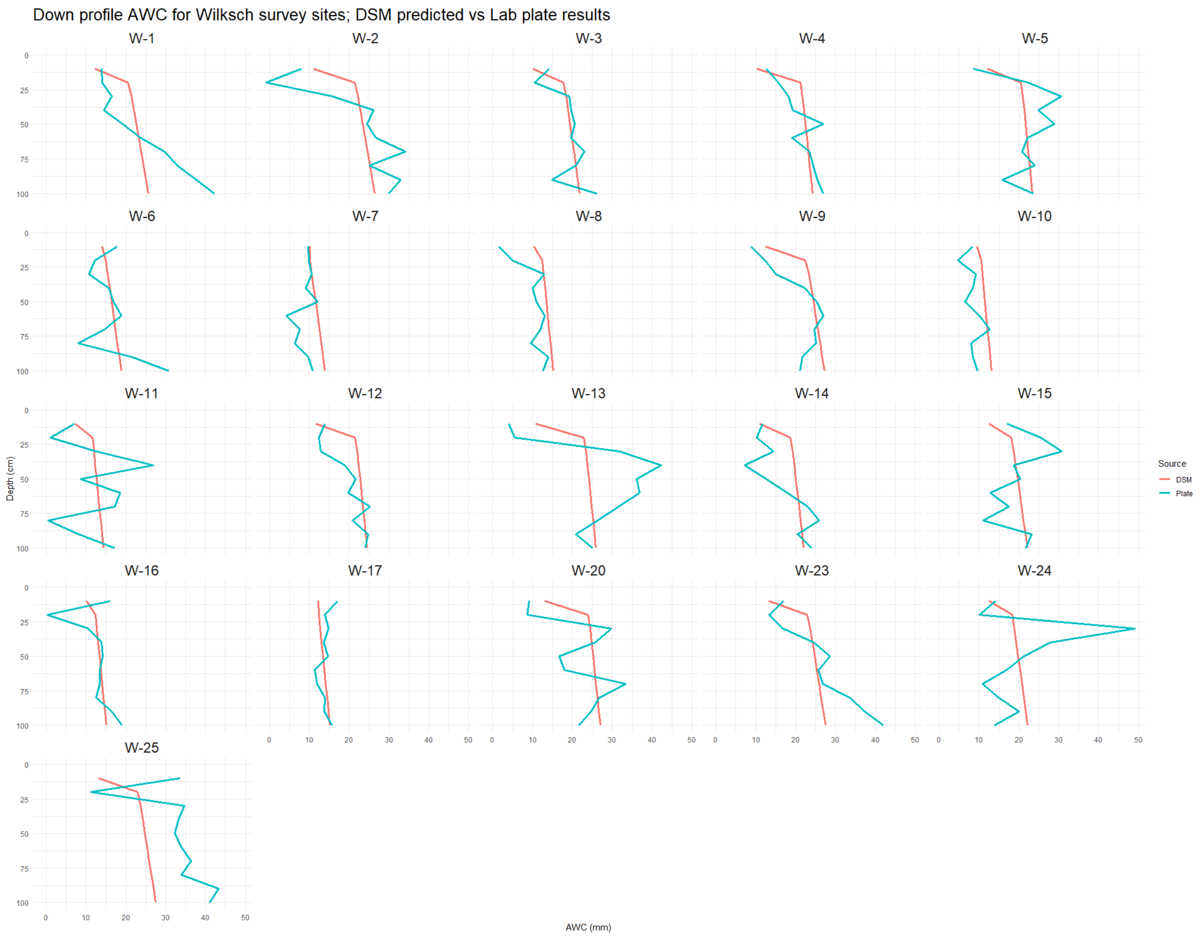

Figure 8. Comparison of down profile DSM and laboratory AWC values

The variance between the DSM and laboratory data at each depth increment (*n* = 422) is also summarised in the scatter plot in Figure 9, which shows reasonable correlation (R^2 = 0.49) between the two datasets. Figure 10 demonstrates the reasonable relationship is followed through to the whole of profile AWC estimations (*n* = 22; R^2 = 0.56). These results indicate that the AWC modelling has been performed quite well by DSM.

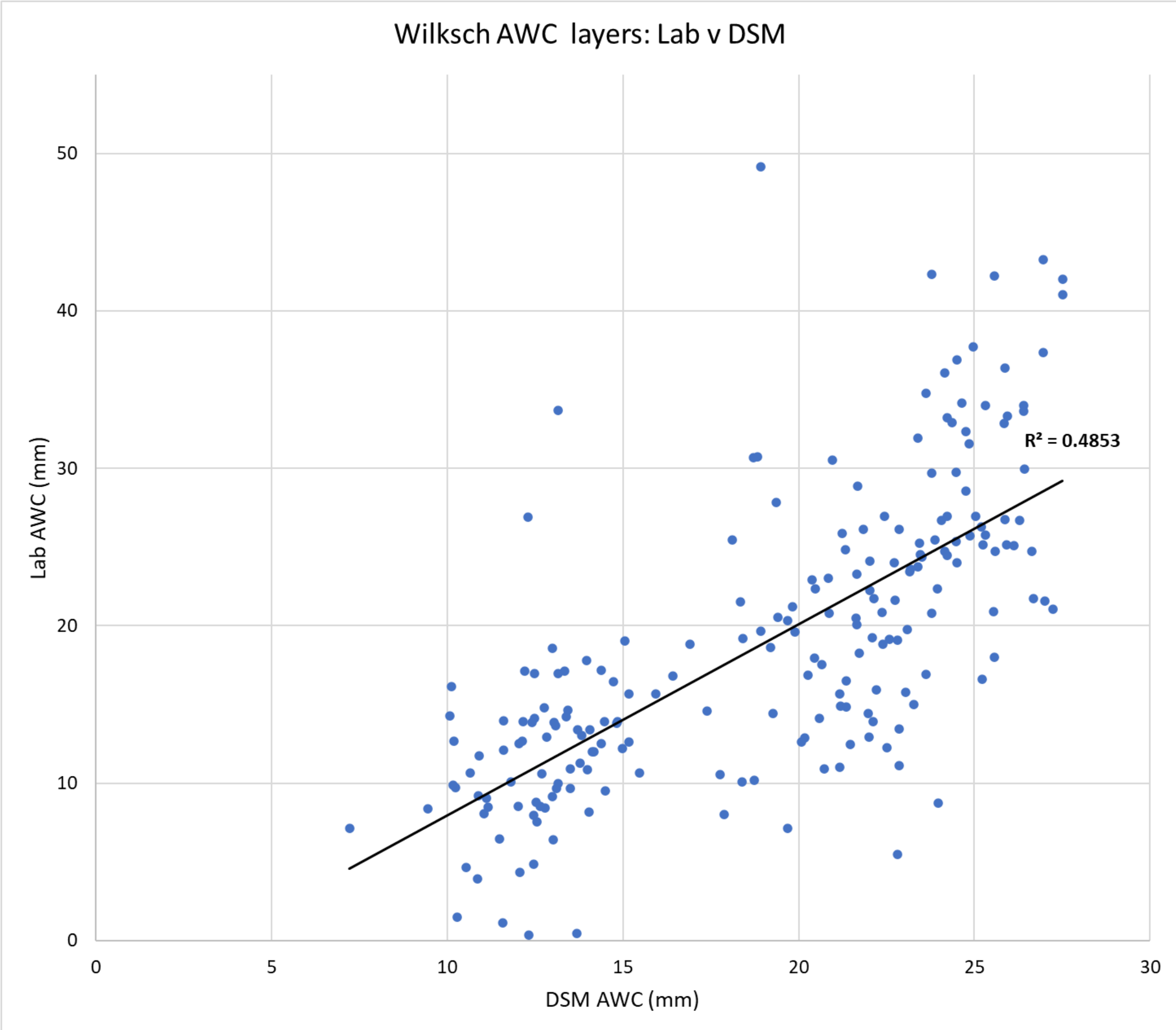

Figure 9. Scatter plot comparing laboratory AWC values against DSM AWC values at each depth layer

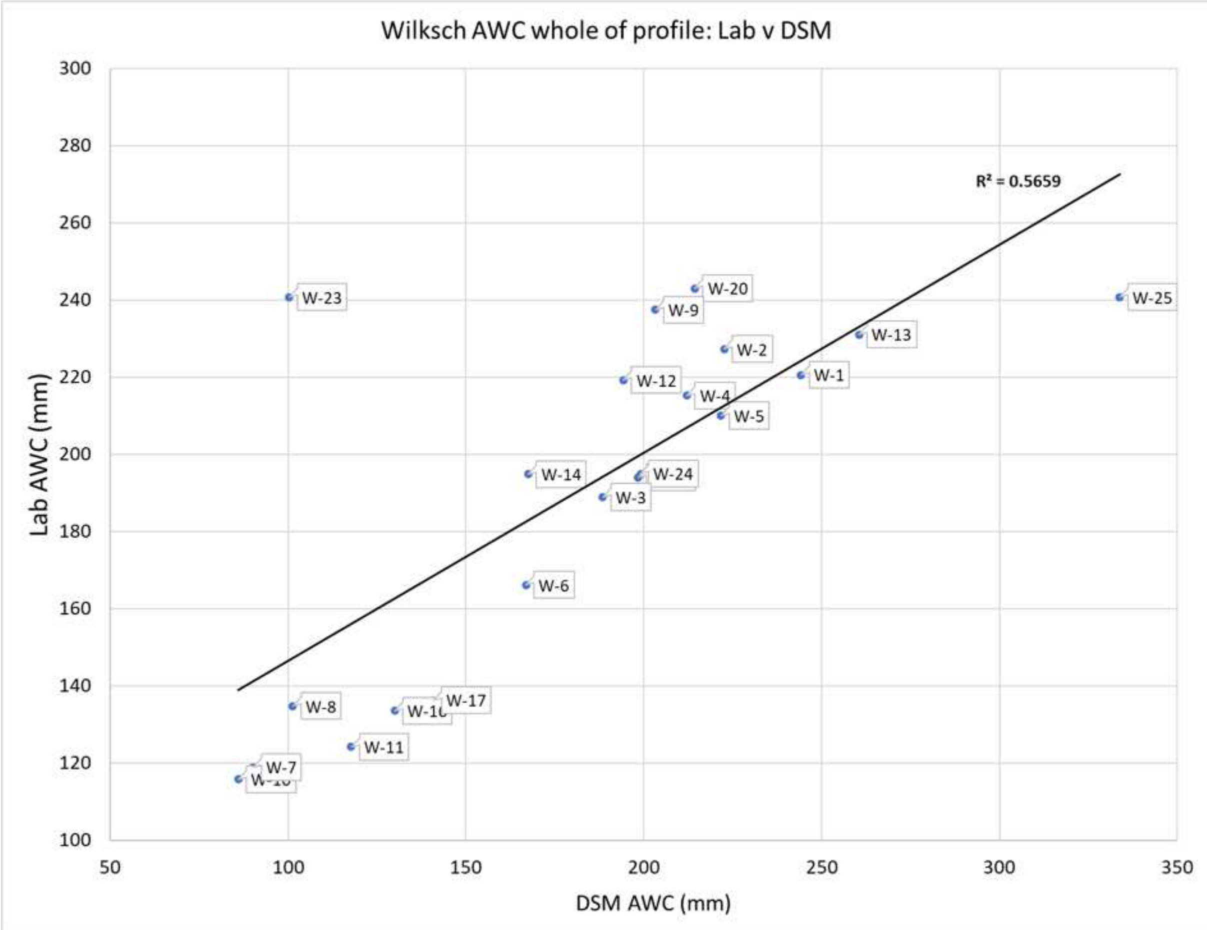

Figure 10. Scatter plot comparing laboratory AWC values against DSM AWC values for whole of profiles to 1 m

Extrapolating moisture signal

The final phase of the pilot involved testing the use of signal from the SW probe soil moisture probe to predict the AWC elsewhere on the farm at various times using the DSM of AWC. This method works under the premise that soil moisture information from the soil moisture probe reflects the contemporary soil moisture status across the farm, and rainfall received does not vary to a significant degree over the farm. Soil moisture data from periodic sampling sites on the farm is used to evaluate to extrapolation.

Soil probe data

Soil moisture has been collected at the Wilksch probe since 2016. The soil moisture to 1 m depth for the period it was functioning is shown in Figure 11.

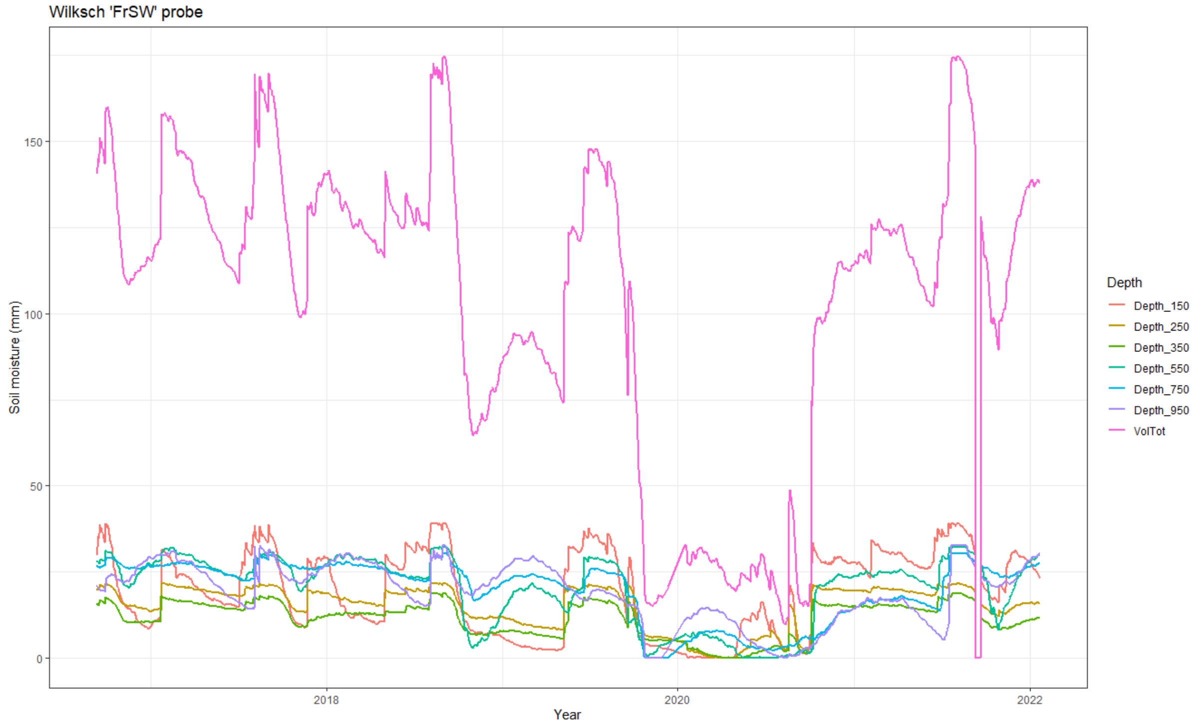

Figure 11. Wilksch probe soil moisture output from Sept 2016 to January 2022 showing various layer soil moisture (volumetric, mm) and total profile to 1 m in pink.

Soil moisture sampling

Soil moisture measurements were collected at various depths increments (0 – 0.1, 0.1 – 0.2, 0.2 – 0.4, 0.4 – 0.6, 0.6 – 0.8, and 0.8 – 1.0 m) from 12 fixed sites on the farm shown in Figure 4. These sites were sampled during 14 May 2021, 8 October 2021, 2 February 2022, 18 March 2022 and 14 July 2022, and moisture measurements made in the laboratory. These were converted to volumetric soil measurements for each depth increment using bulk density estimates derived through GIS intersection of the bulk density mapping from the SLGA.

Using soil the moisture probe to modify DSM AWC

Whole farm whole profile (1 m) water at soil moisture sampling dates was estimated by applying the contemporary FrSW probe signal to the whole farm AWC DSM in Figure 7 (e). This modifier was derived from a normalised[2] multiplier and applying the modifier from the date to the AWC DSM. Figure 12 shows a comparison on values taken from soil moisture sampling sites (Figure 4). The comparison between predicted and measured soil moisture are presented in Figure 12 and shows a reasonably strong relationship (R^2 = 0.60, all dates combined) between the field soil moisture measurements and modified AWC.

[2] (x – minimum)/range, values of 0 - 1

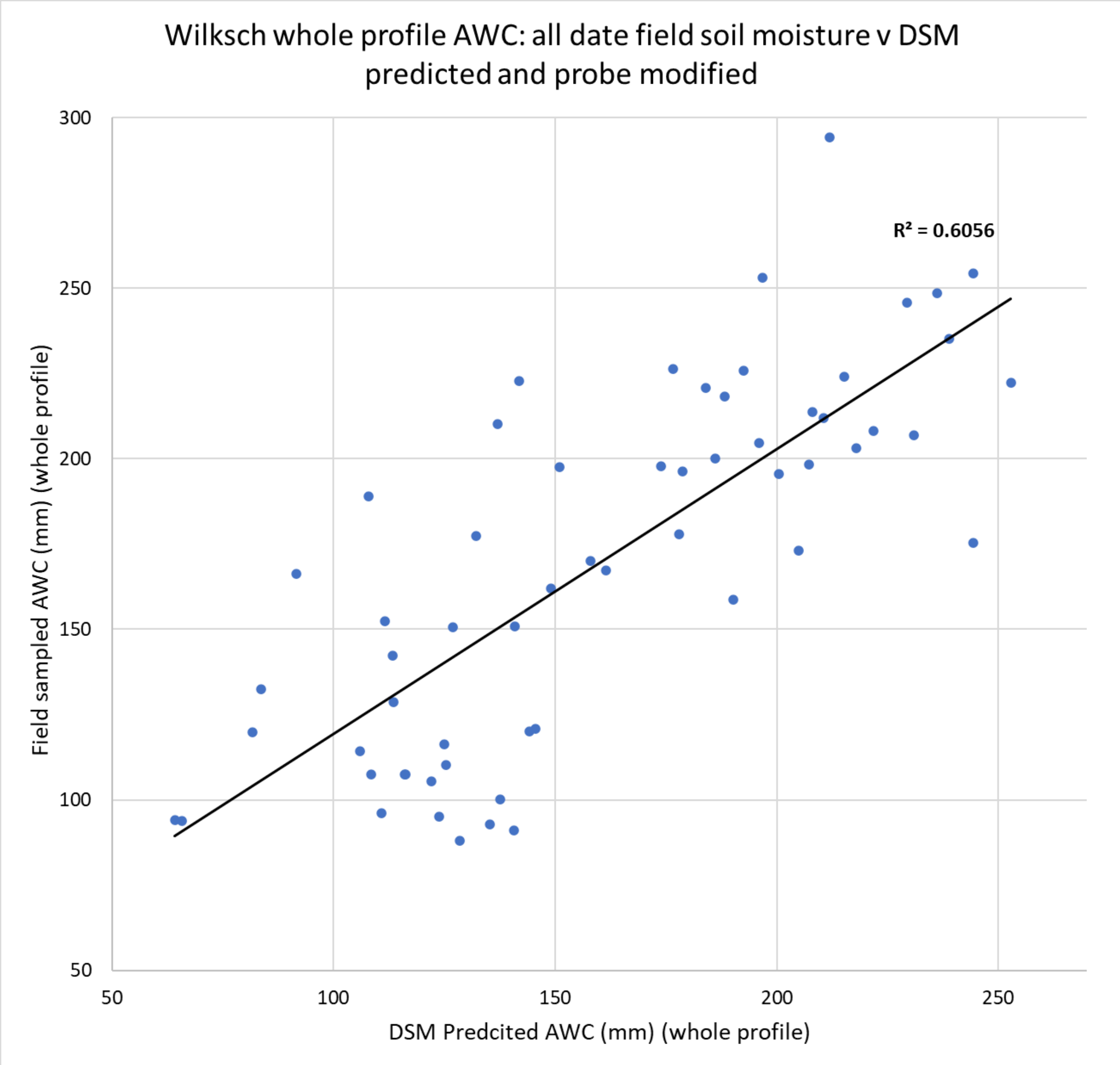

Figure 12. Scatter plot comparing all date soil moisture from all field soil moisture measurements versus DSM predicted and probe-modified. The three dates are shown and best fit line for combined date comparisons

Conclusions and recommendations

The pilot project applied soil-landscape principles to formulate a non-bias and efficient soil sampling design to survey the Wilksch farm. The soils were sampled at 22 sites at both 10 cm and 20 cm increments to 1 m depth. Using laboratory methods available water capability (AWC) was measured for each 10 cm depth increment.

The 10 cm AWC increments were used to model AWC for the whole farm at a 20 m ground raster mapping resolution using computer machine learning digital soil mapping (DSM). Based on the soil survey intensity alone, this mapped output is consistent with a semi-detailed intensity of soil survey, which equates to coarse end of 1:50,000/fine end of 1:100,000 scale mapping, placing the utility of output at the end range of moderately intensive farm planning (Gallant et al., 2008). While this does not support tactical farm decision-making one would expect at the level of precision agriculture (Jochinke et al., 2007), the AWC map gives an appreciation of within paddock variation offering a new level of farmer support/appreciation/understanding - and of course inter-paddock variation. The model delivered a Lin's coefficient of correlation of 0.58 indicating a moderately strong model for AWC across the farm. When the whole profile AWC results derived from DSM and the laboratory measurements were compared, the relationship was moderately strong as well ($R^2 = 0.56$).

Next, the FrSW probe soil moisture data was used to extrapolate soil moisture from 5 sampling dates were compared to DSM AWC modified by the concurrent probe data. Over the 5 dates, the relationship between field soil moisture and DSM was moderately strong (R^2 = 0.60).

The methodology used in this pilot has applied an analytical workflow to test DSM prediction of AWC and temporal extrapolation from soil moisture probe data, and the results for the Wilksch farm appear positive. However, further improvements may be possible, for example, assuring that:

- The soil survey design was optimal and that it had covered all of the soils.
- The DSM approach was the best possible, including the optimal user set up and algorithm; there several model settings that could have been tested, as well as different algorithms like Random Forests (Wright and Ziegler, 2015)
- Similarly, it is acknowledged that the SLGA covariates were likely to have been used beyond optimum given these have been compiled for a smaller scale of application than use here.

One of the key limitations of the approach is the reliance of SLGA data as covariates because of the coarse native spatial resolution of these datasets. Whilst the resolution is inconsistent with precision agriculture-type approaches, the current ability to map AWC across the Wilksch farm with moderate reliability and the ability to predict AWC at various times from a soil moisture probe is an advancement on current capability.

Acknowledgements

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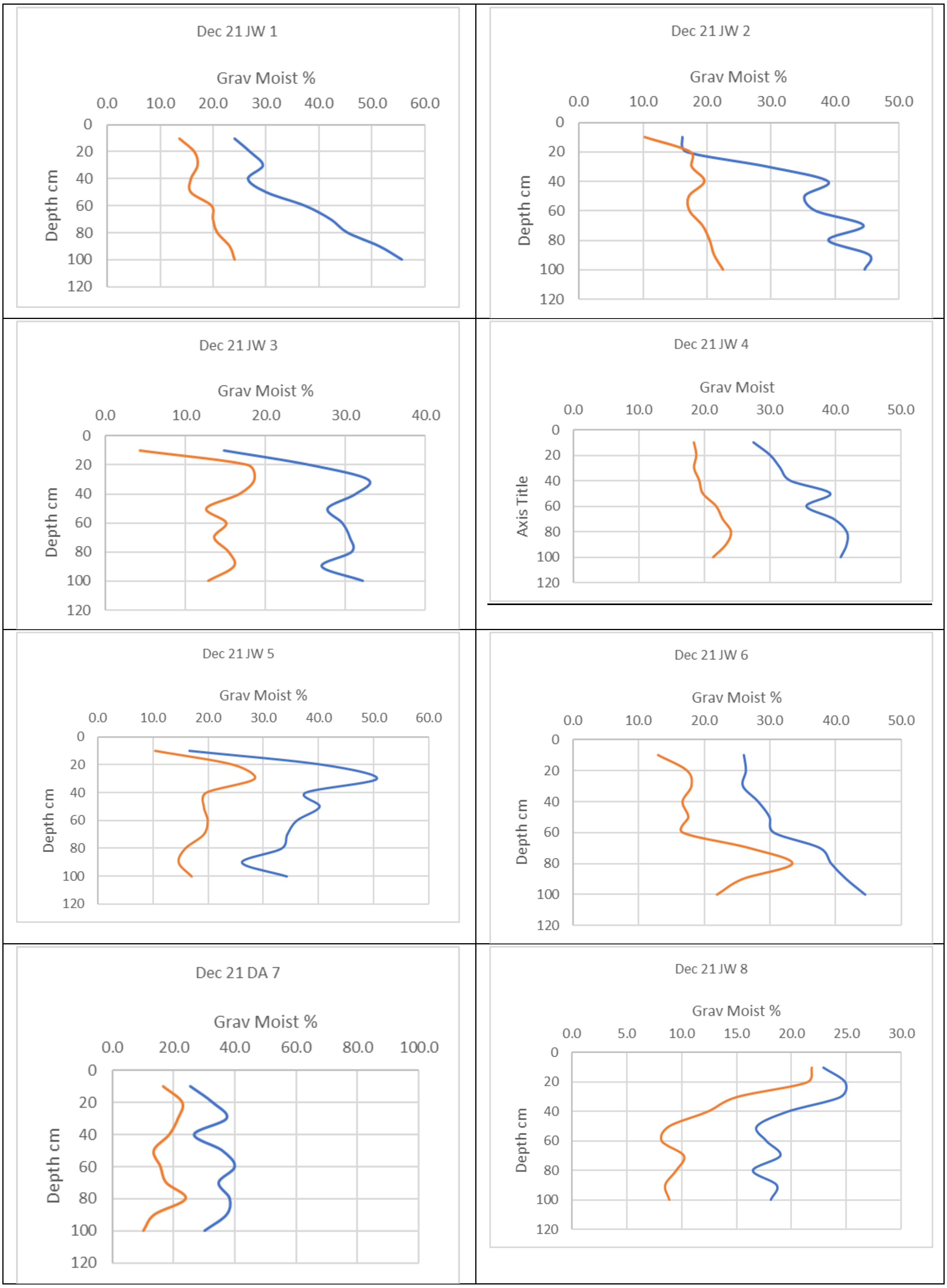
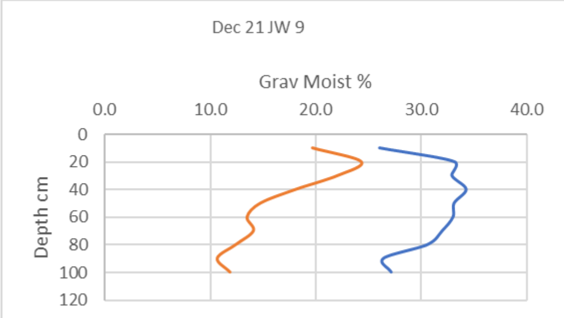
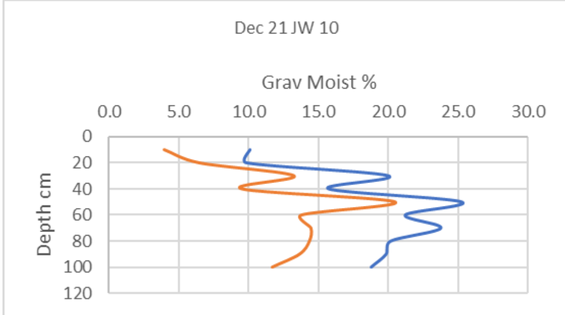
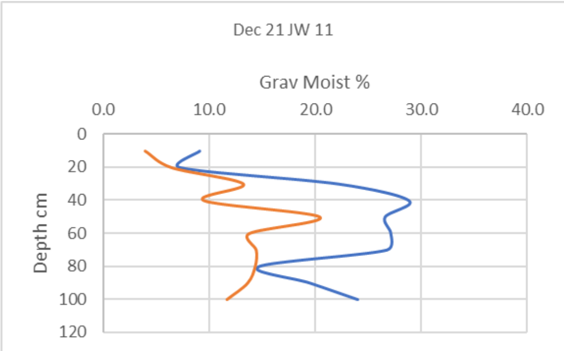
Appendix 1

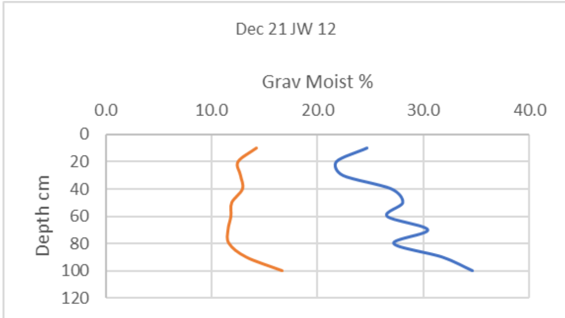
Gravimetric moisture contents of soil profiles to 1 m depth (or core refusal) from laboratory pressure and suction plate analyses. Red line approximates crop lower limits (CLL) and blue line, the drained upper limit (DUL).

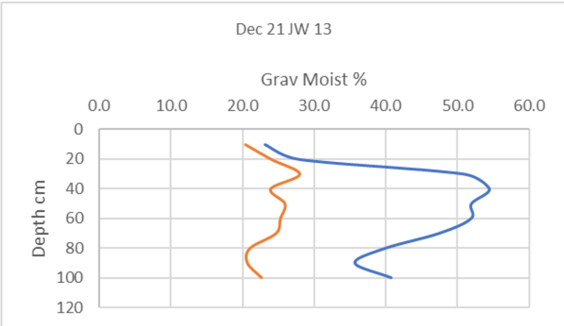


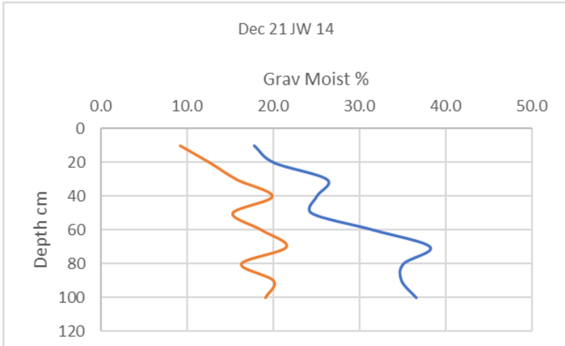

Dec 21 JW 9
Grav Moist %
0.0 10.0 20.0 30.0 40.0
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 10
Grav Moist %
0.0 5.0 10.0 15.0 20.0 25.0 30.0
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 11
Grav Moist %
0.0 10.0 20.0 30.0 40.0
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 12
Grav Moist %
0.0 10.0 20.0 30.0 40.0
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 13
Grav Moist %
0.0 10.0 20.0 30.0 40.0 50.0 60.0
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 14
Grav Moist %
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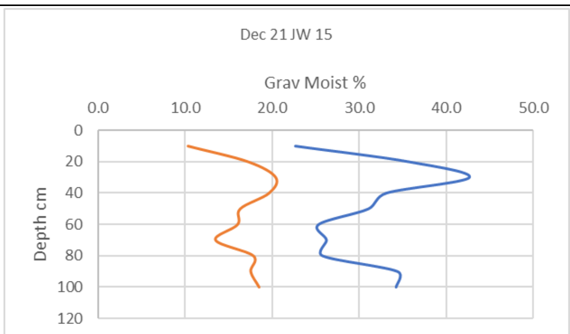
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 15
Grav Moist %
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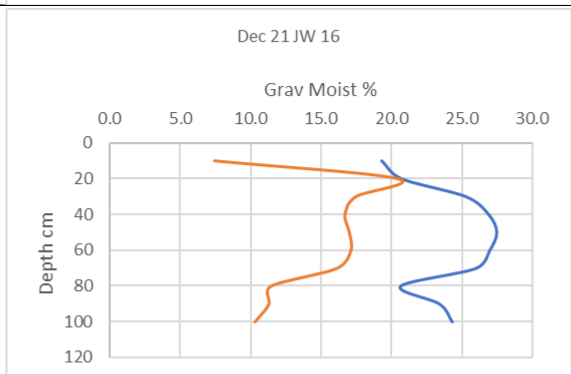
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 16
Grav Moist %
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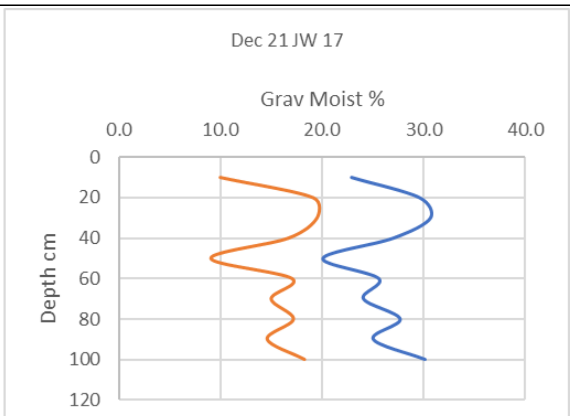
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 17
Grav Moist %
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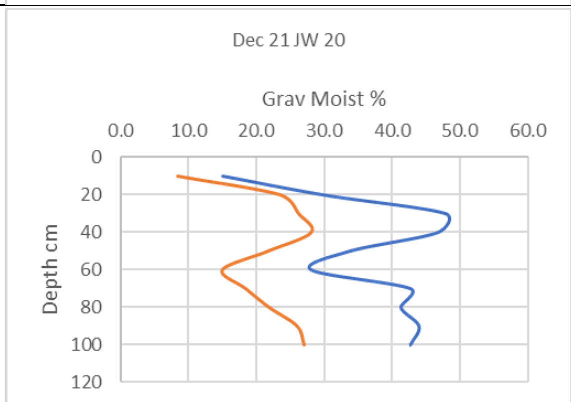
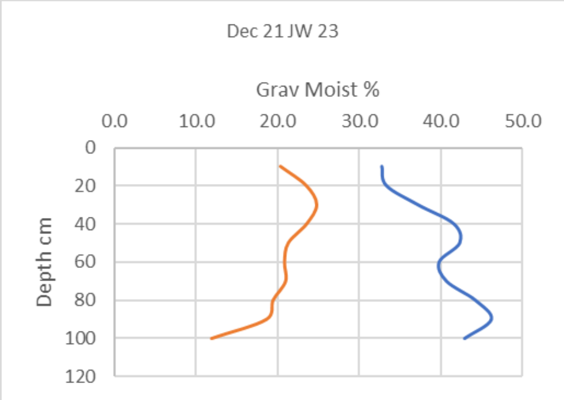
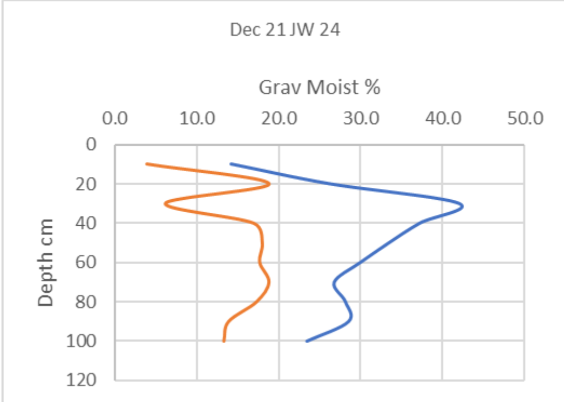
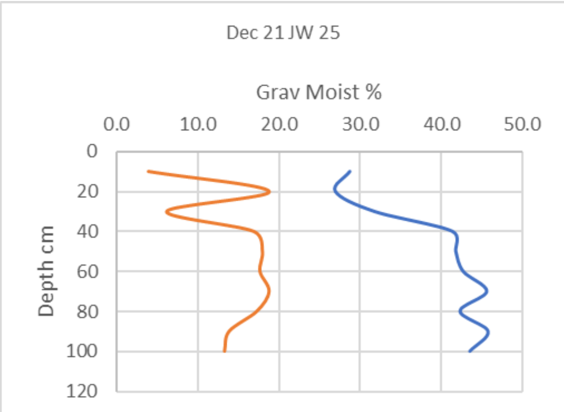
0 20 40 60 80 100 120
Depth cm


Dec 21 JW 20
Grav Moist %
0.0 10.0 20.0 30.0 40.0 50.0 60.0
0 20 40 60 80 100 120
Depth cm







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