final report

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Construction and testing of the first commercial-scale SCANS unit for measuring soil carbon in the Australian red meat industry

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Executive summary

This work was undertaken to assist the development of rapid, non-destructive soil analysis for estimating soil carbon yield. CSIRO had developed a prototype technology using Near Infrared (NIR) and gamma radiation to measure soil carbon stocks in a soil core and this has been licenced to Carbon Link.

Carbon Link constructed a unit in 2018 after the the 2018 Agricultural soil carbon method was released. The questions to be answered include:

- Does the technology actually work?
- Can it measure soil carbon stocks more accurately than conventional methods?
- What problems exist with it on a commercial scale?
- Is the technology cost effective?

The multi-sensor soil core scanning system (CSS) unit (also known as multi-sensing platform or the SCANS Unit) was constructed to measure soil organic carbon in soil cores up to 1.5 m long with a diameter between 45 and 8 5 mm. Construction of the instrumentation was completed by May 2018. It then took over 6 months before it could record information as the software was inadequate. It took a further 9 months to write the software to interpret the data collected.

More than 700 soil cores were collected in 2016 and about 175 fresh cores (130 from Rexton and 45 from Bingara) collected in June 2019 and all transported to Gladstone for scanning. Components were tested as software became available from CSIRO. These included repeatability of the NIR, comparison with a second NIR, subsampling procedures for the NIR calibration, moisture correction and interpretation of the Gamma data. Additionally, a field trial was conducted across 6 strata, 10 samples per strata and replicated with a second randomization.

To date we conclude that:

- The complexity of the system works against its more widespread adoption.
- The cost of processing cores through the SCANS system is around 15% higher than laboratory analysis of full cores at the current rate of productivity (max of 25 cores analysed per day).
- The cost of subsampling for NIR calibration is very high under the current methodology, where there are many Carbon Estimation Areas (CEA)s, and will add significantly to project costs if it cannot be changed.
- The mean C yield (t C/ha) of two randomisations sampled on the same site at the same time, was statistically identical, i.e. repeatable, however, there was huge variation within two of the six strata. We were not able to determine the reasons for the variation.
- Variation between samples taken 20cm apart was 10%, which is understood to be the minimum inherent variability in the project sampled.
- The sensor data has been analysed to assess repeatability and to select subsamples to send to the lab for calibration. The repeat tests showed that the reproducibility of the NIR was very high ($R2=0.95$).
- The stratified sampling design used at this site detected a C increment of 11% or more, with 95% confidence, with very high core numbers. This is a high standard and exceeds the methodology confidence level of 60%. The implications of this are significant as it means the projects with a sequestration rate of less than 1 to 2 t C/ha/annum, will be heavily discounted by the statistics and may not record tradeable changes at 95% confidence. However detectable levels will decrease with the lower confidence level.
- A comparison of LECO (LECO is the trade name of an instrument for elemental analysis of organic materials like soils) results and the SCANS results showed that SCANS was more

accurate with less than half the standard deviation of LECO. There is some evidence that the standard LECO test is very variable and understandably inaccurate given the minute sample size.

- Problems still remain within the SCANS system with regard to a) correction for water content, b) poor to nil correction for gravel above 2mm, c) problems with the gamma bulk density calculation and d) portability restrictions with the gamma.
- We therefore recommend using the LECO standard until such times as the technology is both improved in accuracy and lowered in cost.
- However the economics of doing soil carbon projects, where the sequestration rate is at or above 2 t C/ha/annum, is very favourable at a carbon price of $25/t CO2e. The IRR ranges from 24 to 41% under the assumptions used.
- The largest determinants of the profitability of a soil carbon project to a landholders are
    - Annual sequestration rate
    - Scale, and
    - Carbon price.

  Sampling cost is of much lower order and is a two edged sword. Very low sampling rates and costs are likely to have high variance and hence a saleable carbon penalty. Very high sampling rates may be uneconomic, indicating there will be a sweet spot between the two extremes.
- The scanning unit we have built is still only a prototype and requires more development to commercialize, due to its low capacity. However, with the addition of an X-Ray tomography unit to do bulk density, and electronically sieve out roots and rocks above 2mm (a methodology requirement), soil carbon analytical costs will be well below standard laboratory tests. The X-Ray tomography unit may also improve the accuracy of equivalent soil mass estimates, which are required by the methodology.

Further steps to commercial application of the SCANS system include:

- Updating the software applications which drive the scanning unit, to speed it up.
- Changing the camera and caballing to a more reliable system.
- Removing the Gamma unit from the system. Using Gamma sources places many restrictions on where and who can operate the system and it is also the process which slows down the Scanner. The time to scan a core with NIR only will be reduced from 20 minutes to 1 to 2 minutes if the gamma is removed.
- Developing a specific X-Ray tomography prototype for soil analysis and bulk density. The purpose is to do away with the Gamma Unit and provide an electronic sieve for roots, gravel and large cracks in the core samples. Proof of concept has been done and a prototype is being developed.
- Getting the following changes in the methodology in terms of the technology;
    - A change to the Guidelines to facilitate the use of X-Ray tomography to do bulk density and sieve roots and rocks.
    - Accommodation of the NIR calibration in a more sensible way in relation to CEA numbers.
    - Removal of the need for the Scanner and the X-Ray systems to be used in a NATA accredited laboratory. This just prevents them from being field deployable. The calibration samples will be done through an accredited lab, which should overcome the requirement.
    - Removal of the maximum 5 year sample period. Having to resample after 5 years of drought, makes no economic sense and such projects will go by the wayside if it cannot be delayed.

- Apart from the above changes to the methodology, there are other changes required to achieve large scale uptake of soil carbon projects. These include, but are not limited to:
    - Removal of the T1 discount of 50%.
    - Removal of the arbitrary 20% discount for 25 year projects. The statistical variance and the 5% buffer should be adequate discounts on a measured method.
    - Extend the crediting and permanence periods to 40 years as per the ACR methodology.
    - Combine the current measured method with a modelled method in order to create annual cashflow. The measurement is the final arbiter of crediting however.
    - Lower the auditing costs by using technology such as blockchain

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1 Background

Soil carbon is the single biggest terrestrial carbon pool, estimated to contain 2300Gt carbon (to three metres) - larger than the atmospheric (820Gt) and above ground biomass (610Gt) pools combined. Total emissions from fossil fuel burning and cement manufacture were 10Gt in 2015; as such, the soil could quite feasibly to absorb the world's annual emissions. It can simultaneously improve productivity, profitability, drought tolerance and biodiversity of farmland. When soil carbon is traded, it may precipitate a positive shift in current agricultural practices and encourage thousands of farmers to participate in regenerative agriculture.

To date, carbon trading in the agricultural sector has been dominated by agroforestry and small-scale emission avoidance practices by piggeries and municipal waste. Coinciding with national changes, for example the ERF auctions, and international changes such as adoption of the 4 per 1000 Initiative at the COP 21 in December 2015, Carbon Link has been conducting research and development since 2007. Carbon Link has done the largest scale soil carbon baselining in Australia.

Early work indicated that sequestration rates of 2tC/ha/annum would add significantly to the profitability of graziers, at a carbon price of \$20/t CO2e. Internal research conducted by Carbon Link has indicated a potential of 30 million ha under soil carbon projects under a high adoption rate (10 to 20%) with annual abatement of 200 million t CO2e. After accounting for discounts, this is saleable annual abatement of over \$2 Billion pa.

Soil is the largest carbon pool over which humans can have an influence and as such, offers the greatest potential for dealing with climate change. Fisher et al (2007) have shown that carbon stored in soil at a depth of 20cm is stable for 1,000 to 2,000 years.

This work was undertaken to assist the development of rapid, non-destructive soil analysis for estimating soil carbon yield. CSIRO had developed a prototype technology using NIR and gamma radiation to measure soil carbon stocks (Viscarra-Rossell et al, 2017) in a soil core and this has been licenced to Carbon Link.

Carbon Link has been conducting R&D in the soil carbon space for 12 years and attempted to go commercial in 2016 with the grazing methodology. After baselining 16,000ha, we ceased commercial operations due to problems with the methodology, accuracy issues, lack of knowledge on sequestration rates and low carbon prices to name a few. We then lobbied for the release of the 2018 method and the inclusion of technology from this century.

Some reasons for wanting an upgrade included:

- Use of technology to allow more accurate sampling
- Use of technology to reduce costs
- Use of unequal area stratification
- More suited to agriculture

Carbon Link constructed a unit in 2018 after the the 2018 Agricultural soil carbon method was released. The new methodology allowed the use of this type of technology. The questions to be answered include:

- Does the technology actually work?
- Can it measure soil carbon stocks more accurately than conventional methods?
- What problems exist with it on a commercial scale?
- Is the technology cost effective?

2 Project objectives

The objectives of the project are:

1. Construct and test the SCANS unit in the field; Completed
2. Test the accuracy and repeatability of the system at commercial scale to have confidence to take the technology into commercial use. Completed
3. Complete statistical analysis of soil scan data and produce yield. Completed

It was not possible to test the unit in the field due to Gamma licencing restrictions. Movement of gamma radiation sources is restricted and our licece restricted it to a room in Gladstone.

3 Methodology

3.1 The Core Scanning System (CSS or SCANS) Unit

The CSS Unit is integrated with a combination of proximal sensing technologies, smart engineering, mathematics and statistics to characterize soil C variation, laterally across landscapes and vertically down the profile. The original concepts were developed by CSIRO and licensed to Carbon Link Limited. The multisensor system was developed to measure 1.5 m long soil core samples with diameters between 45 and 85 mm (Fig 1). Measurements of longer soil cores are possible with some small modifications.

Carbon Link received drawings from CSIRO but had to have them redone by engineers to a standard which allowed the unit to be constructed. We next discovered that the machine software that drives the mechanics of the unit was dated and inadequate and all new instruments and software were backdated by 7 years in an attempt to get it working. This process took 6 months and it currently still operates on outdated software. We subsequently discovered that no software extisted to interpret the data. This has been corrected by different staff at CSIRO. These delays have put us 18 months behind schedule.

The platform's housing contains a support structure for the soil core, a linear actuator to move the sensor head along the core, a cable train to allow the movement of cables, and a linear rail to provide additional support to the sensor head (Fig. 2), which holds four sensors:

1. A vis–NIR spectrometer (350-2500 nm),
2. an active γ-ray (gamma) attenuation sensor,
3. a visible camera, and
4. a Lepton long wave infrared camera

Figure 1: Carbon Link Soil core sensing system (CSS) unit

A photoelectric proximity sensor is used to detect the length and position of the core sample on the support platform. The platform includes a safety interlock system for the active γ-ray sensor that is triggered by opening the protective door or an emergency stop button. A touch panel computer is used to control the system via software and a graphical user interface (Fig. 2).

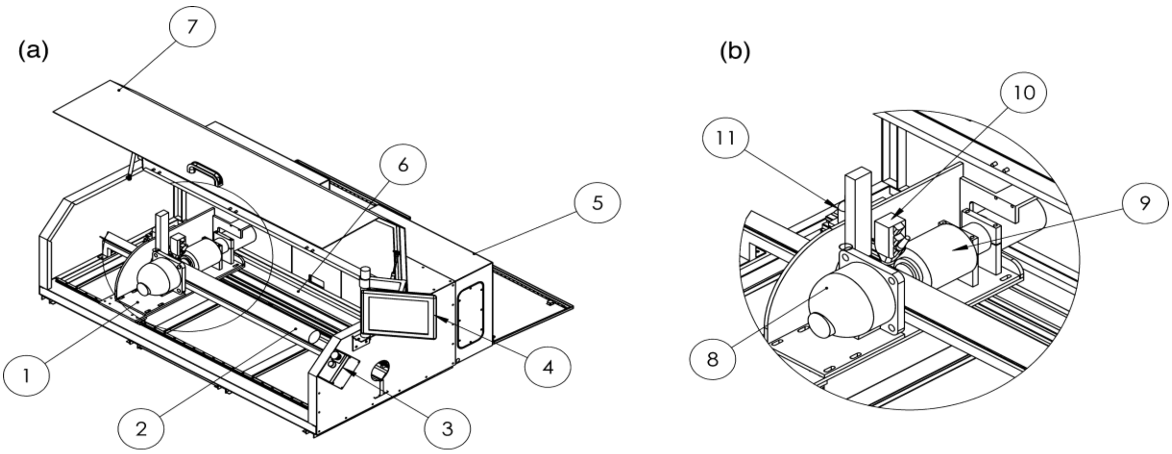

Figure 2: Schematic of the CSS Unit: (a) (1) sensor head, (2) soil core, (3) emergency stop and reset buttons, (4) touch screen PC, (5) electronics boxes, (6) linear actuator, and (7) polycarbonate hood with safety sensors and (b) (8) γ-ray source, (9) γ-ray det

The visible−near-infrared (vis− NIR), active γ-ray attenuation and camera sensors measure the soil cores at user-defined depth intervals. These have been set to each 5cm for the top 30cm and each 10cm below that. The scanning and analysis process was followed as described by Viscarra Rossel et al. 2017. With end-caps in place, and immediately before measurement, a longitudinal section of the core and plastic liner was cut to expose the core surface for the vis−NIR measurements and for capturing the images as below.

Measurements with the CSS can be made at fine depth resolutions, predetermined in software by the user. The sensors, γ-ray densiometer, vis−NIR, and photographs were combined to produce a complete image of each soil core. The time taken to measure each core was approximately 20 min.

The construction and operation of the Unit completed the Phase 1 milestone.

3.2 Cores Scanned

243 air-dried old cores from Rexton and 139 air-dried old cores from Cheyenne have been scanned through the soil CSS unit. In addition, 130 fresh cores from Rexton, QLD and 45 fresh cores from Bingara, NSW have been scanned. Five random cores were selected and scanned 20 times for the repeatability test, making a total of 657. Additionally, many cores have been run multiple times to test the system and spectral analysis, totalling well over 700 scans.

The volume requirement for Milestone 2 has been met.

Figure 3: Physical appearance of cores of CEA 20 before scanning with CSS unit

3.3 Instrument Repeatability

Initially several hundred cores were scanned to test the actions of the scanner, the stability of the NIR and to test the repeatability of the NIR. Finally repeatability was tested using 5 cores scanned 20 times each. Repeatability was also confirmed by scanning the same samples in Canberra and in Gladstone using two different scanners.

3.4 Subsample selection

The subsampling procedure is to take a section of a core, 2.5cm either side of the NIR read location. However the NIR reads only the surface of the soil. We conducted an experiment to compare the correlation of these two soil samples: surface soils and whole 5 cm section of the cores. For this, 9 cores from CEA 12 sections were selected. A comparison was made between the Soil Organic Carbon (SOC) concentration on the surface soil and a 5 cm section of the core. Sixty x 5 cm sections were selected and analysed by LECO at CQUni. The surface was scrapped off with a spoon for separate analysis.

3.5 Comparison of SOC concentration of soil samples

For calibration and validation of CSS spectra, a number of representative samples have to be collected and sent to the lab for reference value. The samples can be collected either from the exact spot where spectra are taken or whole 5 cm section of the core can be processed. 60 x 5 cm long core sections were identified from Unscrambler for reference analysis. The 5 cm sections of 60 samples were sent to the EAL, Lismore for SOC concentration analysis.

3.6 NIR calibration

Under the soil carbon methodology, if the number of measurements (spectra) are less than 200, the SCANS technique requires 60 samples minimum (40 for calibration and 20 for validation) to be selected from each CEA, based on variance in the NIR spectra, removed from the intact cores (2.5cm either side of the spectral sample point) and analysed via LECO for percent carbon. The selection process is quite complex and followed the below process. The selected subsamples for calibration are listed in Appendix 1 (1st Randomisation) and Appendix 2 (2nd Randomisation).

The process included data sorting, smoothing, filtering with Savitzki-Golay, converting the reflectance (R) to apparent absorbance (A=log(1/R), performing principal component analysis (PCA) and explaining spectral variance carried out using R and Unscrambler software. The filtered spectra were standardized via a standard normal variate transformation for baseline correction. The Kennard Stone algorithm has been used to select a total of 240 subsamples from Rexton and 120 subsamples from Cheyenne and Bingara, to send to the lab for LECO soil C analysis to calibrate the spectra.

The Partial Least Squares Regression (PLSR) model was used as a calibration tool to interpret diffuse reflectance spectra to predict SOC. The dataset was randomly divided with 75% used as a calibration set for training the prediction model, and the remaining 25% used as a validation set to assess the accuracy of prediction models. The 75:25 split was repeated 50 times to get a distribution for the accuracy of prediction.

The entire process has been streamlined with the development of eight R script modules (section 3.8).

Examples of scanned spectra and images taken by the CSS unit are presented in Fig 4a and Fig 4b below.

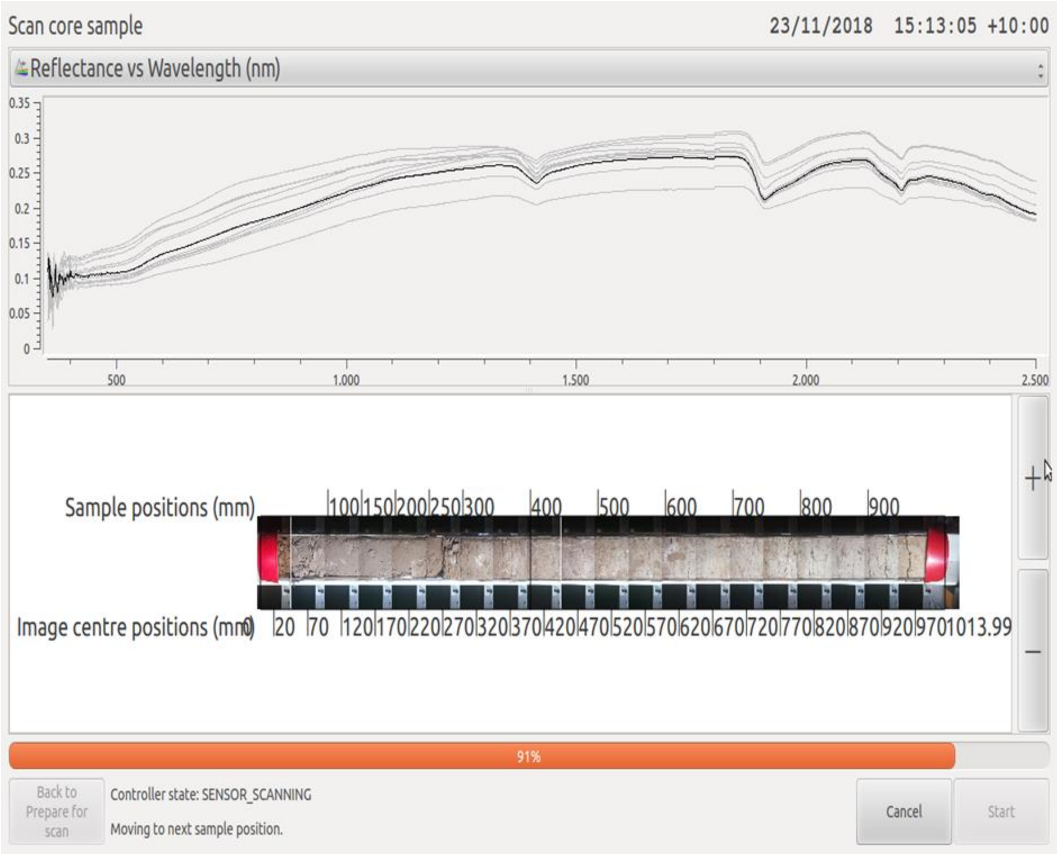

Figure 4a: Spectra and the images at the point where measurements were taken: a) long core (1 m long with both top and sub soils

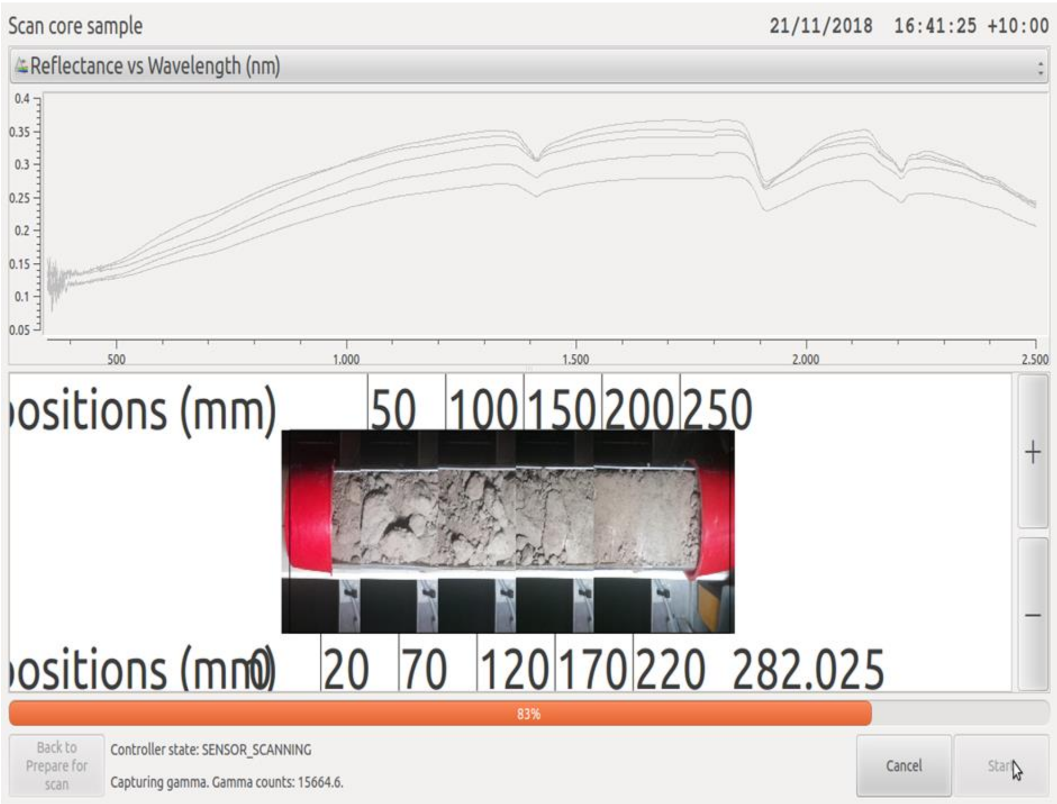

Fig 4b: Spectra and the images at the point where measurements were taken: b) top soil only (0.3m long)

3.7 Gamma-ray attenuation and carbon yield

Using some of the R script modules developed above, the percent carbon calculated after spectral calibration, was then converted into carbon yields (t C/ha) using a moisture correction factor developed from the national NIR spectral library and the Gamma bulk density estimate.

To measure the bulk density of the soil cores, the CSS uses measurements of density from the γ-ray attenuation densitometer and estimates of water content from the vis−NIR spectrometer. The technique is described by Lobsey and Viscarra Rossel (2017). For a soil core that is under field condition, the γ-ray attenuation is a function of its mass and the mass attenuation coefficients of soil and water in the attenuation path. Using the Beer−Lambert law, this can be defined as;

$$\frac{I}{Io} = \exp[-x(\mu s \rho s + \mu_{\mathrm{w}} \rho_{\mathrm{w}} \theta)]$$

Where,

I is the incident radiation at the detector, I_0 is the unattenuated radiation emitted from the source (determined using calibration standards), and *x* is the sample thickness in centimetres. Parameters μ_s and μ_w are in units of square centimetres per gram and represent the mass attenuation coefficients of the soil and water, respectively.

SOC Stocks (MgC/ha) = [Carbon Content (%) ×(1−αm)] × Soil Layer Thickness (cm) × Bulk Density (Mg/m3) × [1−MassFractionofGravel] × 0.1

In this step soil stocks are calculated as follows:

1. Soil carbon stocks for each soil profile for a given equivalent soil mass (ESM)
   - Soil carbon stocks are estimated at the ESMs of 3000Mg, 6000Mg and full core respectively.
   - Soil depth is used to calculate carbon stock for each ESM level.
2. Soil carbon stocks for each profile
3. Total soil carbon stocks of each soil profile.

3.8 Spectroscopic Modelling and Validation

Spectroscopic vis−NIR models were used to simultaneously estimate, at 9 to 13 measurement locations (depends on the length of the core) on each of the soil cores, the NIR spectra and gamma density counts and other soil attributes as required. Excel, R statistics and Unscrambler were used to sort, smooth, changing R to A spectra and PCA (PLSR) analysis as suggested by Lobsey et al 2017. Using the Kennard Stone algorithm, 10% of the sample locations were selected for lab analysis (total soil organic C by total combustion using a LECO carbon analyser) for calibration and validation purposes.

The soil spectra were analysed using the R platform modules as below, which are described briefly in Appendix 5.

1. Initial SCANS data Compilation: Vis-NIR, Gamma data and Camera data
2. Useful information attribution to SCANS data
3. Spectral data pre-processing
4. Determine subset of soil specimens for laboratory analysis
5. Spectral inference of target soil variables
6. Spectral inference of volumetric water content.
7. Estimating Bulk density from SCANS gamma densitometer readings
8. Estimation of soil carbon stocks (as required depths)

Estimates of the independent validation of organic C and the estimates of the soil property profiles that were made with logarithmic models are back-transformed to their original scales.

3.9 Rexton CEA 10 Project Site – Testing the System

Rexton (CEA 10) a grazing property near Goondiwindi, was selected as the testing trial site due to the high variance in CEA 10. It was then split into 6 equal area strata (Fig 5a). Within each stratum, 10 randomly selected locations were sampled and samples analysed for SOC and BD (giving data as SOC percent, SOC stock to fixed depths of 30 cm and 60 cm, and also as SOC stock on an equivalent soil mass basis); these data (58 points due to missing data for two samples) were assumed to be representative of a phase 1 sampling, referred to here as the baseline (T0). A further 10 randomly selected locations from each stratum were sampled (again with two samples missing to give 58 points), giving data representing a T1 sampling, referred to as the condition. This gave a dataset similar in structure to what would be collected for a real SOC accounting study, the difference here being that both sets of data (baseline and condition) were collected concurrently, rather than after a land use change and a sufficient period of time for SOC changes to take effect.

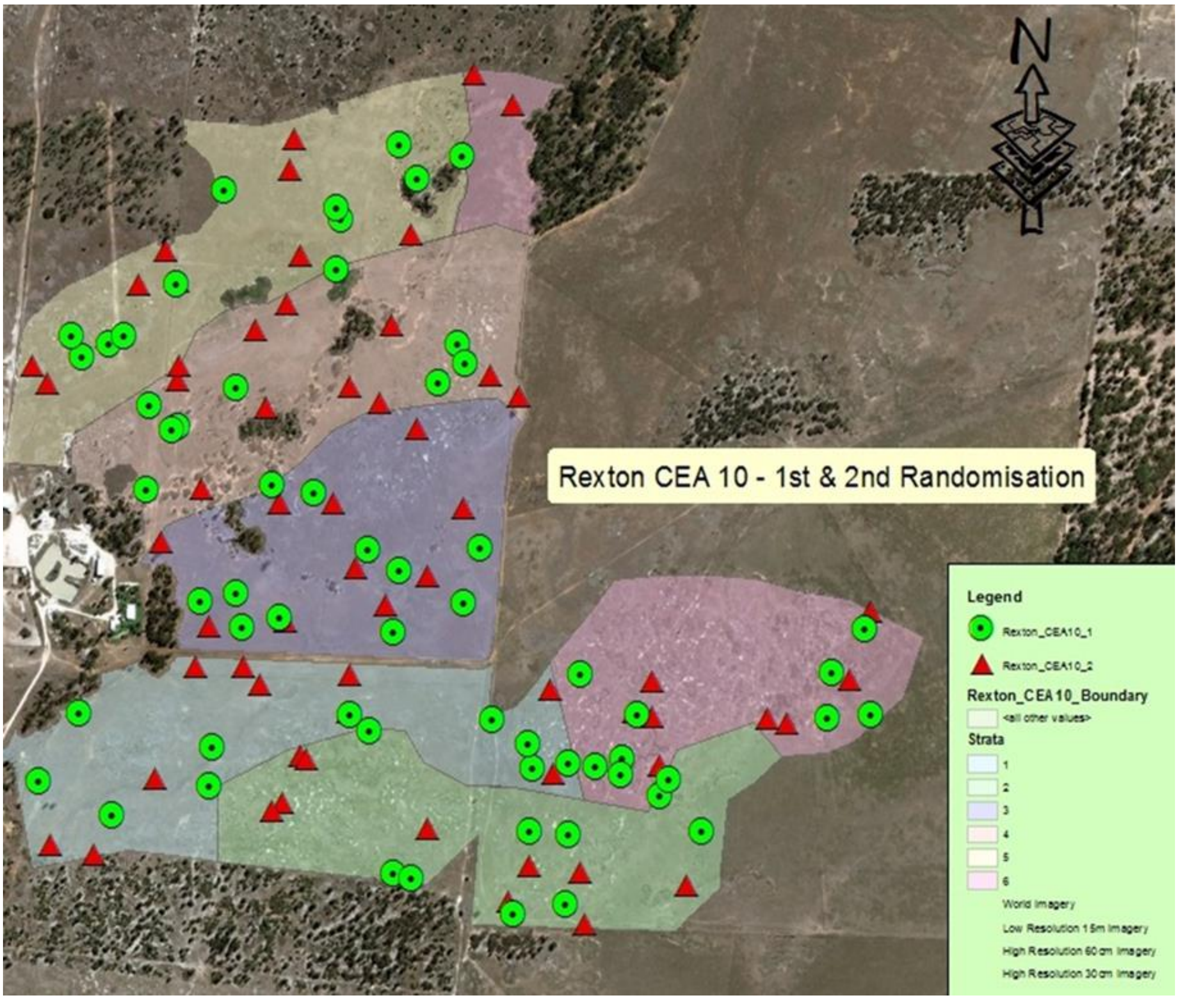

Figure 5a: The six sampled strata and sampling locations

3.9.1 Hypothesis test of two sampling distribution

Null hypothesis (Ho): Mean carbon values of two randomisations/measurements are not different, whereas, the alternative (HA): Mean carbon values of two measurements are different. Z-test was used to test the hypothesis using the following formula:

$$z = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\sigma^2_{\overline{X}_1} + \sigma^2_{\overline{X}_2}}} = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

Where,
$\mu_1 - \mu_2 = 0$ because it belongs to the null hypothesis, or we derived the samples from the same populations so $\mu_1 = \mu_2$.

3.10 Double samples

During the drilling process, a second sample was taken right beside ten original cores (Fig 5b) to determine the underlying close proximity variation in soil carbon in strata 6.

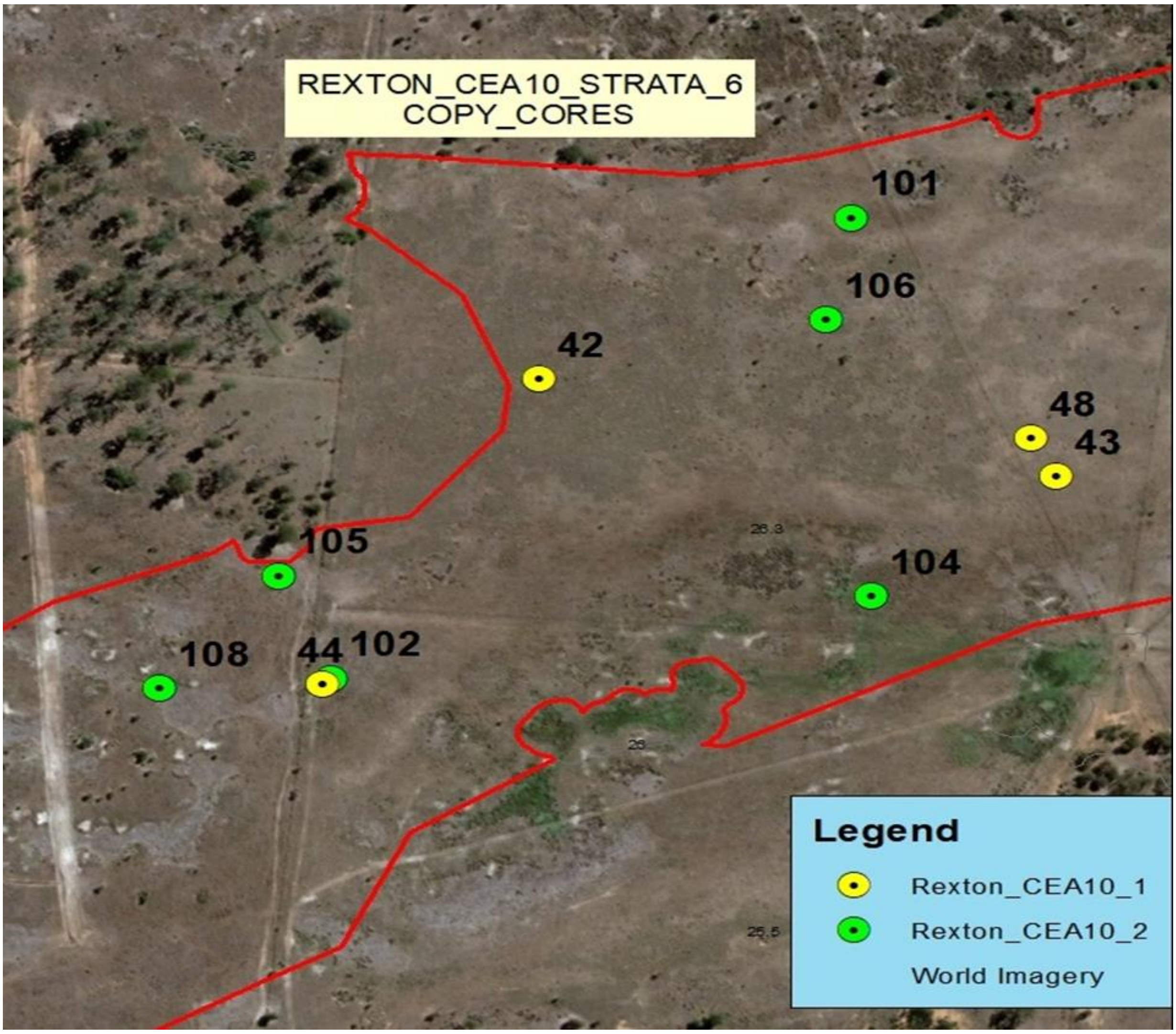

Fig. 5b: Distribution of ten copy core at Stratum 6 (CEA10)

3.11 Calculating minimum detectable changes

A simulation method (a variogram model) was used to assess the Minimum Detectable Difference (MDD) applicable for stratified Random Sampling (rather than the formula that is usually applied assuming simple random sampling), which is described in the appendix 4. The method requires as input values the within-stratum and between-stratum variances, which can be estimated using a linear mixed model. This work was conducted by Dr Tom Orton from DAFF.

3.12 Bingara Carbon Farm – Analysing correlation between SOC measured with the CSS v LECO

The main objective of this study was to conduct correlation analysis of the organic carbon measured with standard chemistry and that determined by the CCS Unit. A secondary objective was to correlate Soil organic carbon with 60 physical and chemical parameters, with a view to determine if a sampling design method using a smaller number of soil samples can be developed to more accurately estimate the organic matter and soil carbon over the area.

The 30 cores have been put through the SCANS system and the calibrations done. This provides a comparison between the SCANS result and the lab analysis.

3.13 Cost comparison and economics

A model was constructed to include all costs and details of each soil analysis method. The comparison was made between composite sampling, analysing each core individualy using LECO based on quotes from EAL and the SCANS system.

The modelling was based on high sample numbers, based on the MDD data.

4 Results

4.1 Spectral repeatability

Around 120 cores (collected from Rexton in 2016) were scanned through the Carbon Link and CSIRO scanners, and the spectra were compared. The concordance values between spectra were found around 0.8 and above (concordance values of 1 are perfect while a value of 0 is very bad prediction). The results were identical as shown below in Fig 6. The spectral pattern is an excellent fit considering the cores travelled a long distance. These results confirm the value of having a high-quality instrument.

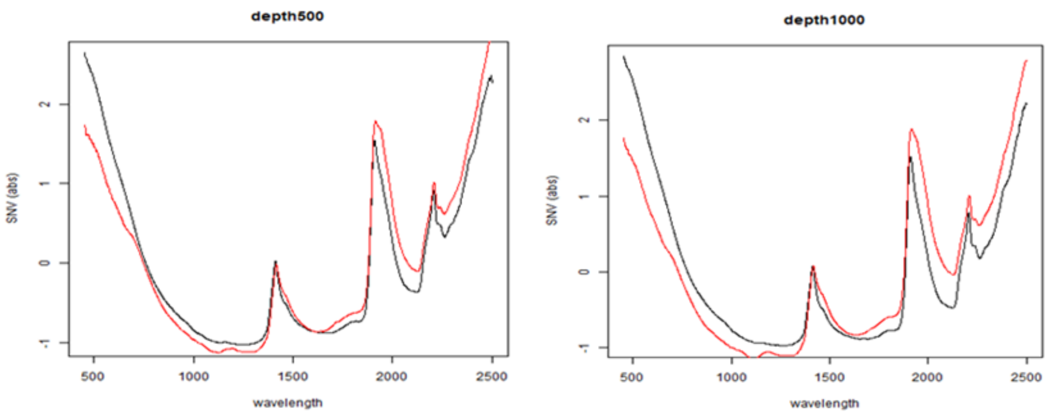

Fig. 6: Absorbance spectra of the Carbon Link and CSIRO spectrometer.

Five cores (1 to 1.14 m long) were scanned 20 times each and the spectra data were analysed to assess the repeatability of the NIR spectrometer unit (Fig 7-Fig 8). The spectra results (Fig 7) showed that the spectrometer was accurate and precise, with very high repeatability (R2 ranges from 0.94 – 0. 99). The PCA analysis showed a clear distinction of spectra at greater depth but clustered nicely with different cores at the same depth (Fig 7 and 8). However, there are a number of factors (such as moisture, gravel, gaps, cracks in the cores) which need to be considered for impact on the SOC yield.

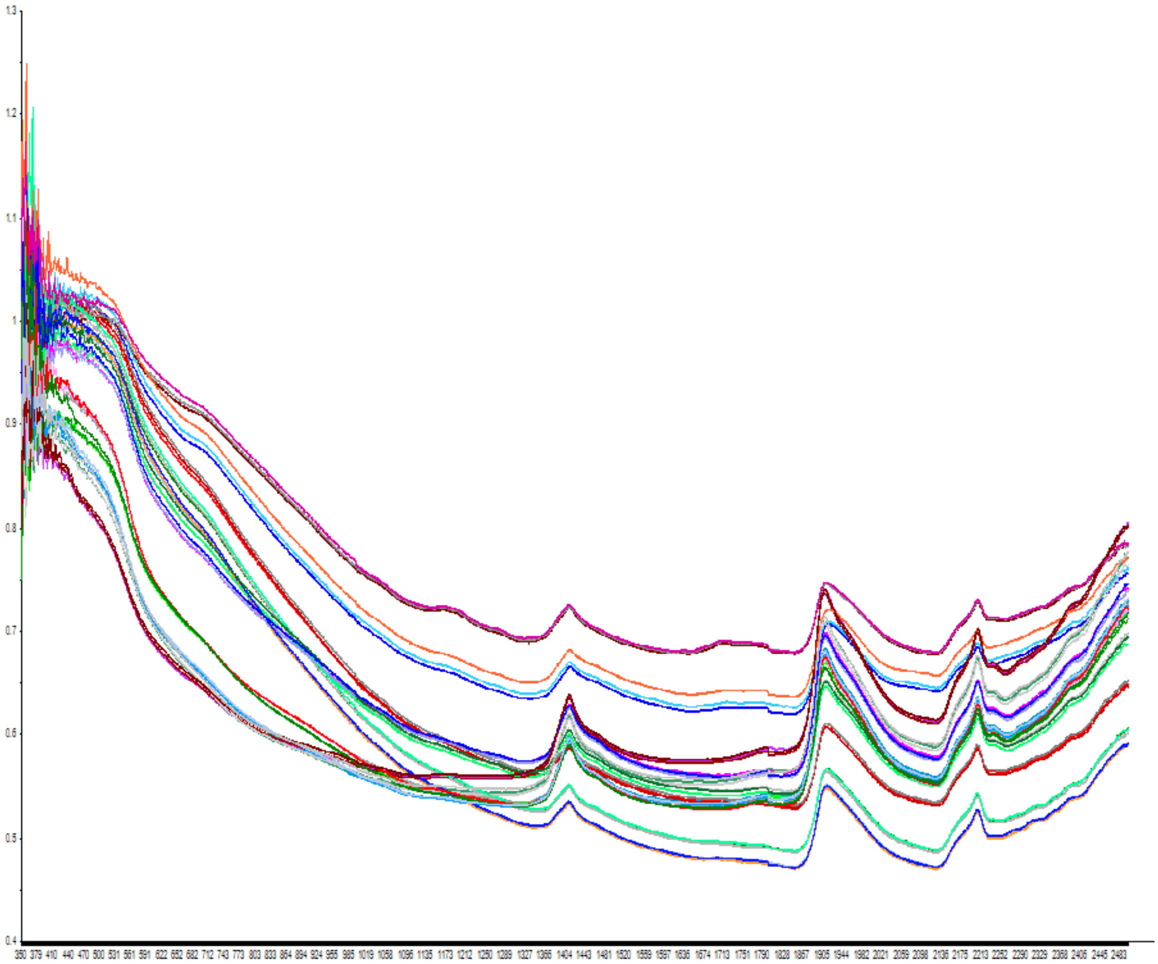

Figure 7a: Absorbance spectra of the repeat tests

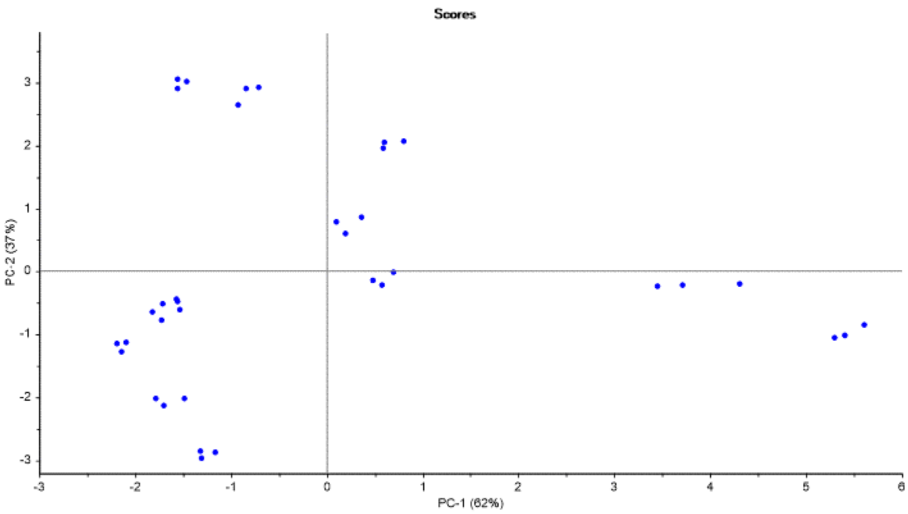

Figure 7b: Principal Component Analysis (PCA)

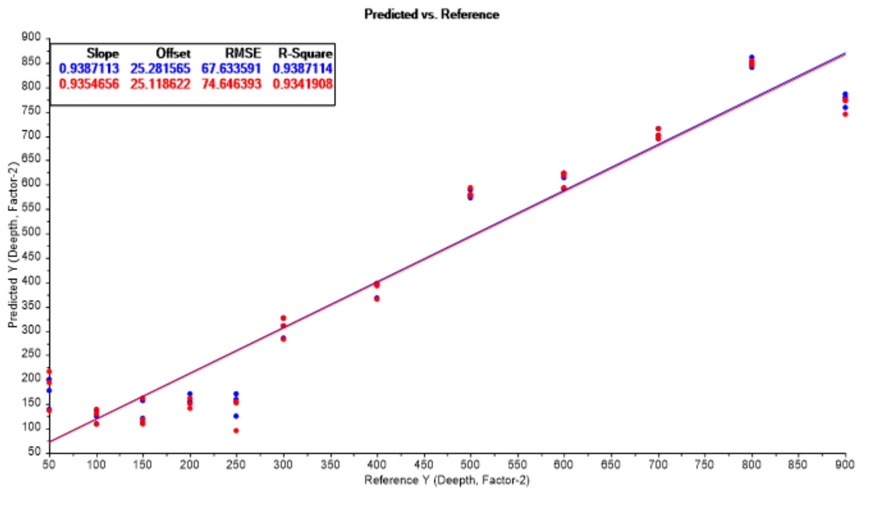

Figure 8: An example of co-relation using PSLR (Partial Least Square Regression) analysis

4.2 NIR Calibration

A number of processes and steps (as described in Appendix 5) were carried out for calibration and validation of soil spectra. Figure 9a shows the raw spectra of 60 Rexton cores (and 803 measurements) with a glitch between the two spectrometers. The glitches were removed or corrected using R program (Fig 9b). The web length of spectral evolution outside the 450 and 2450 nm were removed due to the high signal to noise ration. The reflectance (R) spectra were then converted to apparent absorbance (A) (Fig 10). It is the absorbance data which is used to assess carbon and water content. It essentially the inverse of the reflectance.

Figure 11 illustrates the PCA data and shows that PCA 1 and 2 accounted for 90% of the variability. It must be over 70% as required by the methodology, so 90% is a very good result. Figure 12 illustrates the subsampling process. Samples required for subsampling are in a green box. An R platform processes all individual core's spectra together and produces individual output files as shown in Figure 13, which can be used to check the outliers.

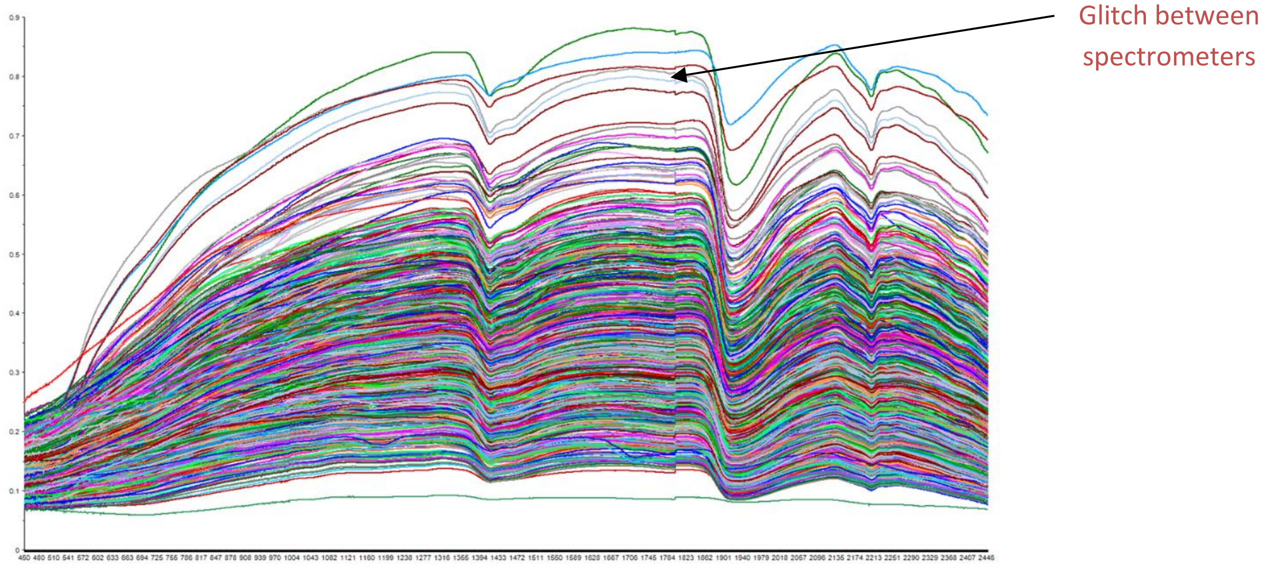

Figure 9a: Raw spectra using Unscrembler with glitch between two spectrometers

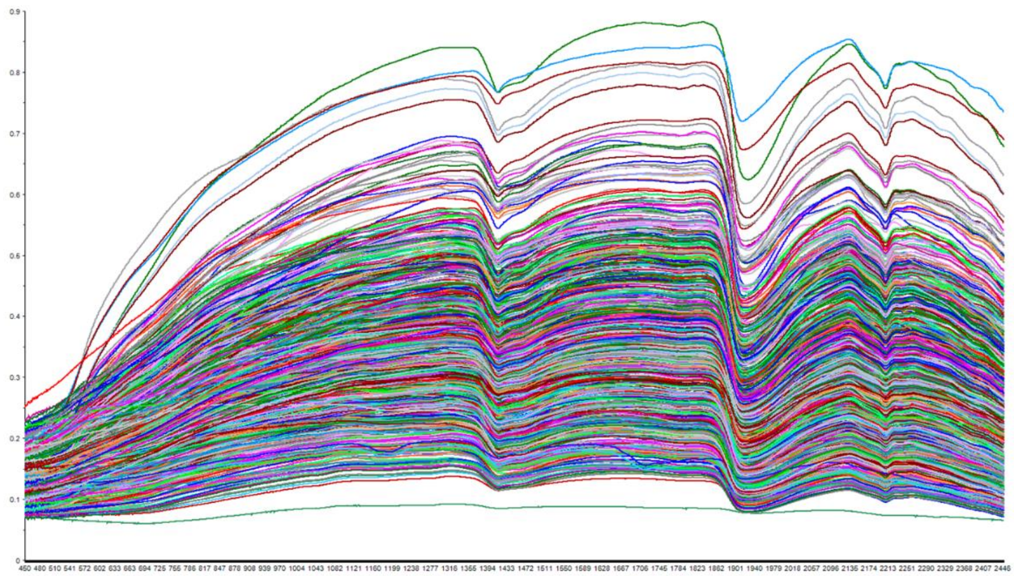

Figure 9b: The splined/corrected spectra using R and Unscrambler (Savitzki-Golay)

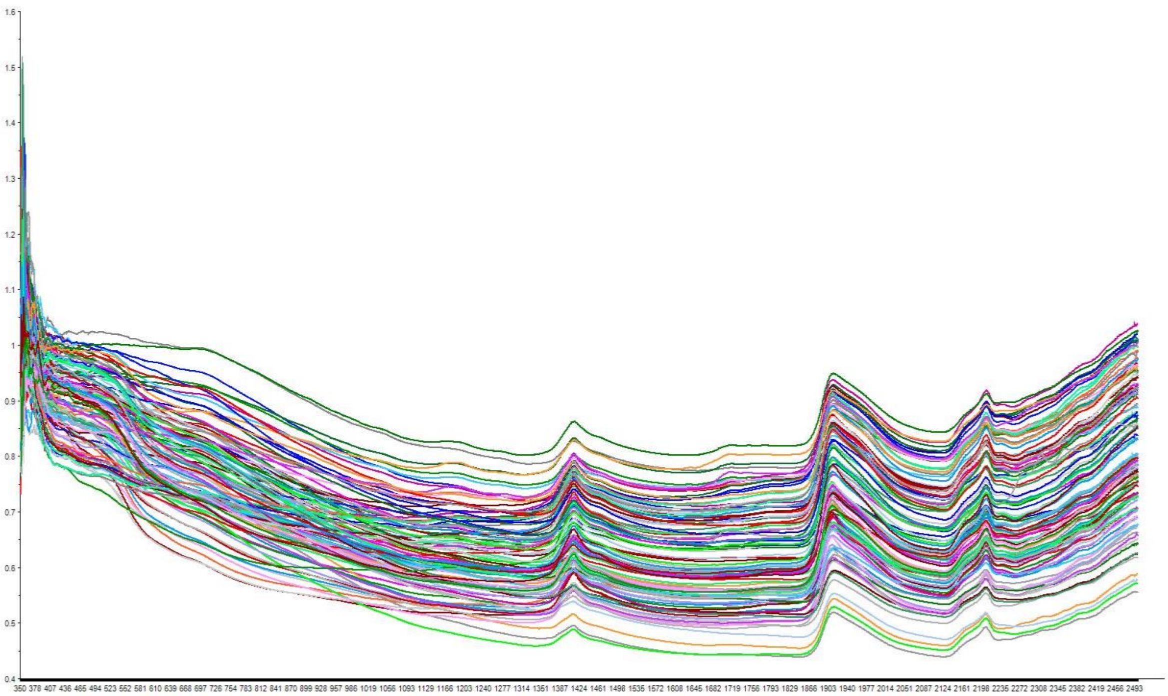

Figure 5: Converting reflectance (R) spectra to apparent absorbance (A)

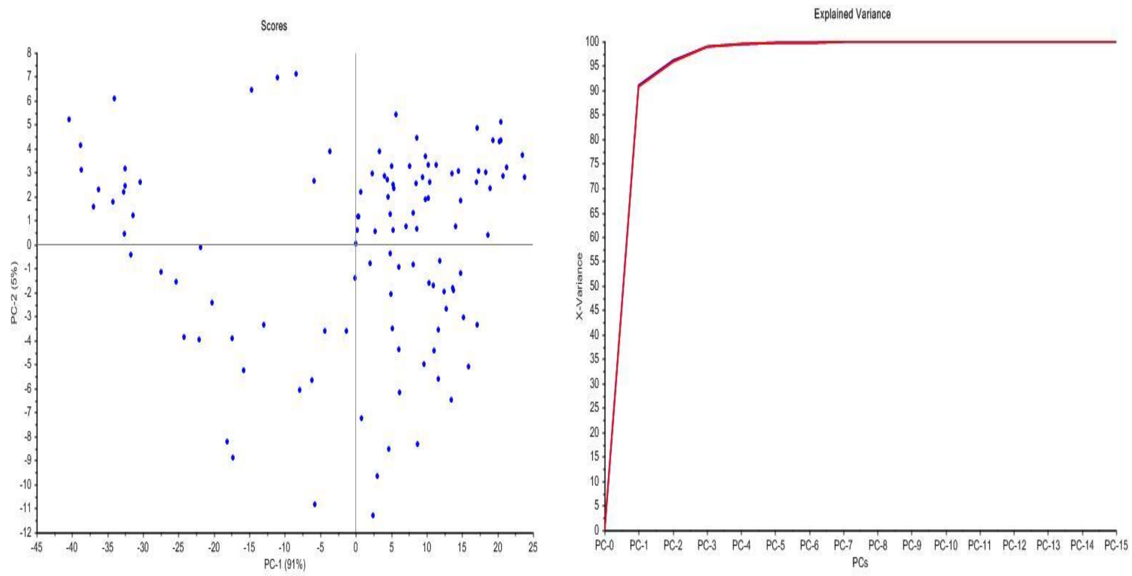

Figure 6: Principle component analysis, a) scores, and b) variance explained 96% of variability (PCA 1 and 2 should be more than 70%)

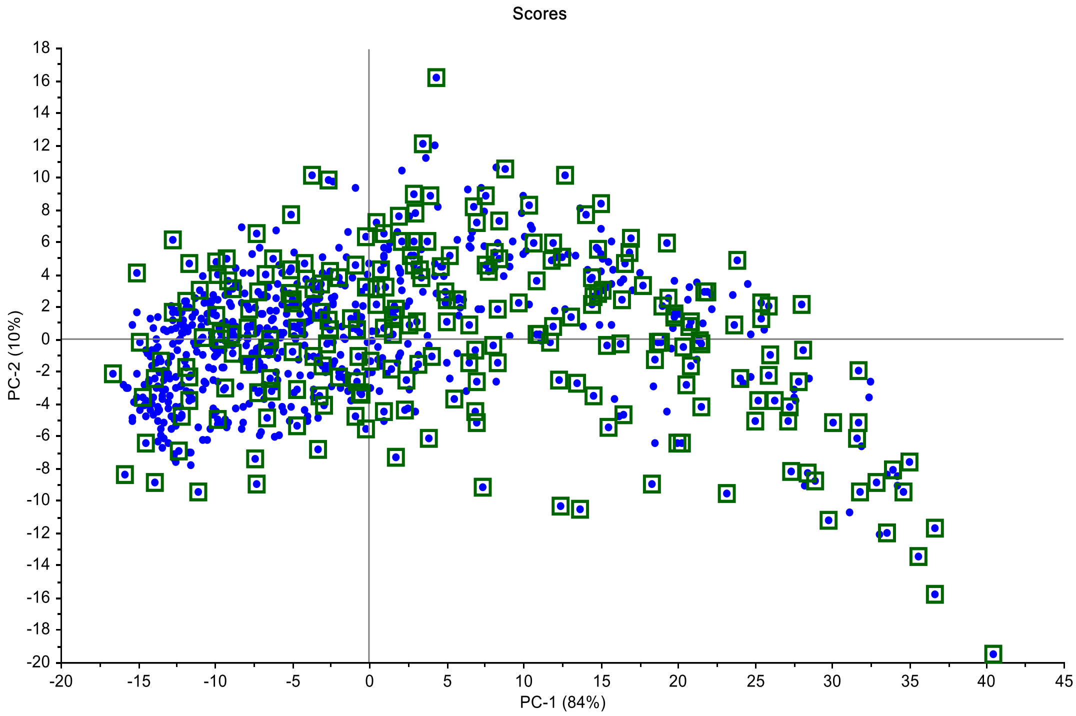

Figure 12: Illustration of the selection of sites for subsampling. Each blue dot is a core result. Each dot surrounded by a green square is required to be subsampled

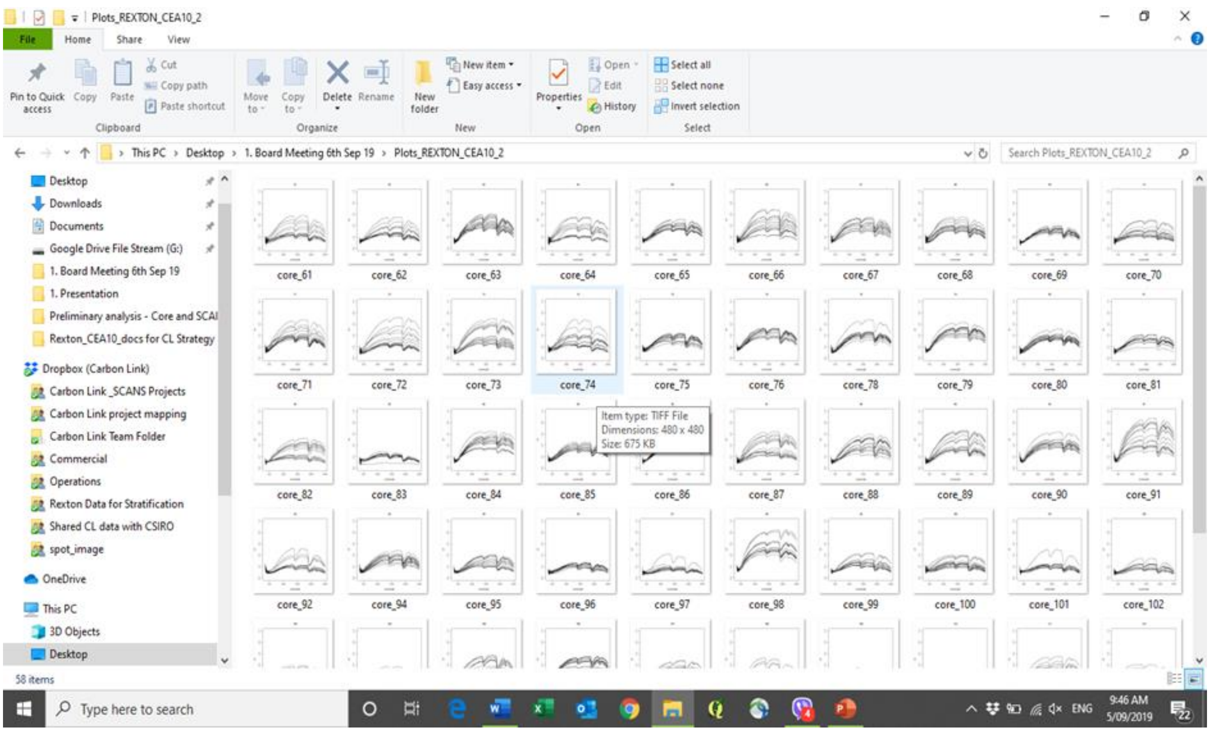

Figure 7: Spectra graph output from R

4.3 Comparative cores

4.3.1 Rexton: Double Samples

Ten cores were collected as double or copy cores from within 20 cm of 10 original cores to compare the SOC concentrations. The results show that the SOC concentration decreases significantly in the deeper depth in both cores and copy cores, which is normal (Fig 14). These two core sets (original and copy cores) were highly correlated (R2=0.9) (Fig 15). However, this data indicates that there is underlying variability of 10% within 20cm of a sample. This becomes significant when we look at the MDD data (Minimum Detectable Difference), which is discussed in the below sections.

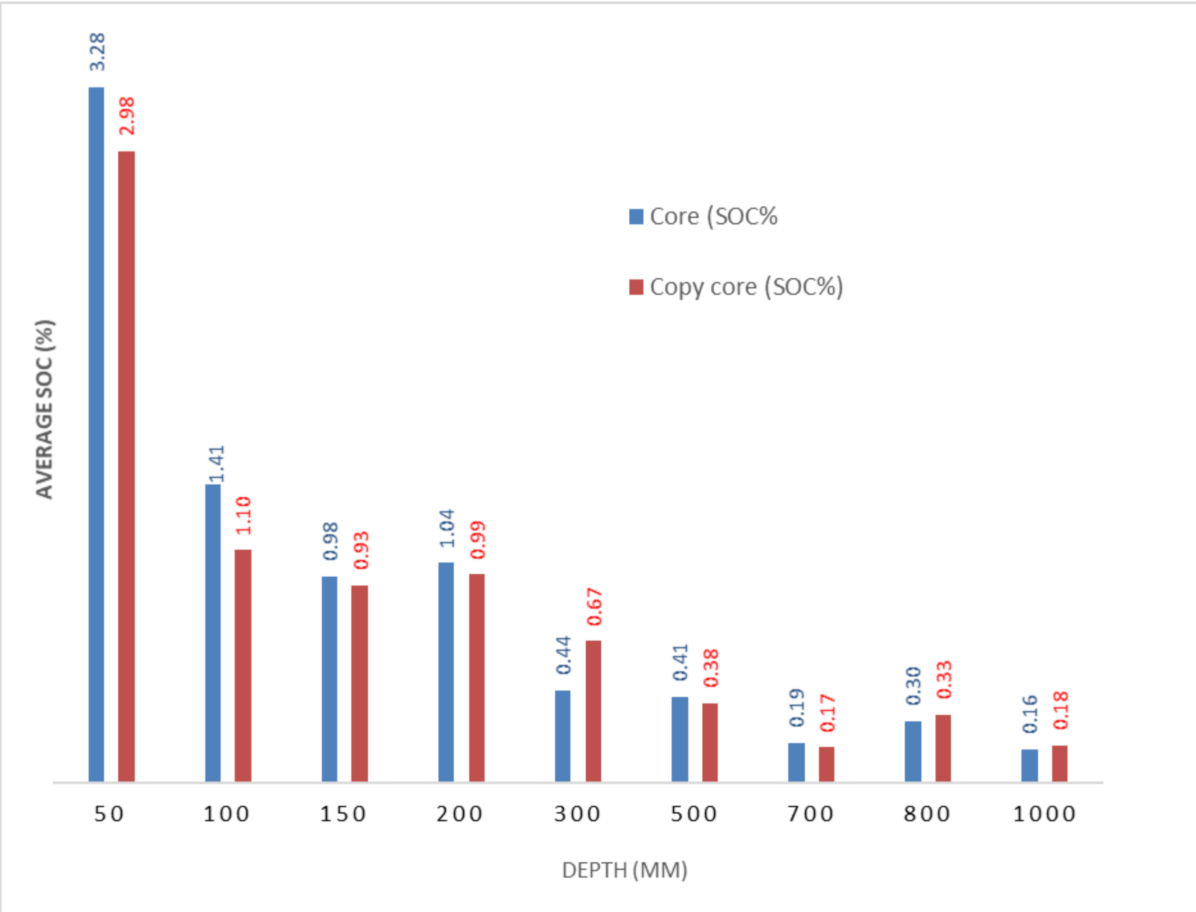

Figure 8: Comparison of SOC concentration between cores and copy cores with different depths

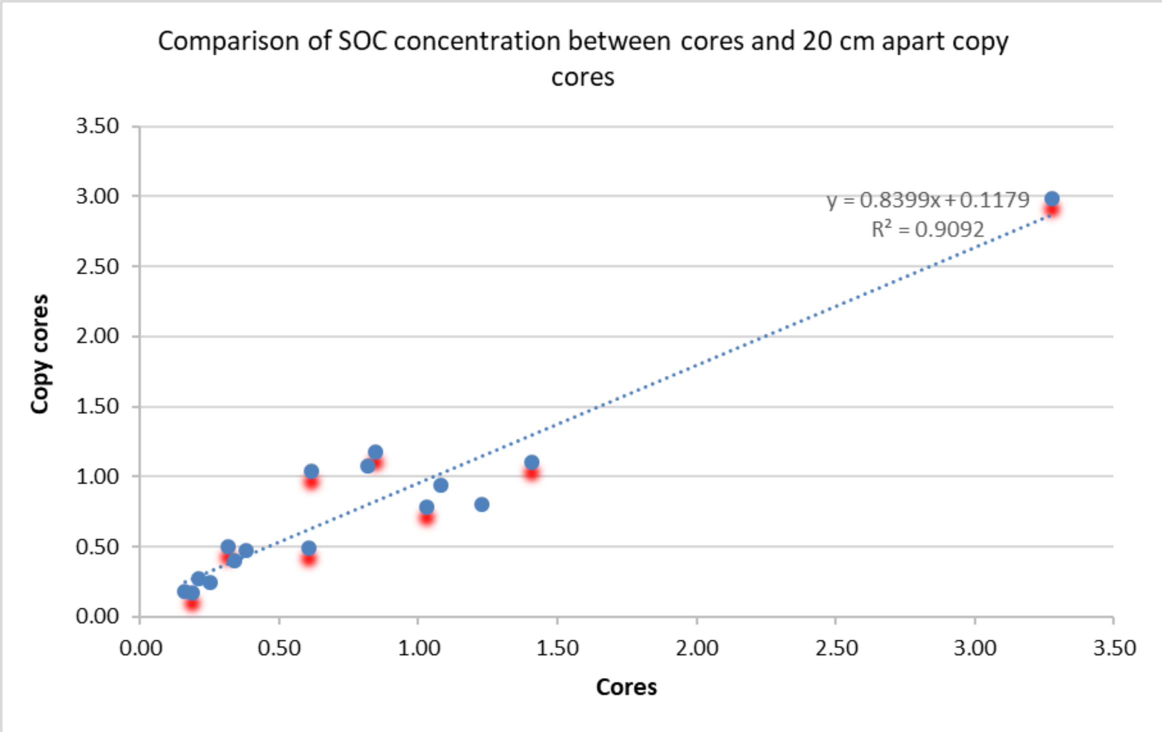

Figure 15: SOC comparison with copy cores (within 20 cm)

Table 1: Comparison of SOC% of double samples (taken within 20 cm) at different depths

Core No.	Core-Position	Core ID	Original Core (SOC%)	Copy Core (SOC%)
42	150	42- 150	0.82	1.08
42	300	42- 300	0.38	0.47
42	700	42- 700	0.19	0.17
44	150	44- 150	1.03	0.78
44	500	44- 500	0.61	0.49
48	500	48- 500	0.21	0.27
101	50	101- 50	3.28	2.98
101	100	101- 100	1.41	1.1
101	150	101- 150	1.08	0.94
101	200	101- 200	1.23	0.8
101	800	101- 800	0.25	0.25
104	200	104- 200	0.85	1.17
105	300	105- 300	0.32	0.5
108	300	108- 300	0.62	1.04
108	800	108- 800	0.34	0.4
108	1000	108-1000	016	0.18
Average SOC%			**0.84**	**0.83**

4.3.2 Bingara: Double Samples

Samples from the Bingara farm were analysed for organic carbon by a lab in Brisbane, using LECO. Companion cores were analysed through the SCANS for comparison.

As the scanning of the cores with the gamma densitometer was incorrectly performed (i.e. BD was less than 1 in most of the cases), it is not possible to reliably estimate soil organic carbon using SCANS, in these soils. The measured values indicate the gamma beam did not interact completely with the soil. The diameter of the Bingara cores was smaller than Rexton's cores (38mm v 50mm). That may be the reason for less interaction with the gamma source.

4.4 Carbon Yield from two randomizations taken at the same time.

The average C yield in the first randomisation was slightly lower (31 ± 5.5 tC/ha) than in the second randomisation (34.6 ± 8.9 tC/ha) (Table 2). Average SOC stock in Strata 1 & 2 in the second randomisation was significantly higher than other strata of both randomisations. The SOC stock variance in T1 was more than double in both strata 1 & 2 compared to the T0 randomisation. However, the carbon yield in both randomisations was statistically identical at a 95% confidence level, even though there was a difference in average yield. The yield of all Individual cores is also presented in Appendix 2.

Table 2: Summary of SOC stock in Rexton CEA10

Strata	1st Randomisation					2nd Randomisation				
	Avg SOC (t/ha)	std	var	max	min	Avg SOC (t/ha)	std	var	min	max
1	**29.78**	3.652	13.34	34.89	24.53	**40.7**	9.5	90	54	25.9
2	**29.33**	5.172	26.75	39.98	20.17	**42.3**	15.7	245.6	67.6	27.2
3	**33.75**	6.927	47.99	45.18	22.71	**28.7**	8	63.6	44.1	15.2
4	**32.28**	7.979	63.66	44.07	19.88	**32**	6.8	46.4	44	21.7
5	**29.2**	5.409	29.26	37.65	21.11	**33.9**	7.3	53.9	46.7	23.6
6	**30.03**	4.134	17.09	34.82	20.72	**29.9**	5.8	34	38.5	18.8
Avg	**30.7**	**5.5**	**33**	**45.18**	**19.88**	**34.6**	**8.9**	**88.9**	**38.5**	**27.2**

The errors in the 1st and 2nd randomisations were 11% and 16% respectively. This indicates that this high intensity sampling design could only detect a change if the SOC yield change is more than 11% in the next sampling round. This have implications for projects with low sequestration rates.

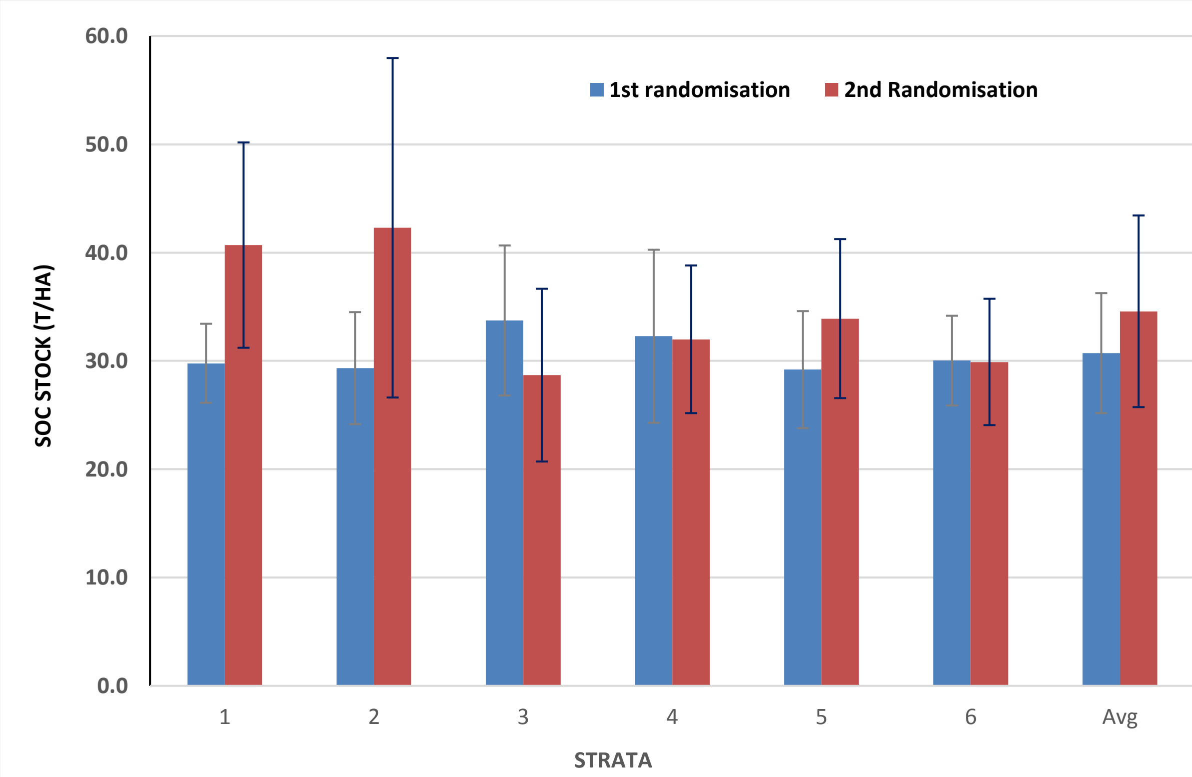

Figure 9: Summary of C yield in 1st and 2nd Randomizations in Rexton CEA10 from 10 samples per strata.

The depth-wise results in three profiles are below:

1. **For depth up to 30cm** -- p values = 0.0976 > 0.05, i.e there is not enough evidence to reject null hypothesis at 5% level of significance,
2. **Depth up to 60 cm** - - p value = 0.6919 > 0.05. No enough evidence to reject null hypothesis.
3. **For up to 110 cm** --p value = 0.38017 > 0.05. No enough evidence to reject null hypothesis.

However, strata 1 & 2 in the second randomisation were significantly different, which might be natural as there were two cores with higher SOC concentration but we have to do further research to determine the specific cause. This is further illustrated in Table 3 below.

Table 3: Summary of significant test of SOC yield among six strata

Strata	Z values	P values	For 0.05 level of significance	Results
One	-2.730	0.006	Less than 0.05	Reject H0
Two	-2.290	0.022	Less than 0.05	Reject H0
Three	1.730	0.084	Greater than 0.05	Cannot reject H0
Four	-0.142	0.887	Greater than 0.05	Cannot reject H0
Five	-1.090	0.274	Greater than 0.05	Cannot reject H0
Six	0.545	0.586	Greater than 0.05	Cannot reject H0

4.5 Spatial distribution of SOC (yield maps)

The Ordinary kriging method was used to estimate the spatial patterns of SOC (Fig 17 and Fig 18). In order to better compare the spatial distributions, maps for both phases (T0 & T1) and depths were plotted on the same scale. The SOC stock distribution ranges from 26.20 to 52.41 tC/ha, however, the majority of SOC stock falls under the first 2 categories (26.2-30 tC/ha and 30-35 tC/ha). It is noteworthy that the maps from two randomisations are different. This appears to be due to samples in the second randomisation, getting into heavier soil in the south.

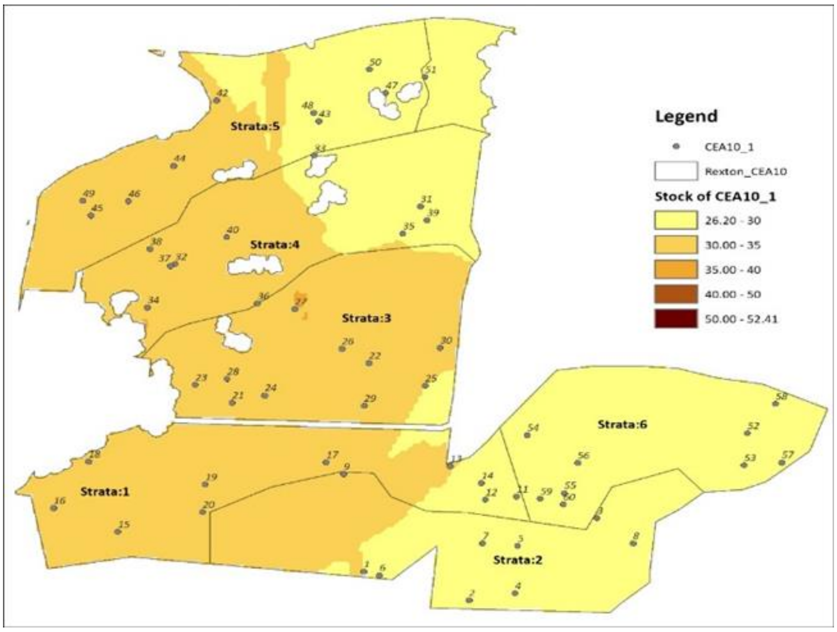

Figure 17: SOC Stock Distribution for CEA10: 1st randomization

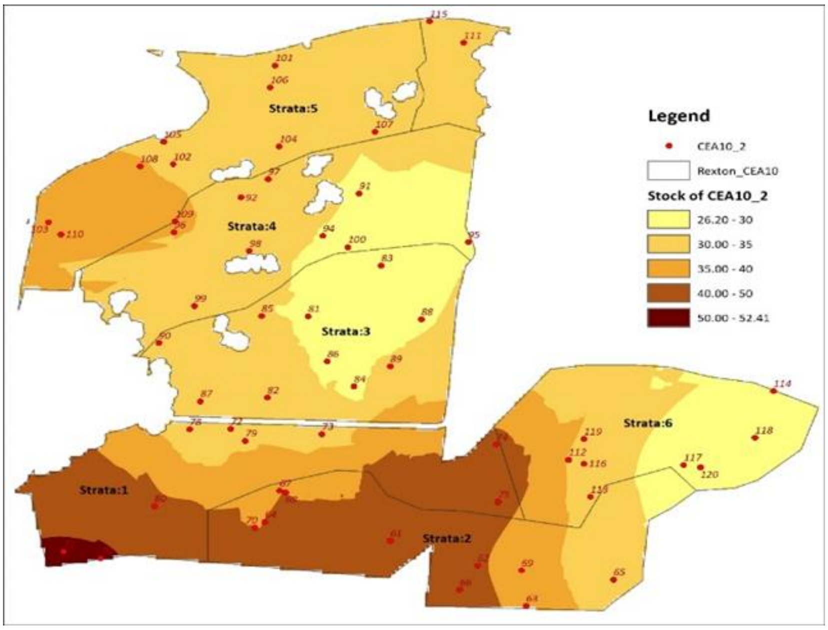

Figure 18: SOC Stock Distribution for CEA10: 2nd randomization

Difference between these averages (CEA10_2-CEA10_1) has been further calculated and visualized as a choropleth map in Fig 19 below. The map shows higher difference between the average stock in strata 1 and 2. These are the strata which had the highest variation in T1 (second randomisation).

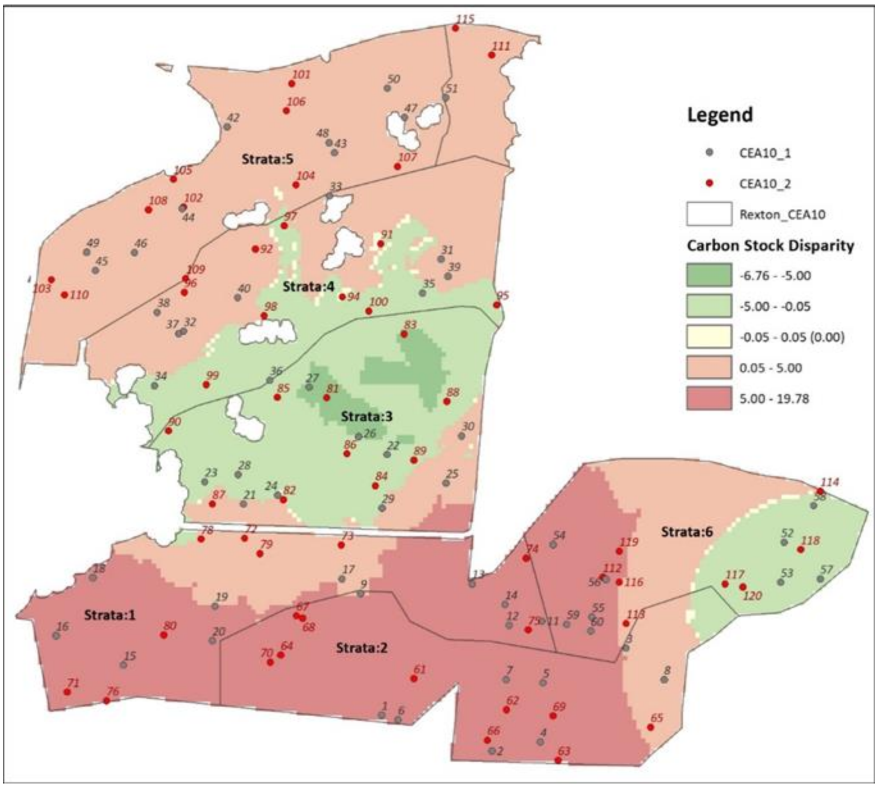

Figure 19: SOC Stock disparity map generated from two randomizations

4.6 Comparison of SOC concentration between surface soils and 5 cm sections

The comparison between a teaspoon of soil at the NIR sample point and a 5cm slice of soil 2.5cm either side of the sample point showed the results were similar. The percentage of SOC in the surface (one teaspoon of soil) and the 5 cm sections, was highly correlated (R2=0.79), shown in the graph below. Though the SOC percentage varies with a number of parameters such as soil types, management systems, texture, and the like, the result indicates that we can use either soil sample collected from the surface (spot where spectra is taken) or 5 cm section of the core for spectra calibration and validation. However it could be expected to be more accurate if only the surface was sdampled.

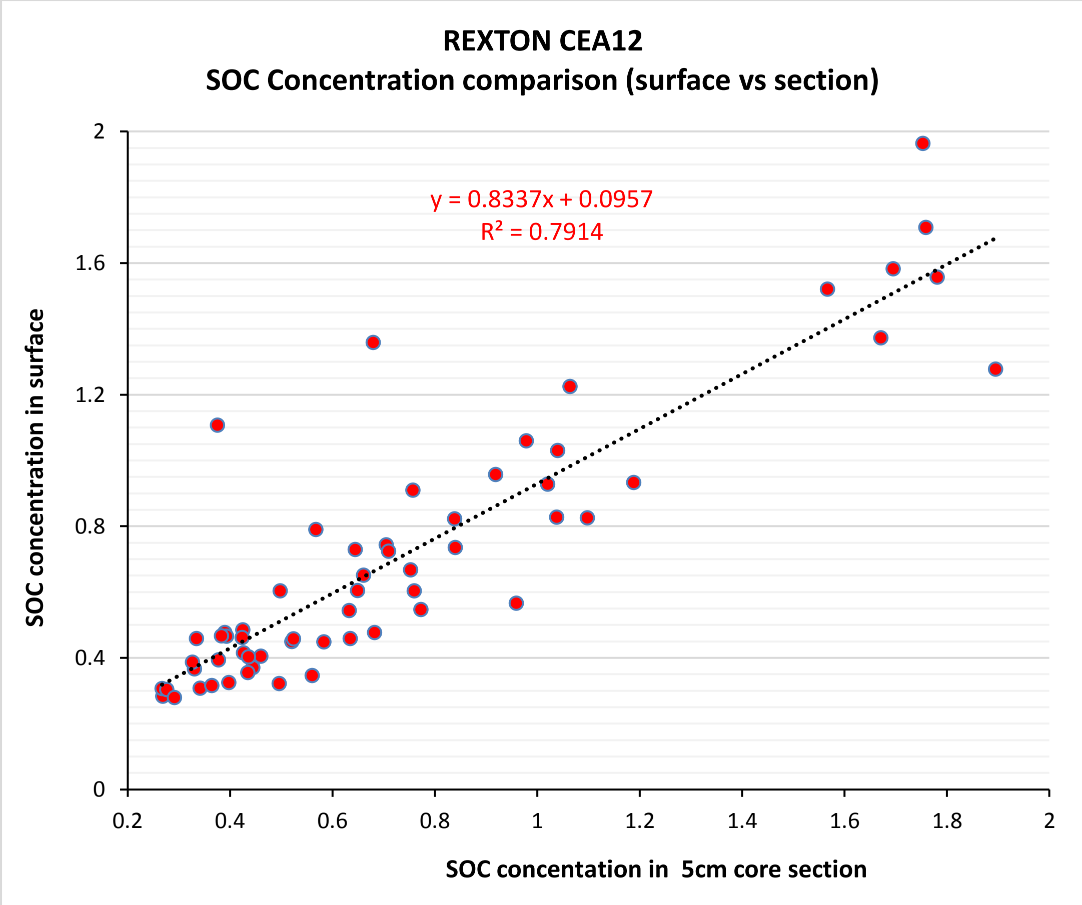

Figure 20: The correlation between surface analysis and 5cm slices

4.7 Comparison of SOC stocks between LECO and SCANS

Fresh soil cores were analysed to compare SOC stock estimation using both the LECO and SCANS techniques (Table 4). The average SOC stock in the 4th stratum in the first randomisation was 37.7±13.6 tC/ha and 34.88+-8.21 with LECO and CSS techniques respectively. The C stock in the same stratum in the second randomisation was nearly equal (29 tC/ha) in both techniques, however the standard deviation was more than double in LECO compared to the SCANS technique. The SCANS techniques was more precise than LECO in both randomisations.

Table 4: SOC Results from First and Second Randomization

Core ID (Stratum)	SOC stock (t/ha) (0-30 cm)	
	LECO	CSS
32 T	39.61	33.32
34 T	52.30	31.19
35 T	39.25	45.71
36 T	46.22	36.44
37 T	44.56	44.92
39 T	29.81	23.15
40 T	11.86	29.41
Average	**37.66**	**34.88**
Stdev	13.35	8.21

Table 5: SOC Results from Second Randomization

Core ID (Stratum 4)	SOC stock (t/ha) (0-30 cm)	
	LECO	SCANS
91 T	15.46	29.54
91 T	26.46	28.54
94 T	35.60	27.82
96 T	42.34	37.5
97 T	17.39	27.19
98 T	28.61	21.73
99 T	38.79	31.17
Average	**29.24**	**29.07**
Stdev	10.34	4.74

The correlations between the C yield estimated by using LECO and CSS techniques were very poor, (first randomisation, R2 = 0.27). See Figure 22 below.

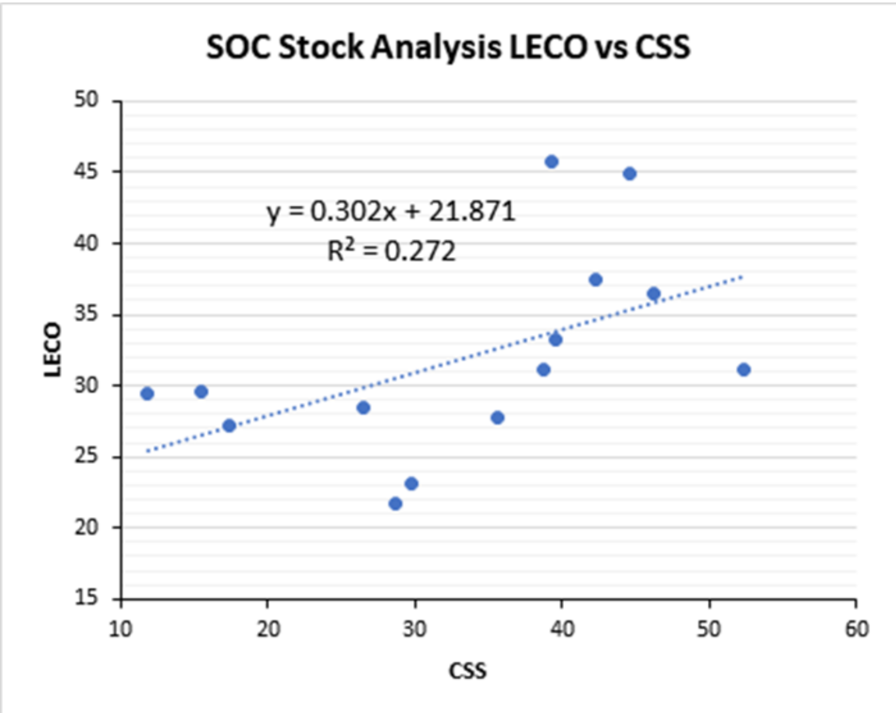

Figure 20: SOC stocks using LECO and SCANS techniques

The average SOC stock in the same CEA in 2016 (using LECO with composite sample analysis) was 44.5±16.5 tC/ha, which compares to 37.7±13.4tC/ha and 29t±10.3tC/ha in the first and second randomisations respectively in 2019. The main difference between 2016 and 2019 (using the LECO technique) was that we used composite sample analysis in 2016 with only 9 samples taken in the CEA and composited to 3 samples for lab analysis. Each core (60 in each randomisation) was analysed separately in 2019, which could have detected more spatial variation than with less cores and composites in 2016. The other key difference is that we were measuring a CEA in 2016 and a strata in 2019, so they are not strictly comparable. However the 44.5 t 2016 estimate can be compared to the totals from SCANS for the CEA. The key data is summarised below in Table 6.

Table 6: Carbon yield Comparisons on CEA10 (tC/ha to 30cm)

	LECO Composite (whole CEA)	**SCANS (whole CEA)**	**SCANS Individual (one strata)**	**LECO Individual (one strata)**
2016 Baseline	44.5±16.5			
2019 1st Randomisation		30.7±5.5	34.9±8.2	37.7±13.4
2019 2nd Randomisation		34.6±8.9	29.1±4,7	29.2±10.3

There are a number of very important points to make about this data:

- Firstly, across 14 samples, there was NO correlation between SCANS and LECO (R2 = 0.27). This is a very low sample number but we could have expected a correlation. The question becomes – which one was incorrect, LECO or SCANS, or both?
- Based on a) the number of sample points recorded by the NIR being 6 times greater per core (to 30cm) than for LECO, and b) the lower variance from SCANS, it would appear that the SCANS system is more accurate than the gold standard of LECO.
- There is no way the land could have lost 10 to 14 tonnes C/ha in 3 years, further indicating that composited LECO samples can be very inaccurate, compared to SCANS.
- The 44.5t/ha baseline estimate in 2016 was based on 9 cores, composited to 3 samples, each shrunk to less than 1 gram of soil for analysis. The SCANS results for the CEA were based on 60 cores in the same area, each with 6 measurement points per core, making a total of over 360 sample points compared to 3. One can assume based on sample density that the SCANS technique provided a more precise estimate of carbon stock in the top 30cm.
- The difference provides an issue in terms of resampling projects done with the original method.

4.8 Cost Comparisons of LECO and SCANS.

Table 7 below outlines a range of cost scenarios based on scale and sampling intensity. Sampling intensity is varied based on number of CEAs and number of strata, each with 5 cores per strata. The data indicates significantly declining costs per ha as scale increases.

A constraint with the SCANS Unit is that it is very slow. It has a maximum capacity of 25 cores in an 8 hour shift, in its current format. The data below (Table 7) reflects this inefficiency whereby the SCANS NIR technique is approx. 15% more expensive than individual core LECO analysis. This concurs with the results of Viscarra Rossel and Brus (2018) who concluded that the additional cost was warranted because of the increased accuracy.

However the solution is to modify the system to achieve reduced costs and high accuracy. Many of the constraints have been identified in this study.

Table 7: A comparison of cost per ha at varying scales, varying CEAs and varying number of strata per CEA

500 ha

PROJECT CHARGE per HA @ 5 CORES/ STRATA

Number of CEAs >>>	1		3		5	
STRATA	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR
3	$48.68	$58.67	$69.26	$84.61	$81.37	$102.07
4	$50.70	$59.48	$75.32	$87.02	$99.93	$114.56
5	$52.72	$60.28	$81.37	$89.43	$118.50	$127.05
6	$54.74	$61.08	$95.90	$100.32	$128.58	$131.07

3000 ha

Number of CEAs >>>	3		5		7	
STRATA	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR
3	$11.54	$16.54	$13.56	$17.82	$16.99	$21.82
4	$12.55	$16.94	$16.66	$19.91	$20.76	$24.17
5	$13.56	$17.34	$19.75	$21.99	$24.52	$26.52
6	$15.98	$19.16	$21.43	$22.66	$28.29	$28.87

8000 ha

Number of CEAs >>>	4		6		8	
STRATA	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR	Individual LECO	SCANS NIR
3	$5.54	$8.04	$6.30	$8.21	$7.58	$9.65
4	$6.04	$8.24	$7.58	$9.05	$9.12	$10.58
5	$7.08	$8.97	$8.87	$9.88	$10.66	$11.52
6	$7.58	$9.17	$9.63	$10.18	$12.20	$12.45

Three alternatives have been identified to speed up the SCANS process. None have been trialled at this stage. However if the time to scan a core can be cut by 75%, the SCANS system will be very cost effective relative to laboratory analysis.

However, the SCANS system does not measure the roots and rocks in the soil, required under the soil carbon methodology. This is still done manually in the laboratory by grinding and sieving the samples. This adds an inaccuracy of crushing some of the rock during the grinding process, and additional cost.

4.9 Estimated benefit to the industry.

We know from the work reported above that an 11% change in SOC stocks can be detected with 95% confidence. This is very close to the variation we saw between cores 20cm apart. Assuming a 50t/ha stock, a sequestration rate of between 1 and 2 t C/ha/annum can be detected over a 5 year period. This confirms that the sequestration rate is a significant driver of profitability and knowing how to achieve those rates as a minimum will be critical to the economics.

The data below (Table 8) is modelled on a CO2e price of $25/t and sequestration of 10t of C/ha (37t CO2e/ha) each five years (2t C/ha/annum). Nett Income is assumed to be 50% of gross value of credits to account for methodology discounts, variances and aggregator costs.

The modelling also assumes an upfront cost of $50/ha for a new activity and after all other costs associated with running a project. The modelling is also based on having 6 strata and 5 cores per strata along with multiple CEAs. The minimum sample level required to run a project is 9 (ie 1 CEA x 3 strata x 3 samples per strata). As shown in Table 8, the sample numbers in these scenarios, significantly exceeds the minimum. This is required to measure low MDD.

Table 8: A comparison of Nett Income at varying scales, varying CEAs and 6 strata and 5 samples per strata

Scale (ha) >>>>	1000	3000	5000
Sample Number >>>>	***60***	***120***	***180***
IRR	24%	38%	41%
Baseline cost ($/ha)	$44	$21	$17
Activity capital ($/ha)	$50	$50	$50
Annualized Return	$30,000	$123,500	$216,000
Nett Cashflow (25 years)	$754,000	$3,088,000	$5,395,000

The data shows the IRRs are in a very profitable range and nett accumulated cash-flow can make a significant contribution to farm profits. Scale affects the return for several reasons. Firstly the overheads associated with a carbon project are similar, regardless of scale. Secondly, the sampling intensity (i.e. ha per sample), is higher as scale reduces.

Low cost baselining can be a trap due to low sample numbers, high variance in results and high minimum detectable Differences (MDD) in carbon stock growth. The data shows that a more expensive investment in measurements can pay dividends by having a lot more carbon to sell.

There are a few points of note in terms of carbon income.

- Income is very lumpy under the current methodology and it will take 10 years before it becomes profitable due to the removal of 50% of credits from sale under the methodology at T1.
- Credits in the directory can be used in poor years to hedge against price or seasonal conditions.
- Demand at present completely outstrips supply, and it is feasible that prices may be higher going forward.
- Carbon added to soil improves water holding capacity, property resilience, food quality and eventually productivity.
- Carbon credits are taxed as off farm income and do not fit into income averaging.

5 Discussion

The project Objectives were;

1. Construct and test the SCANS unit in the field;
2. Test the accuracy and repeatability of the system at commercial scale to have confidence to take the technology into commercial use.
3. Complete statistical analysis of soil scan data and produce yield.

During the project, we had four key questions to answer.

- Does the technology actually work?
- Can it measure soil carbon stocks more accurately than conventional methods?
- What problems exist with it on a commercial scale?
- Is the technology cost effective?

5.1 Construct and Test in the field

The unit was constructed but immediately ran into problems with coding to integrate and operate the instrumentation. It took 6 months to get a working solution, which is by no means the answer. The coding for the whole Unit and its components require rewriting and updating. This may have an impact on its speed of operation.

After it was operational, we were provided with no software or procedures for operation. It took a further 5 months before we were provide with expertise from CSIRO to write it and a further 4 to 5 months to develop algorithms to enable smoother and less labour intensive output. While we are currently able to get results, the software development is not complete.

We could not test the unit in the field because the licence requirements of the Gamma unit would not allow it to be moved from its licenced location.

In conclusion, it has been constructed and tested in its current location.

5.1.1 Does the technology actually work?

The short answer is that it does work. However there are many shortcomings which will need to be addressed before it can become a commercial reality. These are addressed below.

5.2 Test accuracy and repeatability of the system

The NIR component of the system has proved to be both complex and highly repeatable. However there are problems with other parts of the system.

The Gamma unit has several problems.

- Firstly gamma is the system slowing down the whole process. The NIR could scan a core in 1 to 2 min and it is the gamma unit which takes the time out to 20 minutes.

- Secondly, there has been problems with the gamma where cores are damaged or of a smaller diameter.
- Thirdly it is difficult to know if the gamma is accurately calibrated. A very small error in bulk density will make a big difference to carbon stock estimates.
- Fourthly, its location is restricted and it cannot currently be used on location in the field.
- Finally, we have been advised that there is a faster reader for the gamma unit, which may address the productivity issue.

The rasbery pie camera is a major impediment to continuous production. It continuously stops the scanner and will need to be upgraded.

5.2.1 Is it more accurate than conventional methods?

The short answer is yes. It had a lower variance than using LECO to measure carbon stocks in individual cores. Our data and Pallasser et al (2015) also question the accuracy of LECO on large sample sizes. It was somewhat alarming that there was no correlation between the LECO results and the scanner results on the same cores even though the scanner was calibrated using LECO. The standard LECO method analyses a small aliquot of the bulk sample, which means less than 1 gram of soil is used to represent approx 2 kg in a core which may in turn represent 10 ha or more. It seems improbable that this could be accurate.

5.2.2 What problems exist with it on a commercial scale?

Firstly it is more expensive in its current stage of development due to its very low productivity. We estimate it will cost a further $50,000 to upgrade the coding, the camera and the gamma reader. If we were to make this investment, it should be cheaper than laboratory analysis.

The complexity of the system is also of concern from a commercial perspective.

The system as it stands does not estimate roots and gravel above 2mm but the potential of the 5cm calibration subsamples to achieve this, is being investigated by CSIRO.

5.2.3 Is the technology cost effective?

The short answer is – not in its current state – but it can potentially be. The unit we have has cost around $250,000, with a further $50,000 to spend. However if we develop more units, the development cost will be reduced significantly.

There is much to add from a technology perspective. Firstly, the gamma will need to be replaced by X-Ray tomography. Secondly, a core identification system is needed. Thirdly the core handling will need to be automated to reduce labour costs. Fourthly, the software which provides the ouput will have to be upgraded to a user friendly interface.

5.3 Complete statistical analysis and produce carbon yields

As shown above in the results section, substantial levels of statistical analysis has been done on the data. Core numbers for MDD at 95% confidence are around 200. While a lower confidence level is required by the methodology and lower sample numbers will achieve that, higher confidence means more saleable carbon.

6 Conclusions/recommendations

The study has shown the repeatability of the NIR is high with an R^2 of 0.90 to 0.96.

The Unit has been slow to get going due to lack of support from CSIRO, difficulties with personnel at CSIRO and numerous software issues. It has therefore taken 10 months to get reliable data from it after an initial 6 month period to get it even working, a delay of 16 months.

We can currently conclude:

- That we have only a prototype which is too slow and costly to use as a commercial unit. It will need to be speeded up by a factor of four and automated to be economically viable.
- The calibration of the spectra is very expensive and may not be economic without changes to the methodology. To put this in context, the methodology requires a minimum of 60 subsamples to be taken per CEA. Rexton has 24 CEAs. The subsampling cost would be 60 x 24CEAs x $36/ sample, a cost of over $51,000 to calibrate the spectra. A solution going forward is to plan with considerably less CEAs.
- The SCANS unit does not account for roots and gravel, which is a laborious process by itself. We have shown in previous R&D that a dual X-Ray unit can account for these.
- The SCANS unit is more precise than LECO.
- There was no correlation between LECO and SCANS based on 14 cores and we assume the SCANS unit is more precise based on its sampling intensity and core profile.
- The repeatability of the NIR was high, however, variance in SOC within the strata was high.
- The preliminary MDD analysis shows that it required high sample numbers (approx. 200) to detect a 10% changes in SOC in a specific CEA, with 95% confidence. This sounds a warning about low sample numbers in carbon measurement. The exceedance in the methodology is 60% which is s less onerous target.
- Carbon projects where sequestration is above 2t C/ha/annum, will be very profitable for the industry.

Further work is required as follows:

- Significant software development and re-engineering is required to achieve adequate productivity from the SCANS UNIT, to enable it to be cost competitive. This is estimated to be $50,000.
- A system for accurately accounting for roots and gravel, potentially using X-Ray tomography, will need to be developed.
- Carbon Link has also appointed a Doctoral candidate to work on data analytics, stratification processes, geo-statistics, and programming to streamline the processes and reduce costs.

Getting the following changes in the methodology;

- A change to the Guidelines to facilitate the use of X-Ray tomography to do bulk density and sieve roots and rocks and calculate soil mass.
- Accommodation of the NIR calibration in a more sensible way.

- Removal of the need for the Scanner and the X-Ray systems to be used in a NATA accredited laboratory. This just prevents them from being field deployable. The calibration samples will be done through an accredited lab.
- Removal of the maximum 5 year sample period.

7 Key messages

The key messages include:

- Soil carbon can be measured with a variation of 10 to 20% using current best practice. However that best practice can be improved in both cost effectiveness and accuracy over the next two years as improvements and new concepts are added.
- Soil carbon projects which off set sequestration can be a very profitable addition to a grazing business if the right practice changes are made. The practice changes which will increase sequestration rates include but are not limited to:
    - Time control grazing systems following regenerative principles.
    - Multi species cover cropping as a pasture cropping system used to fill feed gaps.
    - Deep rooted legumes such as Desmanthus and Leucaena spp.
    - Correcting plant deficiencies
    - Landscape rehydration
- Adoption of practices which lift soil carbon will increase productivity and profit and generally reduce input costs via;
    - Increased soil water storage
    - Increased mineral cycling due to increased humic colloid sites and increased biological activity
    - Increased environmental resilience
    - Providing an additional income stream
    - Using carbon credits as a hedge against seasonal and price downturns

However, organisations such as MLA will need to use their market power to help improve the methodologies to make them amenable to the vagaries of agriculture as opposed to being a bureaucratic straight jacket.

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9 Appendix

9.1 Appendix 1: Core selection for subsampling

S.N.	Core ID	Core Posit	S.N.	Core ID	Core Posit	S.N.	Core ID	Core Posit
1	1	150	91	66	150	181	141	800
2	1	50	92	66	50	182	143	1000
3	3	500	93	67	500	183	144	50
4	2	700	94	68	700	184	146	100
5	4	800	95	69	800	185	147	600
6	4	50	96	69	50	186	149	800
7	5	250	97	70	250	187	150	100
8	6	300	98	71	300	188	152	150
9	6	400	99	71	400	189	153	250
10	7	900	100	72	900	190	155	900
11	8	200	101	73	200	191	156	50
12	9	300	102	74	300	192	158	800
13	9	150	103	74	150	193	159	50
14	10	200	104	75	200	194	161	100
15	11	250	105	76	250	195	162	600
16	11	300	106	76	300	196	164	800
17	12	600	107	77	600	197	165	50
18	13	50	108	78	50	198	167	400
19	13	300	109	79	300	199	168	900
20	14	50	110	79	50	200	170	300
21	15	200	111	80	200	201	171	600
22	16	300	112	81	300	202	173	50
23	16	600	113	81	600	203	174	100
24	17	800	114	82	800	204	176	150
25	18	300	115	83	300	205	177	200
26	18	400	116	84	400	206	179	250
27	19	1100	117	84	1100	207	180	300
28	20	50	118	85	50	208	182	400
29	20	300	119	86	300	209	183	500
30	21	900	120	88	900	210	185	600
31	25	800	121	91	800	211	191	800
32	25	1000	122	91	1000	212	192	1000
33	26	50	123	92	50	213	194	50
34	26	100	124	96	100	214	195	100
35	27	600	125	96	600	215	197	600
36	29	800	126	97	800	216	198	800
37	31	100	127	99	100	217	200	100
38	35	150	128	100	150	218	201	150
39	36	250	129	102	250	219	203	250
40	36	900	130	103	900	220	204	900
41	35	50	131	104	50	221	206	50
42	40	800	132	106	800	222	207	800
43	41	50	133	107	50	223	209	50
44	42	100	134	109	100	224	210	100

45	43	600	135	110	600	225	212	600
46	45	800	136	111	800	226	213	800
47	46	50	137	113	50	227	215	50
48	48	400	138	114	400	228	216	400
49	49	900	139	116	900	229	218	900
50	50	300	140	117	300	230	219	300
51	52	600	141	118	600	231	221	600
52	53	50	142	120	50	232	222	50
53	55	100	143	121	100	233	224	100
54	56	150	144	123	150	234	225	150
55	58	200	145	124	200	235	227	200
56	59	250	146	125	250	236	228	250
57	60	300	147	127	300	237	230	300
58	62	400	148	128	400	238	231	400
59	63	500	149	130	500	239	233	500
60	65	600	150	130	600	240	234	600
61	131	150	151	141	800			
62	132	50	152	143	1000			
63	135	500	153	144	50			
64	137	700	154	146	100			
65	139	800	155	147	600			
66	141	50	156	149	800			
67	143	250	157	150	100			
68	145	300	158	152	150			
69	147	400	159	153	250			
70	149	900	160	155	900			
71	151	200	161	156	50			
72	153	300	162	158	800			
73	155	150	163	159	50			
74	157	200	164	161	100			
75	159	250	165	162	600			
76	161	300	166	164	800			
77	163	600	167	165	50			
78	165	50	168	167	400			
79	167	300	169	168	900			
80	169	50	170	170	300			
81	171	200	171	171	600			
82	173	300	172	173	50			
83	175	600	173	174	100			
84	177	800	174	176	150			
85	179	300	175	177	200			
86	181	400	176	179	250			
87	183	1100	177	180	300			
88	185	50	178	182	400			
89	187	300	179	183	500			
90	189	900	180	185	600			

9.2 Appendix 2: First phase (T0)

Strata	Core ID	easting	northing	carbon_stocks_30cm	carbon_stocks_60cm	carbon_stocks_total	total_soilthickness
1	1	6854354.091	259404.4	39.53	61.48	105.57	115
	2	6854276.194	259648	32.46	47.67	113	125
	3	6854500.17	259944.8	25.39	52.86	89.33	115
	4	6854295.84	259754.7	29.41	47.79	93.3	115
	5	6854424.84	259760.7	40.27	60.72	76.96	115
	6	6854344.464	259440.4	31.53	53.72	99.47	115
	7	6854431.328	259679.7	33.77	50.75	72.8	125
	8	6854431.616	260028.3	35.39	51.18	55.21	115
	9	6854618.977	259357.7	29.8	41.72	65.78	125
2	11	6854558.578	259758.5	20.05	29.43	46.93	115
	12	6854550.149	259686.5	34.5	58.36	114.98	115
	13	6854640.101	259604.2	28.19	51.03	86.56	115
	14	6854594.909	259677.2	33.88	57.57	82.21	115
	15	6854462.691	258834.4	31.35	63.52	123.31	125
	16	6854526.81	258685.9	45.15	72.13	92.7	125
	17	6854651.095	259317.3	33.37	64.66	119.78	125
	18	6854653.07	258766.6	27.04	60.6	123.23	115
	19	6854591.278	259036.9	35.06	50.44	106.87	125
	20	6854516.097	259030.9	38.31	71.07	119.93	115
3	21	6854813.135	259099.2	50.44	82.95	117.63	115
	22	6854920.757	259416.2	33.5	57.17	100.94	125
	23	6854861.564	259013.8	41.63	74.78	144.98	115
	24	6854833.036	259175.2	44.29	83.83	164.95	115
	25	6854858.828	259546.5	41.6	72.36	127.83	115
	26	6854959.802	259353.5	31.8	60.51	88.1	105
	27	6855067.298	259244.2	30.2	53.96	85.87	115
	28	6854877.192	259087.7	24.28	43.27	71.1	115
	29	6854804.944	259405.3	39.75	76.95	141.29	115
	30	6854961.833	259581.5	30.08	48.87	73.28	105
4	31	6855345.781	259535.5	23.82	41.07	64.29	105
	32	6855189.283	258967.8	33.32	57.61	102.98	125
	33	6855483.306	259289	24.32	39.68	67.82	105
	34	6855070.994	258903.1	31.19	54.43	93.91	115
	35	6855272.094	259494.6	45.71	82.33	99.78	115
	36	6855082.255	259158	36.44	60.09	77.69	95
	37	6855184.292	258956.7	44.92	82.59	143.62	125
	38	6855230.202	258909.4	37.16	54.91	66.4	95
	39	6855308.239	259550.8	23.15	44.47	73.48	115
	40	6855261.734	259086.5	40.8	53.12	82.62	125
	42	6855633.732	259063.5	42.12	65.03	69.53	95
	43	6855576.929	259299.9	35.37	55.91	77.2	115
	44	6855455.779	258963.9	25.61	47.88	80.95	105
	45	6855320.82	258773.1	33.57	54.94	77.48	105

5	46	6855359.973	258858.9	33.7	50.01	70.43	105
	47	6855654.152	259454.7	24.4	57.61	82.8	105
	48	6855599.336	259288.4	26.42	49.69	85.44	95
	49	6855360.986	258753.5	27.93	43	62.41	95
	50	6855717.356	259416.7	38.89	60.43	105.13	115
6	51	6855697.27	259545.8	31.47	53.11	98.7	115
	52	6854730.04	260293.4	36.55	67.24	109.75	115
	53	6854643.034	260285.4	32.53	64.94	140.32	115
	54	6854725.185	259783	34.09	55.47	107.08	115
	55	6854568.009	259869.1	35.73	66.66	109.87	115
	56	6854649.566	259899.6	28.3	50.22	76.65	115
	57	6854651.017	260372.4	42.83	64.43	74.7	115
	58	6854809.858	260358.5	33.38	62.59	137.09	115
	59	6854552.012	259813.1	30.27	49.92	77.11	115
	60	6854537.033	259866.7	22.71	42.46	88.52	125
			avg	33.60	57.47	94.96	113.97
			std	6.66	11.63	25.44	8.31
			Var	44.35	135.23	647.09	69.09
			Max	50.44	83.83	164.95	125.00
			Min	20.05	29.43	46.93	95.00

9.3 Appendix 3: Second phase (randomisation)

Strata	Core ID	longitude	latitude	carbon_stocks_30cm	carbon_stocks_60cm	carbon_stocks_total	total_soil thickness
1	61	150.5447	-28.4144	49.59	78.92	112.48	115
	62	150.5468	-28.4151	35.23	52.63	79.17	115
	63	150.5479	-28.4161	46.03	62.02	69.74	125
	64	150.5417	-28.4139	45.24	94.27	157.76	105
	65	150.55	-28.4155	35.11	66.58	120.77	115
	66	150.5463	-28.4157	54.87	85.52	122.89	115
	67	150.5421	-28.4132	36.43	68.56	112.25	105
	68	150.5422	-28.4132	54.15	76.16	131.52	115
	69	150.5478	-28.4152	27.93	43.22	85.38	115
	70	150.5415	-28.4141	39.61	72.05	112.1	115
2	71	150.5369	-28.4146	57.28	75.87	92.49	125
	72	150.5409	-28.4116	34.28	58.38	84.23	115
	73	150.5431	-28.4118	31.47	55.24	93.06	115
	74	150.5473	-28.4121	58.02	94.54	137.55	125
	75	150.5473	-28.4135	48.6	75.49	116.14	115
	76	150.5377	-28.4147	72.72	106.63	169.77	115
	78	150.5399	-28.4116	32.33	56.07	102.11	115
	79	150.5413	-28.4119	36.59	68.38	117.66	115
	80	150.5391	-28.4135	30.97	55.72	109.44	125
3	81	150.5428	-28.4089	29.72	52.8	99.82	105
	82	150.5418	-28.4109	32.72	63.69	104.22	115
	83	150.5446	-28.4077	12.23	25.73	42.05	95
	84	150.5439	-28.4106	27.39	47.71	86.66	115
	85	150.5417	-28.4089	40.02	65.07	123.42	115
	86	150.5433	-28.41	28.82	45.83	101	115
	87	150.5402	-28.4109	46.62	75.94	117.34	115
	88	150.5455	-28.409	23.44	42.41	82.75	115
	89	150.5448	-28.4101	34.12	64.29	94.58	115
	90	150.5393	-28.4095	25.04	46.41	78.74	115
4	91	150.5441	-28.4059	33.12	47.97	58.92	115
	92	150.5413	-28.4059	45.11	69.3	85.72	105
	94	150.5432	-28.4069	28.92	48.24	77.92	115
	95	150.5467	-28.4071	35.99	58.59	94.22	105
	96	150.5397	-28.4068	40.06	65.39	91.02	105
	97	150.542	-28.4055	27.73	39.37	54.39	105
	98	150.5415	-28.4073	26.85	54.16	89.53	115
	99	150.5401	-28.4086	31.02	50.97	72.11	115
	100	150.5438	-28.4072	39.91	56.56	89.96	125
5	101	150.5422	-28.4027	36.8	55.86	84.59	105
	102	150.5397	-28.4051	28.83	45.87	60.1	95
	103	150.5367	-28.4065	37.45	44.49	47.37	105
	104	150.5422	-28.4047	36.35	55.22	76.39	105

	105	150.5395	-28.4046	25.03	41.11	57.9	115
	106	150.5421	-28.4033	30.01	44.69	63.42	125
	107	150.5445	-28.4044	32.27	57.26	87.66	105
	108	150.5389	-28.4051	48.35	62.13	78.8	105
	109	150.5397	-28.4065	41.13	56.65	77.8	105
	110	150.537	-28.4068	39.91	57.01	79.58	105
6	111	150.5467	-28.4022	42.4	62.01	83.41	125
	112	150.549	-28.4125	26.55	43.99	58.34	115
	113	150.5495	-28.4134	37.18	59.78	89.63	115
	114	150.5539	-28.4109	31.76	47.6	65.18	125
	115	150.5459	-28.4017	31.16	47.5	66.26	115
	116	150.5493	-28.4126	33.97	49.64	71.24	115
	117	150.5517	-28.4127	19.63	38.94	73.49	125
	118	150.5534	-28.4121	26.35	46.54	58.26	115
	119	150.5494	-28.412	36.9	56.16	76.13	105
	120	150.5521	-28.4128	27.29	51.2	100.55	115
			Avg	36.28621	58.453966	90.12034	113.2759
			STDEV	10.40699	14.945669	25.74209	7.288041
			VAR	108.3055	223.37301	662.6552	53.11555
			Max	72.72	106.63	169.77	125
			Min	12.23	25.73	42.05	95

9.4 Appendix 4: A simulation method to define the MDD for stratified sampling

Suppose that the data have a between-stratum variance of s_s^2 and a within-stratum variance (residual variance) of s_r^2, and that we would like to be able to detect a SOC increase at significance level $\alpha = 0.05$ with 90% probability ($\beta = 0.1$). Then the MDD for a sampling strategy with M strata, m_1 data per stratum in phase 1 and m_2 per stratum in phase 2 can be approximated by the following algorithm:

(i) Simulate a dataset with the variances s_s^2 and s_r^2, with the given M, m_1 and m_2 and with $\mu_2 = \mu_1 + \mu_d$, $\mu_1 = 0$

(ii) Calculate a p value for an increase in SOC (using a z-test with the difference in the stratified estimates of μ and the sum of the stratified estimates of the variances of $\hat{\mu}$; although this z-test is a bit biased, p values too small, for small N, it seems reasonable for larger N >10 in the case of simple random sampling)

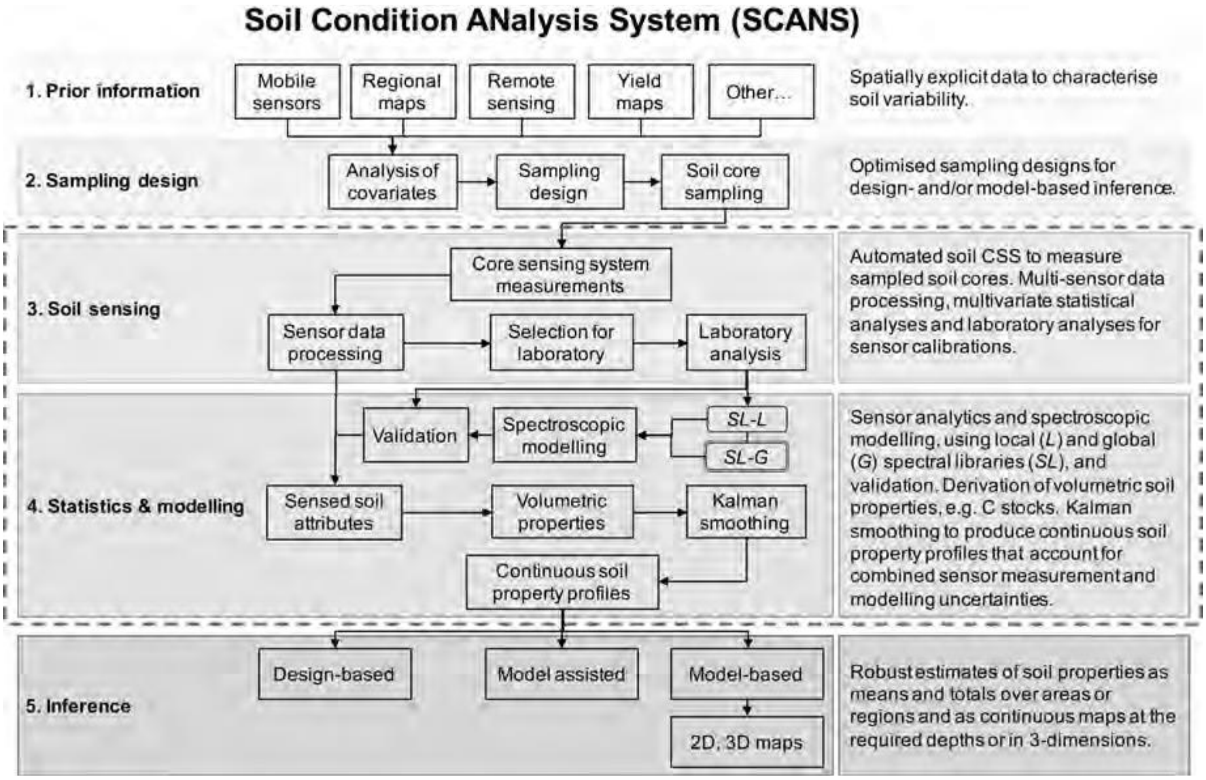
(iii) Repeat steps (i) and (ii) for a large number of simulated datasets and calculate the proportion of simulated datasets, ρ_d, where a significant SOC increase was detected at significance level $\alpha = 0.05$; define β_d as 1 - ρ_d

(iv) Repeat steps (i) to (iii) with different values of μ_d in step (i) until an acceptable match is found between β_d and the required β value of $\beta = 0.1$; the final value of μ_d is the MDD.

9.5 Appendix 5: *A* recipe guide for prediction of SOC using the soil core scanner

Introduction

This guide provides a step-wise workflow for estimating soil carbon stocks in soil cores that have undergone scanning and inspection by a *Soil Condition Analysis System*, or SCANS. The potential of the system has been described in Viscarra Rossel et al. (2017). This guide sets in place the practical steps required to process the raw data that comes from this system through to generate estimates of soil carbon stocks.



The sequence of steps with detail process are as follows:

1. Initial SCANS data compilation:
2. Useful information attribution to SCANS collected data (mainly about appending location and depth interval information):
3. Spectral data pre-processing:
4. Using spectral properties of the soils to determine a subset of soil specimens to be subjected to laboratory analysis:
5. Spectral inference of target soil variables (here this guide is purely interested in soil organic carbon:
6. Spectral inference of volumetric water content:
7. Estimating soil bulk density from SCANS gamma densiometer readings:
8. Estimation of soil carbon stocks

For some background, a soil profile is placed on an analysis platform and is subjected to various forms of investigation via vis-NIR spectroscopy and gamma radiation attenuation, plus via imagery from a mounted camera. From the vis-NIR data, soil carbon concentration estimates can be inferred given a suitable model calibration that links soil spectra with actual observed soil carbon concentration data. In this current workflow we select a subset of soil specimens from the available soil profiles so that they can be laboratory analysed after which this data is used to fit a spectral model.

An alternative approach, but not used in the current workflow is the have an *a priori* calibrated model developed from some specified soil spectral library that may or may not have been compiled in the same area where the soils were collected from and analysed by the SCANS system. Also, from the vis-NIR data, volumetric soil water (VSW) estimates are also inferred. As to be discussed further, we need VSW to infer soil bulk density.

We do not predict VSW in the way that we will infer soil carbon, but instead use an *a priori* calibrated model from an available soil spectral library and associated soil information relating to the hydraulic properties of the collected soils. This *soil-water* library are a collection of about 160 soil specimens from around Australia that were subjected to a sequence of pressure potentials to measure the retention of water (volumetrically) at those given potentials. Parallel to this process, vis-NIR spectra were collected from each specimen as it equilibrated at the given pressure potential. Given the number of soil specimens and the varying water contents, a skillful volumetric soil water spectral model was developed. It is entirely possibly to develop ones own models of soil volumetric water in the same way that we will demonstrate for the prediction of soil carbon concentration. However, VSW is difficult and timely to measure relative to soil carbon.

VSW is necessary in the process of estimating soil bulk density. The SCANS system in fact *senses* bulk density via gamma attenuation. For one to get a useful estimate of bulk density, we need to have an idea how much water is stored in the soil at the time of scanning as the attenuation profile of the soil when it is dry is quite different when it is moist. We will come to this later in more detail.

With an understanding of the soil carbon concentration and bulk density we can estimate soil carbon stocks using the relatively simple equation:

SOCstocks(MgC/ha)=[CarbonContent(%)×(1−αm)]×SoilLayerThickness(cm)×BulkDensity(Mg/m3)×[1−MassFractionofGravel]×0.1SOCstocks(MgC/ha)=[CarbonContent(%)×(1−αm)]×SoilLayerThickness(cm)×BulkDensity(Mg/m3)×[1−MassFractionofGravel]×0.1

In addition to estimating the soil carbon concentration (via vis-NIR) and bulk density we also need to know the thickness of the soil layer that measurement is based on and the mass fraction of gravel or proportion of the total sample material that is >2mm. The soil layer thickness can be gleaned indirectly from the SCANS system because of the way it collects measurements from a soil profile and making some assumptions around what the sample support of the collected information is from. The SCANS system will take measurements along a soil core to some defined interval, for example every 5cm or every 10cm along the length. This is entirely up the user. It is known that for some sample intervals maybe every 5cm for the 10cm, then every 10cm thereafter. Whichever the way the measurement is performed, the working assumption is that the site where the scan (vis-NIR and gamma reading) is collected from represents a mid-point of a soil thickness interval. For example, if the SCANS sampling interval is every 5cm, and the first sample occurs at 2.5cm, the sample interval for the collected data is 0-5cm. The second sample depth then will be 7.5cm (5cm-10cm) and so on. This sample support stuff becomes important later on once we begin to estimate soil carbon stocks and calculating soil masses and importantly soil carbon stocks at equivalent soil masses. Estimation of the gravel content of soils is a sticking point in the process of estimating soil carbon stocks.