# Final report

.

## *P.PSH.2103 - Application of spaceborne imaging for soil carbon quantification*

Project code: P.PSH.2103

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# Abstract

Carbon sequestration in livestock producers' soils has the potential to be a significant contributor to the red meat industry achieving carbon neutrality.

A critical first step in achieving this is to rigorously baseline individual farms' current soil carbon stocks in a cost-effective way that scales to an industry wide level. The objective of the project was to use data from space to reduce the number and spatial density of costly physical soil samples required to still have confidence in the accuracy of the results.

The project demonstrated that in target regions, by combining and ground truthing data from space with as few as 6-9 physical soil samples per farm, soil carbon stock levels can be accurately quantified to provide results that producers and the red meat industry can have confidence in reporting.

The project has created a subsequent pathway to prove and establish this approach at a nationwide scale in alignment with Australia's soil carbon methodology and work towards achieving the Commonwealth Governments target of $3/ha quantification.

# Executive summary

## Background

As a part of MLA's carbon storage partnership, carbon sequestration in soil has the potential to be a significant contributor to the red meat industry achieving carbon neutrality. The CN30 roadmap has a target of producers using soil carbon sequestration methods to increase soil organic carbon (SOC) in 30% of improved grazing grounds by 50-100kg CO2-e/ha/year.

A critical step towards achieving this target is to empower producers to rigorously baseline their current SOC stocks. One of the key barriers this project is addressing is the prohibitively high cost of achieving this through a 'sampling-only' approach, which is due to the high number of physical soil samples that have been required to achieve confidence in the results.

The goal of this project is to validate the efficacy of an alternative approach to SOC baselining whereby physical samples and spaceborne remotely sensed data are combined with machine learning (ML) to localise a modelled quantification of SOC.

The objective is to demonstrate that by taking this hybrid approach it is possible to significantly reduce the density of physical samples required to achieve confidence in the results.

The aim is to create a pathway to delivering the Australian federal government's stretch target of $3/Ha.

The results of this project will be shared with the Clean Energy Regulator and the Department of Climate Change, Energy, the Environment and Water to help inform the direction of future soil carbon methodologies, and work with the red meat industry supply chain to optimise an approach to massively scaling up the baselining of Australian producer's soil carbon in order to contribute to CN30 roadmap targets.

## Objectives

1. The project validated the primary objective to prove that using soil samples to localise a data driven machine learning model is more accurate and cost effective than the current sampling only approach.
2. The project has initiated the integration of soil carbon data with commonly used farm management tools, but further work is required to join-up carbon data in the red meat supply chain.
3. The project has mapped out a pathway to achieving the CN30 soil carbon storage targets, and was a successful applicant in the National Soil Carbon Innovation Challenge as a route to achieving this.

## Methodology

The Cloud Agronomics model uses remote sensing imagery, physical soil samples, and other spatial covariates relating to soil carbon distribution (topographic and edaphic variables, long and short-term physical climate and weather proxies) to calculate SOC stocks.

Two rounds of physical soil sampling were carried out to generate the data to initially train the model for Australian soil conditions, and then localise the model to the target geographies.

Blind validation Carbon Estimation Areas (CEAs) were used to verify the accuracy of Cloud Agronomics hybrid approach versus the traditional sampling only method.

## Results/key findings

The results support the case that using a low number of physical soil samples to localise a data driven machine learning model is significantly more accurate and cost effective than using the current minimum of 9 samples alone to quantify soil carbon.

Based on the validation CEAs, significant performance gain was observed when the model was localised against just 6 soil samples per CEA, and a diminishing return was observed after the model was localised against 9 samples per CEA.

Decreasing the number and spatial density of physical soil samples required for accurate SOC quantification is going to be the biggest contributor to achieving the National Soil Carbon Innovation Challenge stretch goal of $3/ha.

The results of this project support the view that at this point in time a remotely sensed only approach to soil carbon quantification is unlikely to achieve the confidence level required by carbon markets. If a critical mass of soil sample data (e.g. data set of 10,000 samples distributed across livestock grazing lands) is made available to localise a data driven approach to soil carbon quantification, then the industry will be in a position whereby a remote-only approach could achieve the levels of confidence required by the red meat supply chain, industry reporting tools, and carbon markets.

## Benefits to industry

The project has identified two compelling avenues to reduce the requirements for physical sampling, and therefore significantly decrease the costs for red meat producers:

- Reducing the number of samples required to localise the model on each CEA to 6 physical samples or fewer.
- Reducing sampling densities to broader regional calibration CEAs to achieve the required level of confidence in SOC quantification at a CEA level across a whole target geography.

## Future research and recommendations

The Australian red meat industry should aim to develop a data set of 10,000 samples distributed across livestock grazing lands by 2024. Achieving this critical mass of data would enable the localisation of nationwide data driven machine learning SOC models and establish a baseline peer reviewed metric for both the Australian Beef and Sheep Sustainability Frameworks.

In order to demonstrate and quantify the impacts that farm management changes have made on paddock-level SOC stocks, historical predictions of SOC should be produced and related to farming practice changes.

Furthermore, work with the Department of Climate Change, Energy, the Environment and Water and the Clean Energy Regulator is needed to develop a set of recommendations and/or a supporting module for a future Soil Carbon Method which details best practices for applying and validating data driven machine learning SOC quantification approaches.

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# 1. Background

As a part of MLA's carbon storage partnership, carbon sequestration in soil has the potential to be a significant contributor to the red meat industry achieving carbon neutrality. The CN30 roadmap has a target of producers using soil carbon sequestration methods to increase soil organic carbon (SOC) in 30% of improved grazing grounds by 50-100kg CO2-e/ha/year.

A critical step in achieving this target is to empower producers to rigorously baseline their current SOC stocks. One of the key barriers this project addresses is the prohibitively high cost of a 'sampling-only' approach, which is largely due to the high number of physical soil samples that have been required to achieve confidence in the results.

The goal of this project is to validate the efficacy of an alternative approach to SOC baselining whereby physical samples and spaceborne remotely sensed data are combined with machine learning (ML) to localise a modelled quantification of SOC.

The objective is to demonstrate that through taking this hybrid approach it is possible to significantly reduce the density of physical samples required to achieve confidence in the results.

The aim is to create a pathway to deliver the federal government's stretch target of $3/ha.

The results of this project will be shared with the Clean Energy Regulator and the Department for Industry, Innovation and Science to help inform the direction of future soil carbon methodologies, and work with the red meat industry supply chain to optimise an approach to massively scaling up the baselining of Australian producers' farms in order to achieve the CN30 roadmap targets.

# 2. Objectives

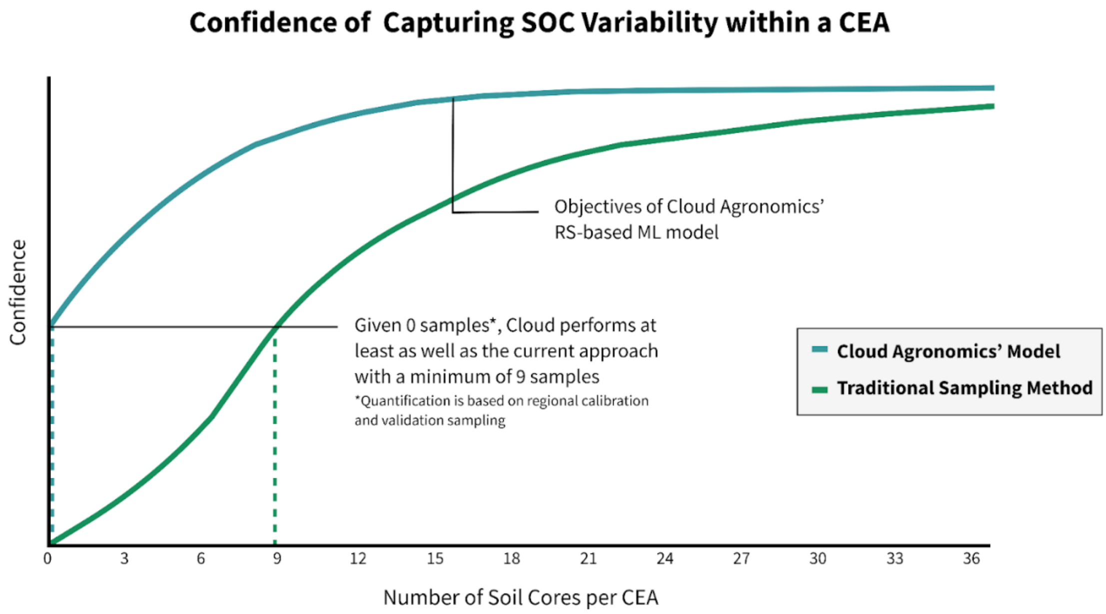
The project was developed to address the significant financial and logistical barriers to the mainstream adoption of soil carbon measurement posed by current methods of physical soil coring and laboratory analysis. Current 'measurement only' methods are not poised to widely enable farmers to actively work to increase soil carbon content over the coming years.

As an alternative hybrid approach, Cloud Agronomics combines physical samples with spaceborne remotely sensed data, and other geospatial data layers such as topography, and uses machine learning (ML) to localise a modelled quantification of SOC.

The specific objectives of the project are to:

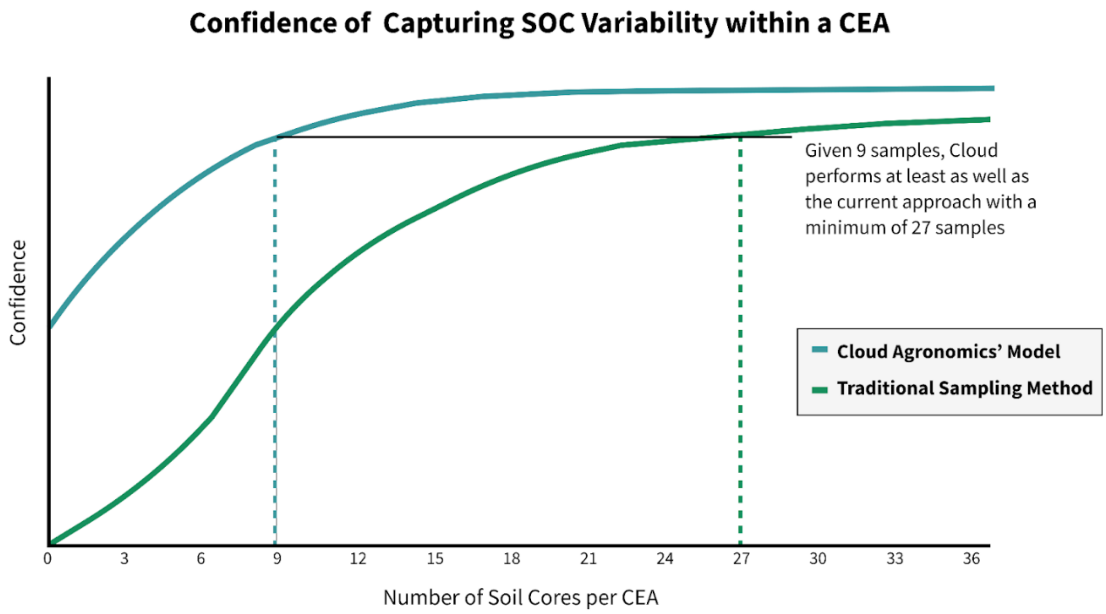
1. **Validate that remote carbon measurement is at least as accurate in quantifying field-level SOC content as the minimum requirements set out in the Carbon Credits (Emissions Reduction Fund (ERF) – Sequestering Carbon in Soils in Grazing Systems) Methodology Determination 2021 for physical soil coring and lab analysis.** Fig. 1. below illustrates that the Cloud Agronomics model is aiming to achieve the same level of confidence in SOC quantification using only a modelled result (e.g. zero samples from that CEA to localize against) compared to the traditional method of taking the minimum 9 samples per CEA, with the number of samples being used on the X axis.

**Fig. 1. Objective of Cloud Agronomics model using 0 samples compared to 9 samples following the traditional method (graph is for illustrative purposes only)**



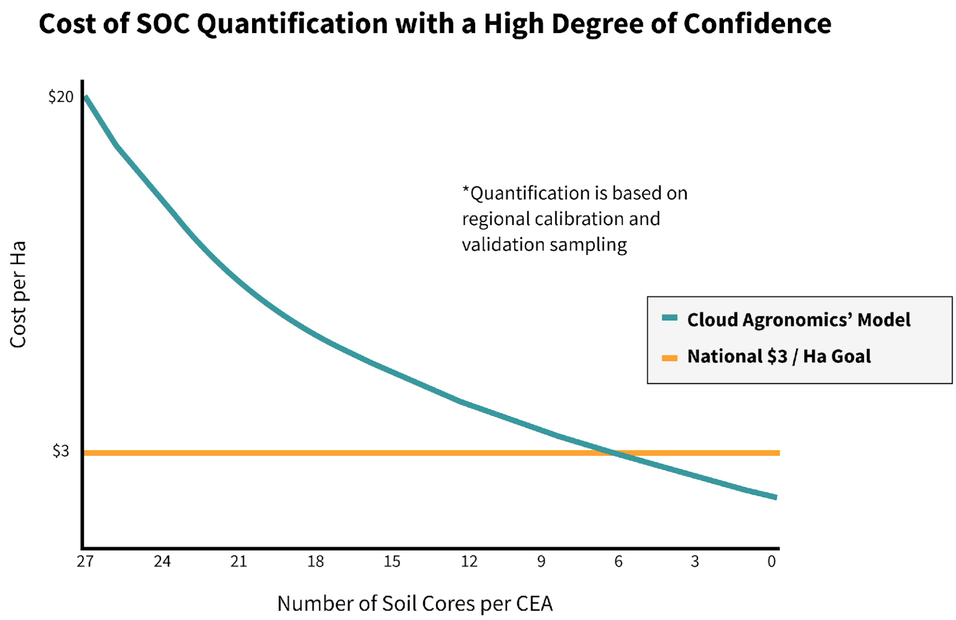
As illustrated in Fig. 2. below, validate that given the current minimum 9 samples per CEA to localise against, validate that the Cloud Agronomics model can generate a result that creates the same confidence level as the traditional sampling only approach does with 27 soil cores:

**Fig. 2. Objective of Cloud Agronomics model using 9 samples compared to 27 samples following the traditional method (graph is for illustrative purposes only)**




2. **Demonstrate that the new approach will be significantly more cost-effective than the current 'measurement only' approach of physical soil coring and lab analysis.** The primary cost driver of SOC baselining is physical soil sampling, and as illustrated in Fig. 3 below, the current costs of approximately \$20/ha is driven by requiring up to 27 samples per Carbon Estimation Area (CEA) to achieve confidence in the data. The objective of the Cloud Agronomics hybrid approach is to achieve this same level of confidence with just 9 or less samples per CEA, with the cost benefit to producers of creating a pathway for achieving the National Soil Carbon Innovation Challenge stretch target of \$3/ha.

**Fig. 3. Objective of Cloud Agronomics to reduce the number of physical soil samples to achieve cost benefit targets (graph is for illustrative purposes only)**



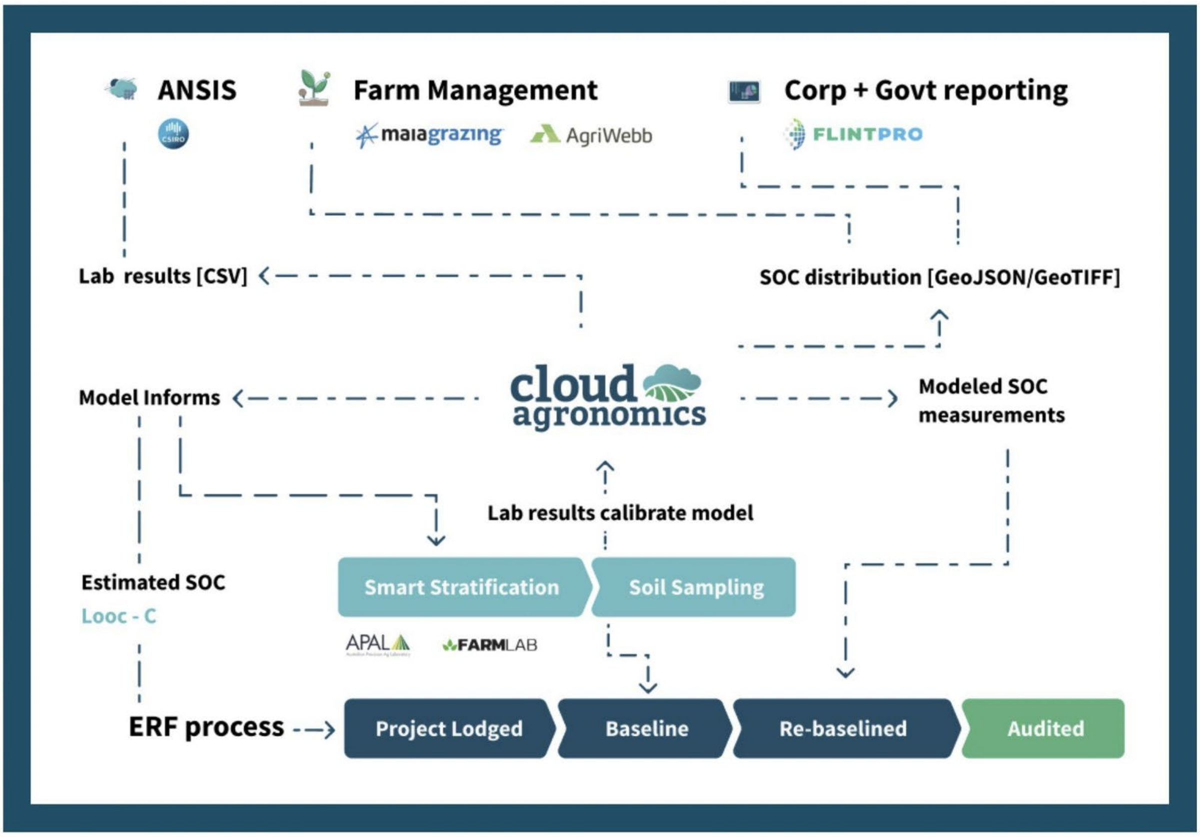

3. As Illustrated in Fig. 4. below, Cloud Agronomics mapped the soil carbon ecosystem and identified key stakeholders to integrate with in order to generate a joined-up solution for producers and the red meat industry and supply chain.

   Make remotely sensed soil carbon data from Cloud Agronomics interoperable with farm management tools commonly used by livestock farmers. The data interoperability will enable farmers to see their initial soil carbon variability to inform their management decisions, and subsequently the impact that management changes make over time as their paddocks are re-measured by means of remote sensing.

   Make remotely sensed soil carbon data from Cloud Agronomics interoperable with corporate and industry-wide carbon accounting tools such as FLINTpro.

   Enable remotely sensed soil carbon data interoperability with software such as FarmLab that are commonly used for managing and auditing soil carbon projects, thereby enabling greater uptake of soil carbon Emissions Reduction Fund (ERF) methodologies.

**Fig. 4. Cloud Agronomics integration with the wider Australian technical ecosystem**




As outlined in the subsequent results section, the project has met its primary objectives around proving out the efficacy of the Cloud Agronomics hybrid approach to SOC quantification. The two objectives that have only been partially met at this stage are the integration with leading livestock management tools such as MAIA Grazing and AgriWebb, as well as industry wide reporting tools such as FLINTpro. Productive collaboration and meetings have been occurring since the outset of the project, and paddock boundaries from the farm management tools have been used as a part of the soil sampling and stratification process, but SOC quantification maps and data generated by Cloud Agronomics haven't been integrated back into the 3rd party platforms at this stage.

# 3. Methodology

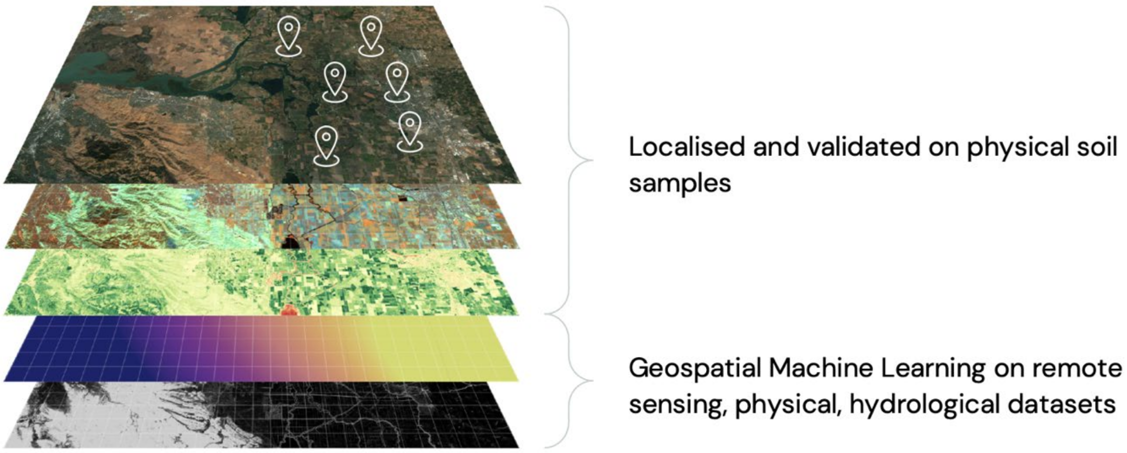
## 3.1 Cloud Agronomics data driven approach

Cloud Agronomics treats SOC quantification as a data driven challenge, rather than exclusively a remote sensing problem. Data driven methods use remote sensing as one data source amongst many that are likely to be predictive of SOC content.

In addition to using physical soil sample data to localise against, the other spatial covariate data incorporated into the Cloud Agronomics model includes:

- Topographic
- Edaphic variables
- Long-term physical-climate proxies
- Short-term physical climate and weather proxies
- Optical remote sensing
- Synthetic aperture radar measurements

**Fig. 5. Illustration of the layers that Cloud Agronomics uses as a part of a data driven approach to SOC quantification**




## 3.2 Sampling design

The project was designed to align with the Schedule 2 'Measure-Model-Measure' approach of the 2021 Soil Carbon Methodology which enables a model assisted method to soil carbon quantification.

Physical soil samples were collected in phases and were used to progressively train and localise Cloud Agronomics' model to the trial region. The performance of the model was tested against blind validation Carbon Estimation Areas (CEAs)

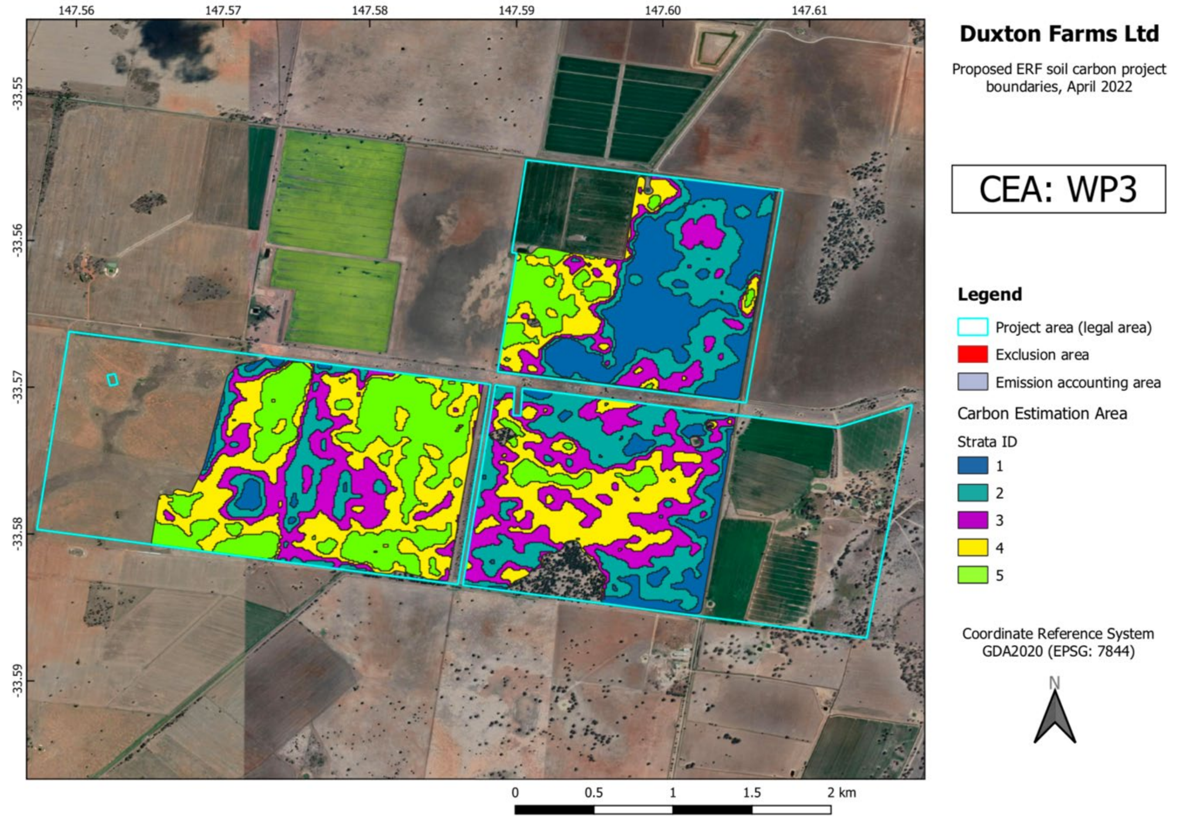
CEAs were created in consultation with the landholders on each farm. The CEA boundaries were drawn using QGIS software, and then further stratified into 3-5 sampling strata based on the producers' knowledge of their land.

CEAs were also created so that they averaged in size between 42.9ha and 225ha to ensure consistency in sampling density, while providing enough variability to generate comprehensive results (sampling density was 4x higher in the smallest CEA compared to the largest).

The selected CEAs were pastureland used for grazing livestock, which include a range of practices such as grazing on stubbles post-harvest and grazing on native pastures or improved pastures.

Between 18-27 sample points (6-9 per strata) were then randomly generated, ensuring that the project followed best practice sampling design to ensure confidence in the results, and significantly exceeded the minimum 9 samples per CEA (3 samples per strata) that the 2021 Methodology requires.

**Fig. 5. Example CEA stratification following the 2021 Soil Carbon Methodology**




Independent of the Cloud Agronomics team, blind validation CEAs were also created in the target geographies using FarmLab software. These CEAs were also split into 3 strata, with 27 randomly generated sampling points (9 per strata) in each.

0-30cm depth soil samples were collected by SYNC Agri using a 38mm diameter corer following the 2021 soil carbon sampling protocol. An external GPS was used to ensure positional accuracy of <1m and all samples were georeferenced using the coordinate reference system GDA2020.

**Fig. 6. 38mm soil corer used for 0-30 cm sampling (image courtesy of SYNC Agri)**

Samples were analysed by Eurofins APAL Labs. The samples were tested for:

- Total Organic Carbon
- MIR Australian Soil Texture
- Bulk Density
- Gravimetric Gravel Content

Samples were collected in a fixed volume core and analysed at the lab for bulk density. The samples were sieved to remove >2mm soil and oven dried at 105°C. Sample bulk density was then analyzed for <2mm dry soil, where soil moisture and coarse fragments were analysed to calculate the density of the soil in which organic carbon is sequestered.

Samples were finely ground using a puck mill. If carbonate presence was detected, a chemical pre-treatment was applied to remove inorganic carbon prior to Total Organic Carbon analysis. Total Organic Carbon (TOC) was then analysed for each sample using dry-combustion, where combustion occurs at 950°C and non-dispersive infrared (NDIR) is used to determine total (organic) carbon.

With the data from the blind validation CEA's, the results from the lab were passed directly into the FarmLab platform where it was held in escrow away from Cloud Agronomics to ensure 3rd party verifiability of the results.

## Project Geographies

Geographies were selected to cover a variety of rainfall levels (with annual variability from an average >600mm to <300mm), soil types (primarily chromosol and sodosol), levels of soil visibility and farming management practices in order to demonstrate generalisability of the approach.

From an NRM region perspective, the geographies that the project covered were:

- Riverina

- Southeast NSW
- Central West NSW
- Northern & Yorke SA

Fig. 7 and Fig. 8 below also illustrate the additional NRM regions that Cloud Agronomics proposes to build on as a part of the future Soil Carbon Innovation Challenge (South East SA, Eyre Peninsula, Adelaide and Mt Lofty, South East Queensland)

**Fig.7. Variability of annual average precipitation levels**

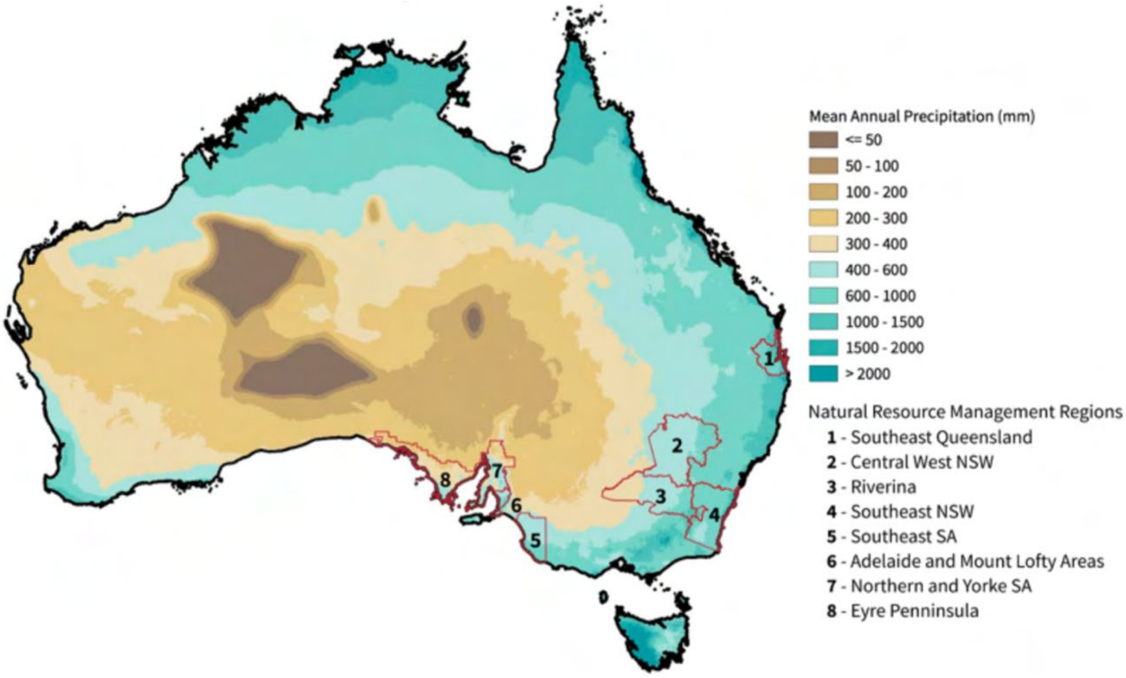
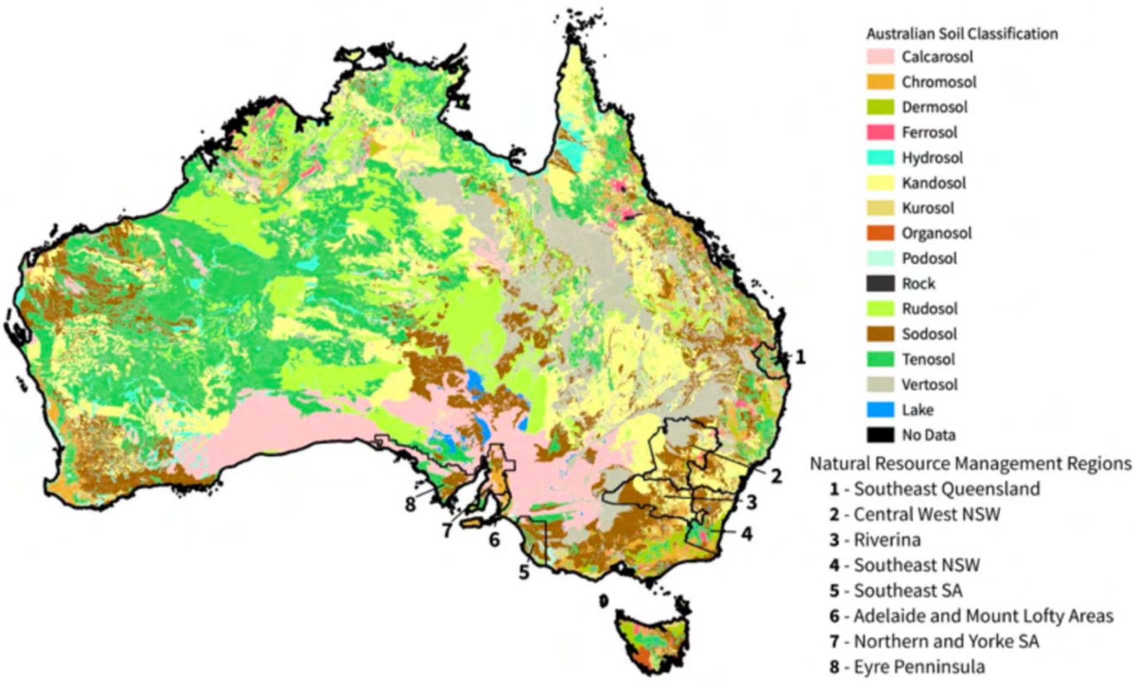


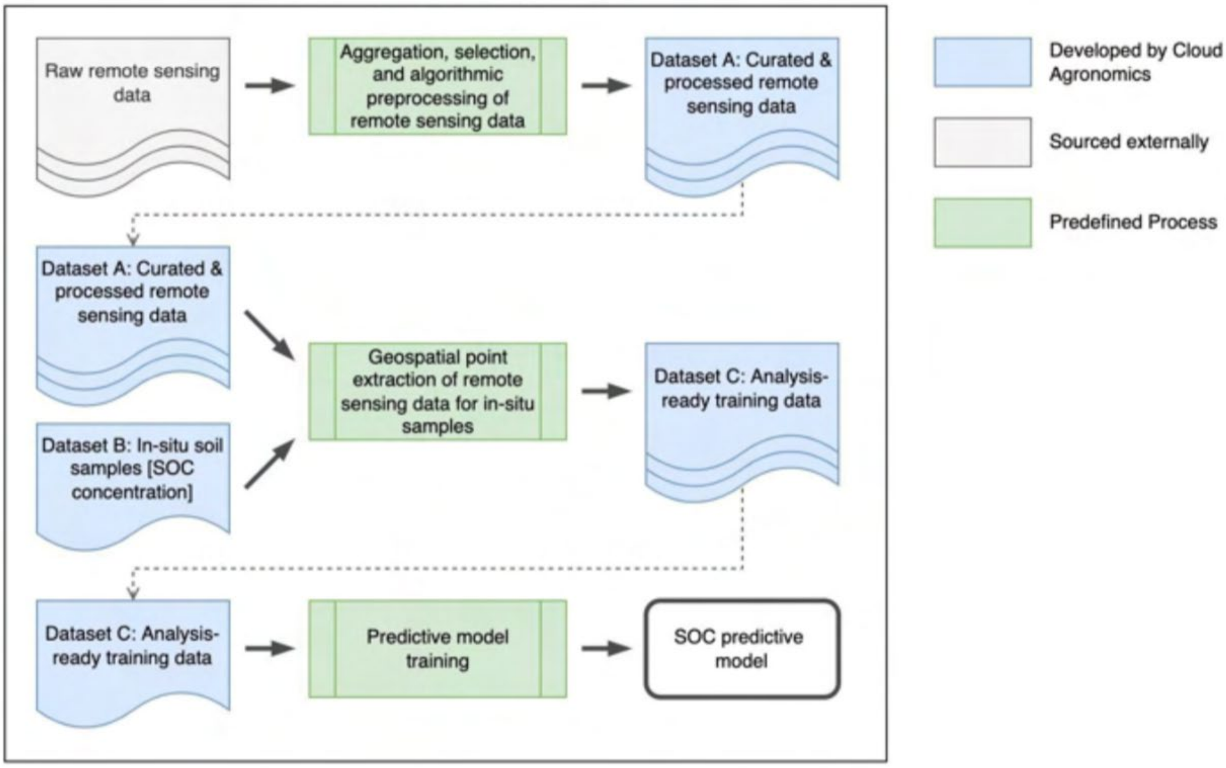

**Fig. 8. Variability of soil type**



## 3.3 Phases of the development of Cloud Agronomics SOC model

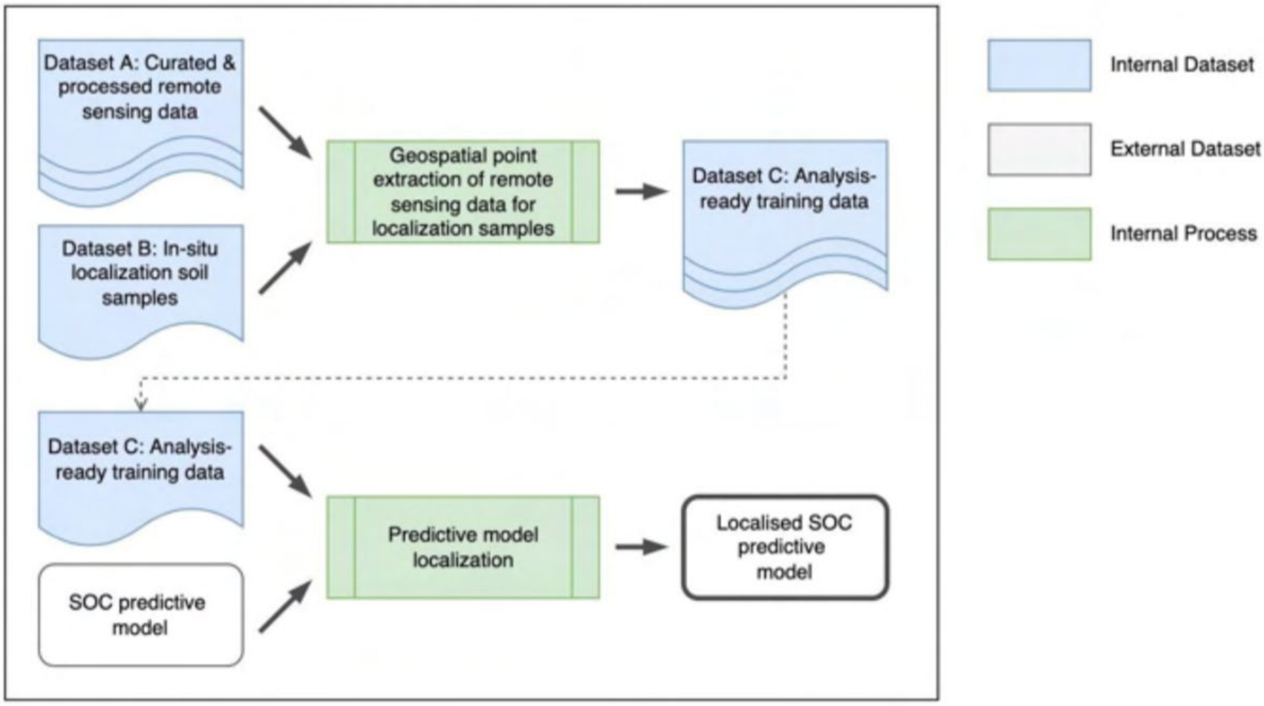
The figures below illustrate the process of initially training Cloud Agronomics model for Australia, and the subsequent process of localising and validating it in the target geographies of the project.

**Fig. 9 Initial phase of Australian SOC model development**



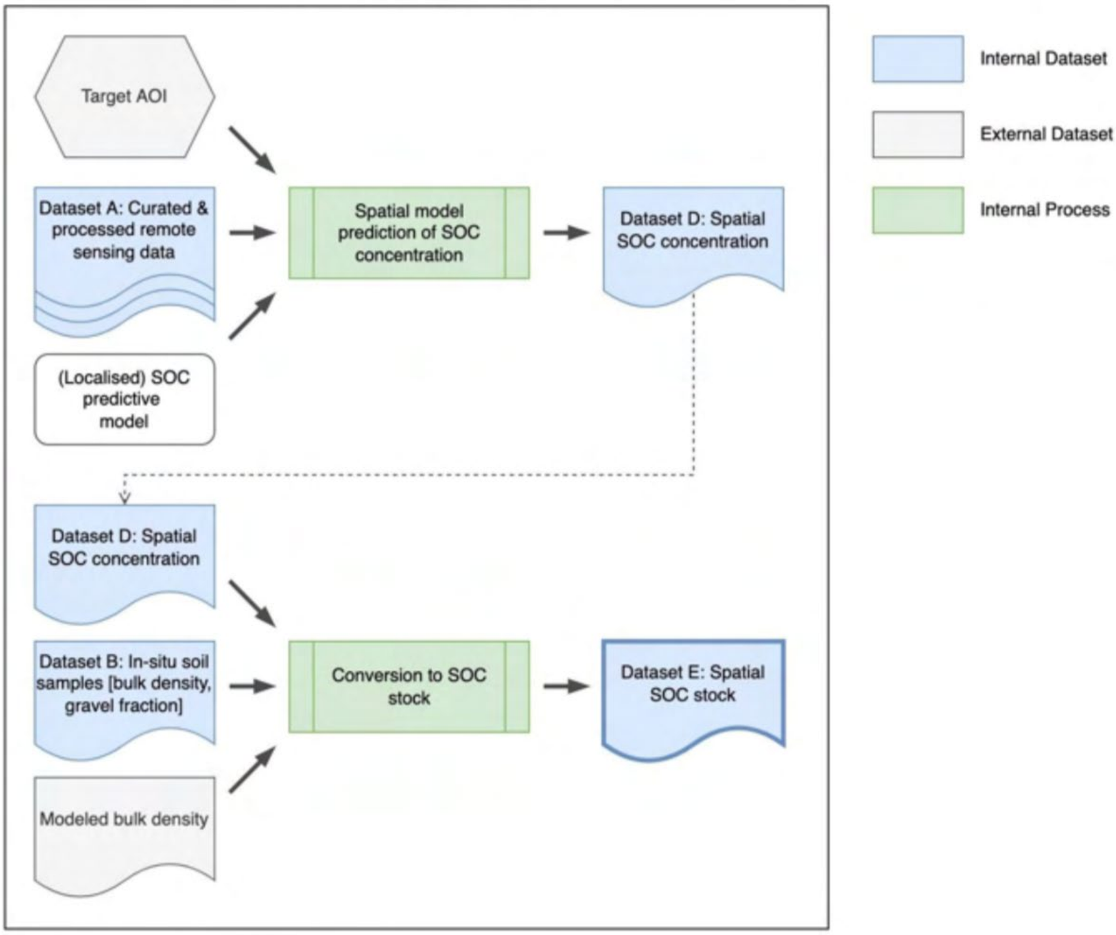

Training data (CSIRO SCARP data as well as additional soil samples from Cloud Agronomics taken outside of this project) were joined against spatial predictors within the Cloud Agronomics pipeline and fed through an iterative training process by the data science team.

**Fig. 10. Localisation of SOC model for a target geography**




The SOC model is localised by adding soil samples from the target area of interest for localisation. The model is retrained with these samples until it accurately represents the localisation data.

**Fig. 11. SOC stock prediction**




Once the SOC model has been localised, it is used to predict SOC concentration at the CEA level by assembling spatial predictors across a continuous region of space, using these as input to the model, and saving the result as a spatial raster. The SOC predictions are extracted for the CEA and converted to units of SOC stock by incorporating bulk density measurements or estimates, and saved as a SOC stock raster image and a set of summary statistics.

SOC stock is calculated on each CEA using inputs of SOC percent by mass (%), bulk density, gravel fraction, and CEA area from a mixture of physical samples and model predictions.
The following formula is used for measured SOC stock calculations:

$$S = \frac{P}{100} \cdot B \cdot (1 - G) \cdot D \cdot A$$

$S$ = SOC stock to 30 cm depth (grams)
$P$ = mean SOC percent by mass in the field to 30 cm depth (%, 0-100)
$B$ = bulk density (g/cm$^3$)
$G$ = gravel fraction (decimal value, 0-1)
$D$ = depth (cm), fixed at 30 cm
$A$ = field area (cm$^2$)

## 3.4 Testing the Cloud Agronomics SOC model against blind validation CEAs

27 samples were taken in each of the blind validation CEA's to establish the physical field mean stock values to compare Cloud Agronomics' quantification against.

SYNC Agri provided varying numbers of randomly-selected samples to Cloud Agronomics to be used for model localisation and to generate a series of quantifications outlined below. This was designed to determine the point of diminishing returns from the number of samples required by the Cloud Agronomics model to generate a quantification with a similar level of confidence to the sampling only approach. Our objective is to develop a model which demonstrates that this point of diminishing returns occurs at less than 9 samples, thereby significantly reducing the cost of baselining SOC stock in order to hit the CN30 targets. Cloud Agronomics quantified the CEA-level SOC a number of times incorporating an increasing number of samples being used for model localisation:

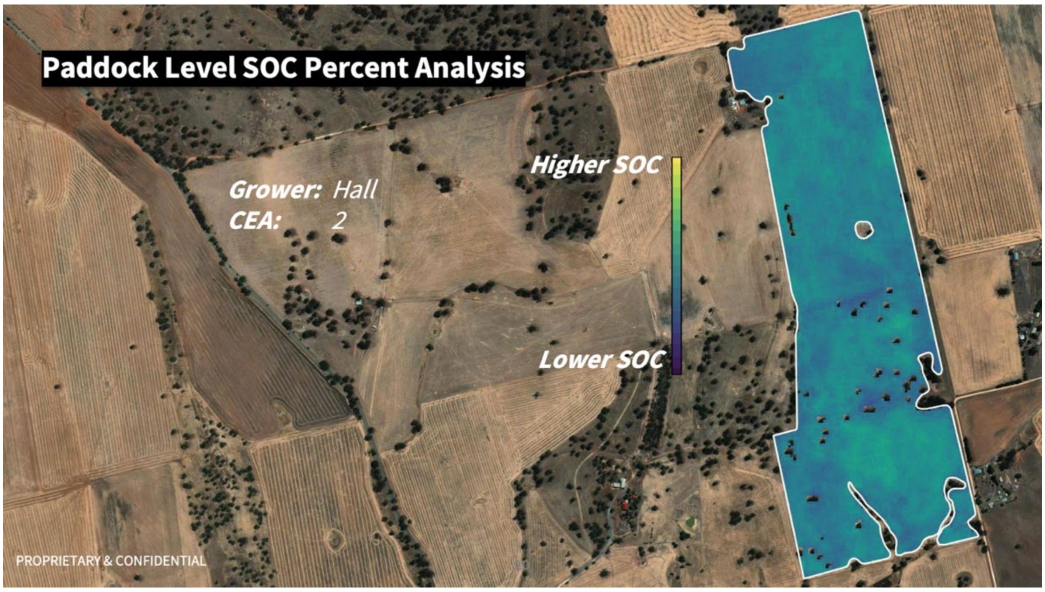
- QUANTIFICATION #1: The Cloud Agronomics model is given 0 samples per strata to localise. Instead, a sparse set of regional samples are used for localisation.
  QUANTIFICATION #2: The Cloud Agronomics model is given 1 sample per strata to localise against (3 samples per CEA).
- QUANTIFICATION #3: The Cloud Agronomics model is given 2 samples per strata to localise against (6 samples per CEA).
- QUANTIFICATION #4: The Cloud Agronomics model is given 3 samples per strata to localise against (9 samples per CEA).
- QUANTIFICATION #4: The Cloud Agronomics model is given 4 samples per strata to localise against (12 samples per CEA).
- QUANTIFICATION #4: The Cloud Agronomics model is given 5 samples per strata to localise against (15 samples per CEA).
- QUANTIFICATION #7: The Cloud Agronomics model is given 6 samples per strata to localise against (18 samples per CEA).
- QUANTIFICATION #8: The Cloud Agronomics model is given 7 samples per strata to localise against (21 samples per CEA).
- QUANTIFICATION #9: The Cloud Agronomics model is given 8 samples per strata to localise against (27 samples per CEA).

# 4. Results

## 4.1 Hybrid quantification of soil carbon distribution at 10m$^2$ resolution

Cloud Agronomics' model generated SOC quantifications for each of the CEAs in the Phase 2 sampling. In the visualization in Fig. 12 below, each of the pixels represent a 10 x 10m$^2$ area where an individual prediction of SOC percent has been generated. The visualization shows a distribution map of higher and lower percent SOC measurements across the Hall 2 CEA.

**Fig. 12. SOC distribution map for 'Hall' CEA in the Mid North region of SA**




A paddock level output was also generated at a regional level using the Cloud Agronomics model; Fig. 13 and 14 below illustrate how the paddocks in the 'Hall' validation CEA compared to neighbouring paddocks in relation to the deviation from the estimated mean SOC at a regional level of the Upper North of South Australia.

**Fig. 13. Spatial map of regional level SOC distribution across a section of the Mid North of SA**

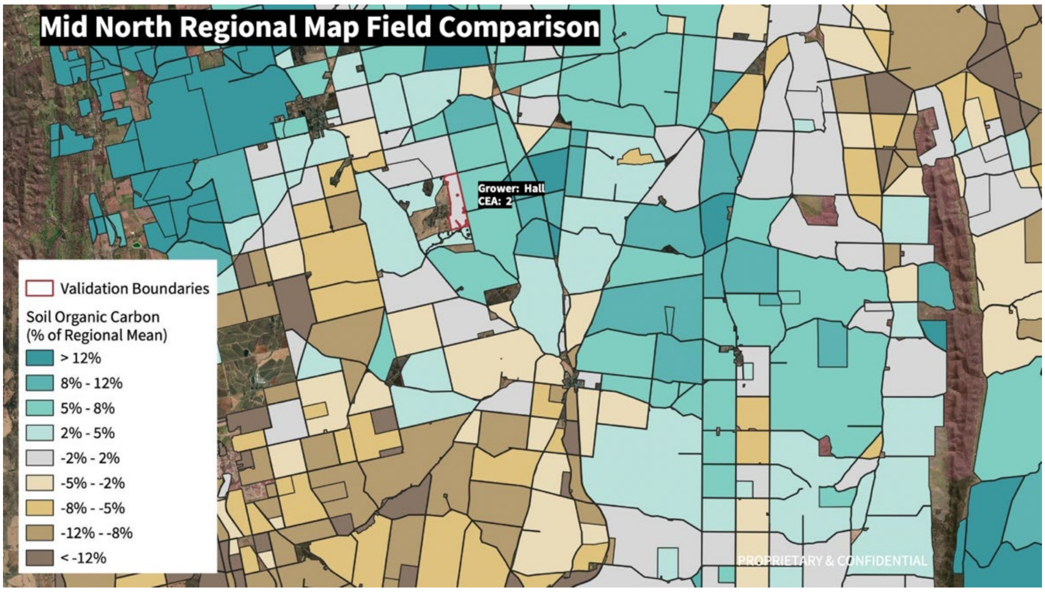
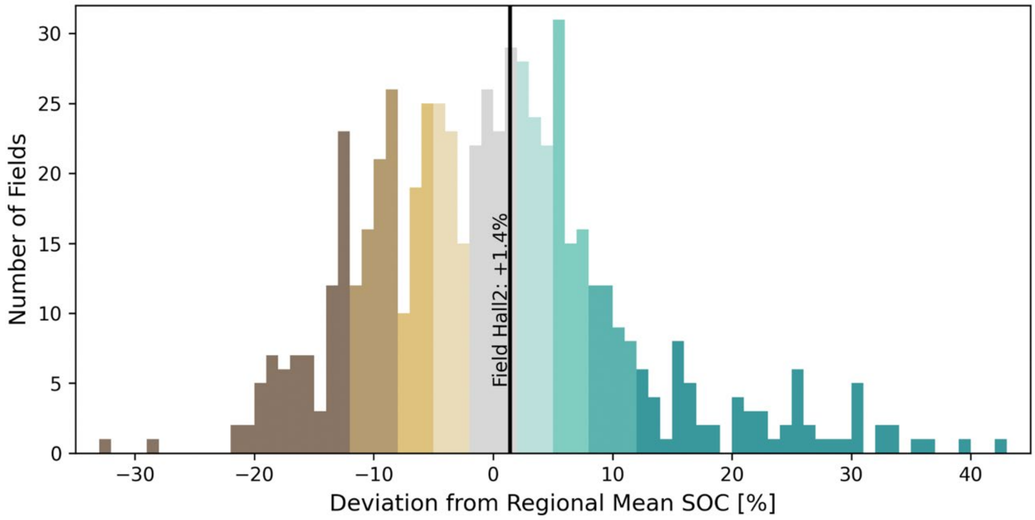



**Fig. 14. Histogram of CEA level SOC distribution across a section of the Mid North of SA**




The functionality to create SOC predictions on a per paddock / per farm level across an entire geography of interest which highlights the deviation from regional mean SOC generates a number of future opportunities for the red meat industry and the Clean Energy Regulator. From a Quality Assurance perspective, it enables a system to highlight physical sampling results that are anomalous, which may require further investigation or re-sampling. With regards to future research, it enables work to be carried out to identify any correlations that exist between previous management practices and whether those paddocks are indexing significantly higher or lower than the regional mean for that geography.

## 4.2 Hybrid quantification using a low number of physical soil samples

One of the overall objectives of the project is to demonstrate that the accuracy of Cloud Agronomics' model responds rapidly to localization with a low number of physical soil samples from a given CEA.

Table 1 below illustrates:

- The physical sampled mean for each of the Validation CEAs, which is the 'Physical Sampled Stock' column on the left (generated through taking 9 samples per strata, with a total of 27 across the CEA)
- The 'Cloud Agronomics Modelled Stock' column in the middle is the SOC quantification that the Cloud Agronomics model remotely generated without any soil sampling data to localize against ('Quantification #1' in the method)
- The 'Cloud Agronomics Localised Modelled Stock' column on the right shows the SOC quantification that the Cloud Agronomics model generated when it was randomly given just 2 samples per strata (6 samples per CEA) which is 'Quantification #3' in the method

**Table 1. Comparison of the sampled SOC mean stock (left column) to Cloud Agronomics modelled mean SOC stock (middle column) and Cloud Agronomics localized model mean SOC stock (right column)**

| Grower, CEA | Physical Sampled Stock (metric ton / hectare) | Cloud Agronomics Modelled Stock (metric ton / hectare) | Cloud Agronomics Localised Modelled Stock (metric ton / hectare) |
|---|---|---|---|
| **Nottle, 2** | 44.2 | 53.1 | 45.7 |
| **Evans, 3** | 60.2 | 57.5 | 59.8 |
| **Keynes, 2** | 51.3 | 46.9 | *41.4** |
| **Hall, 2** | 44.5 | 45.6 | 44.8 |
| **Average Percent Error (across all fields)** | – | 8.9% | 6.0% |

Table 1 illustrates the model's performance using Mean absolute percentage error (MAPE) as a metric for understanding the deviation between the SOC stock calculated from physical samples and the SOC calculated using the model from Cloud Agronomics. The following calculations were used to determine the MAPE values for each CEA:

Absolute Percent Error (APE):

$$APE = 100 \times \left| \frac{S_{sampled} - S_{predicted}}{S_{sampled}} \right|$$

Mean Absolute Percentage Error (MAPE) across all fields:

$$MAPE = \frac{\Sigma\ APE}{N} \quad (3)$$

Where:

$S_{sampled}$ = calculated field-level SOC stock (to 30 cm depth) from samples

$S_{predicted}$ = predicted field-level SOC stock (to 30 cm depth) from Perennial model

$N$ = number of field

Fig. 15. Comparison of Field Mean Percent SOC and Modelled Field Mean Percent SOC

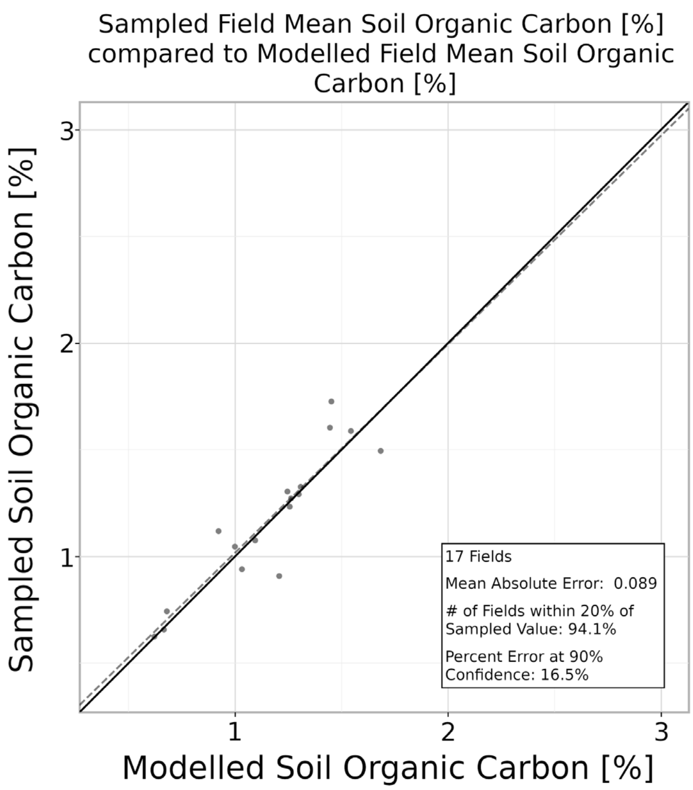


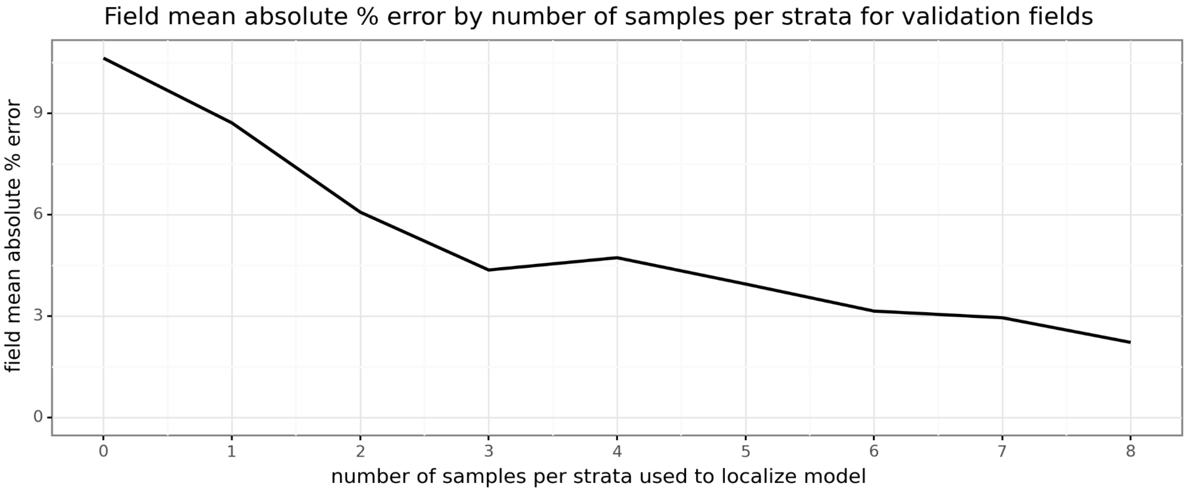

Figure 15 above illustrates the comparison of field mean SOC values from physical samples and the modelled field mean values. This comparison is provided for the 17 non-validation fields sampled for this analysis.

The mean absolute error of the modelled values compared to the samples was 0.089. The modelled mean SOC values for 16 fields, or 94.1% of the examined fields, were within 20% of the mean sampled SOC values.

The error at a 90% confidence interval was 16.5%.

Figure 16 below is a graph of the variation between the physical sampled mean and the SOC quantification that Cloud Agronomics generated based on the received number of physical samples along the X axis. Each CEA was divided into 3 sampling strata, with 3 samples assigned to each strata to amount to the minimum of 9 samples per CEA that the 2021 Methodology requires

**Fig. 16. Variation between the sampled physical sampled mean and Cloud Agronomics SOC quantification based on receiving a number of physical soil samples for that CEA**




The results from Table 1 show a significant performance improvement on 3 of the 4 Validation CEAs when the Cloud Agronomics model was given just 6 samples per CEA, and the current model sees diminishing localization returns after only 9 samples per CEA (3 per strata)

- The sampled stock for Nottle was 44.2t/ha and the Cloud Ag model predicted 45.7t/ha
- The sampled stock for Evans was 60.2t/ha and the Cloud Ag model predicted 59.8t/ha
- The sampled stock for Hall was 44.5t/ha and the Cloud Ag model predicted 44.8t/ha

The exception to these results is the Keynes CEA which has a measured SOC stock value of 51.3t/ha. The Cloud Ag model initially predicted 46.9t/ha for this CEA when using just the remotely sensed model (e.g. excluding physical samples to localize against) however, the performance declined to a stock value of 41.4t/ha after receiving 6 soil samples to localize against.

The reason for the drop in performance was that the physical sampled mean contained 2 samples out of the 27 samples that were outliers compared to everything else that the Cloud Agronomics model had seen:

- Fig. 16 below illustrates the 27 samples that were taken for the CEA and their distribution against SOC% along the X axis, the combination of these samples provides the physical sampled mean for the SOC stock for that CEA.
- The samples in grey were the ones that were randomly chosen to be given to Cloud Agronomics to localise the model against

- There were 2 physical samples that had over 3% SOC (samples on the right hand side of the graph below), but neither of these were given to the Cloud Agronomics model to localise against, and these SOC levels are above any SOC percentage values that the model had been exposed to in this geography
- This resulted in the model under quantifying SOC compared to the physical sampled mean. Potential contributors to outlier SOC measurements could include biochar in the sample after a fire in the Lower North region and organic material falling through cracks in the clay.

**Fig. 16 Keynes CEA - SOC % of all the samples compared to the ones randomly selected for the model to be localised against**


As illustrated in Fig. 17, the distribution against SOC % on the x-axis of the 6 samples (in grey) that were used to localise the model were representative of all of the other 21 samples (in salmon pink) that were used to generate the physical sampled mean for that CEA in all of the 3 farms apart from Keynes in the top right.

**Fig. 17 - SOC % of all the samples compared to the ones randomly selected for the model to be localised against**

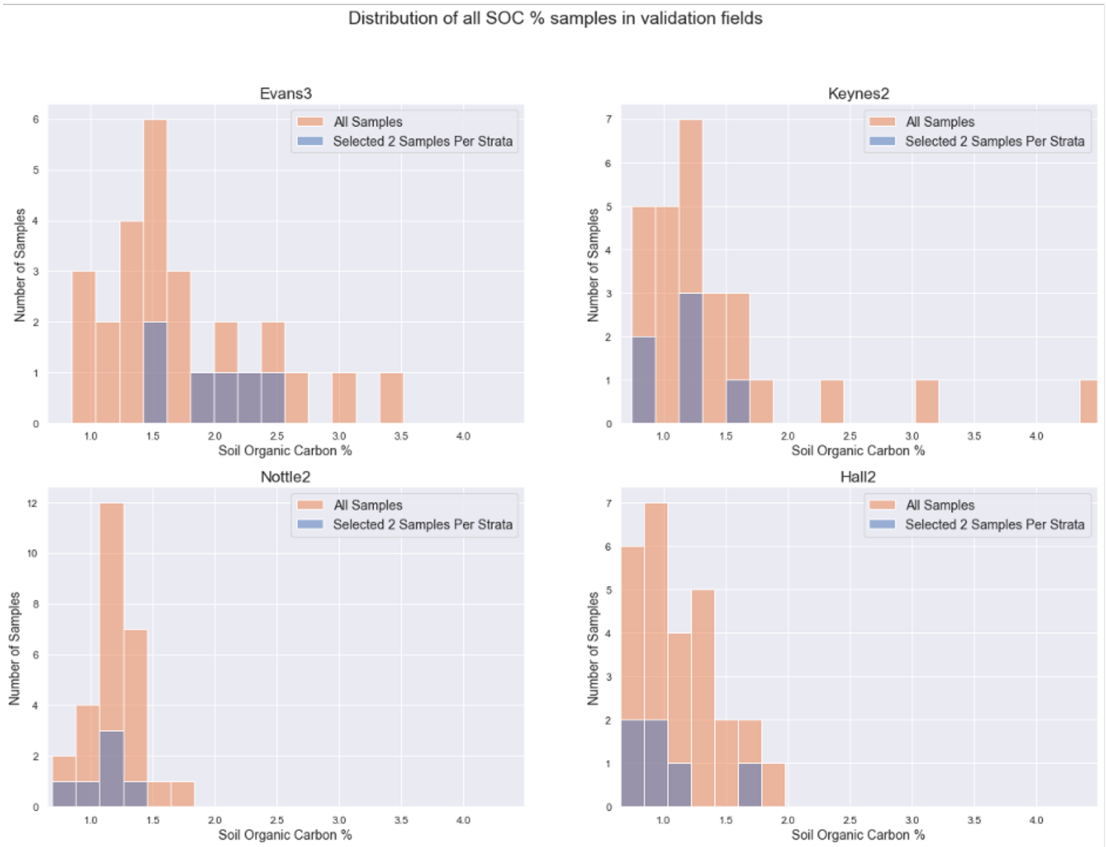



Table 2 below shows that, aside from the Keynes CEA, the model performs favourably compared to CSIRO's LOOC-C platform on the remaining 3 CEAs when it is both 'Localised to Region' (e.g. no samples from that CEA being used in the prediction) and 'Localised to the CEA' (e.g. Cloud Agronomics using just 6 samples from that CEA to localise against)

**Table 2. Comparison of the prediction that LOOC-C makes for each CEA compared to the Cloud Agronomics modelled prediction prior to sample inclusion 'Cloud Agronomics Model' and after the inclusion of just 6 samples 'Localised to the CEA.'**

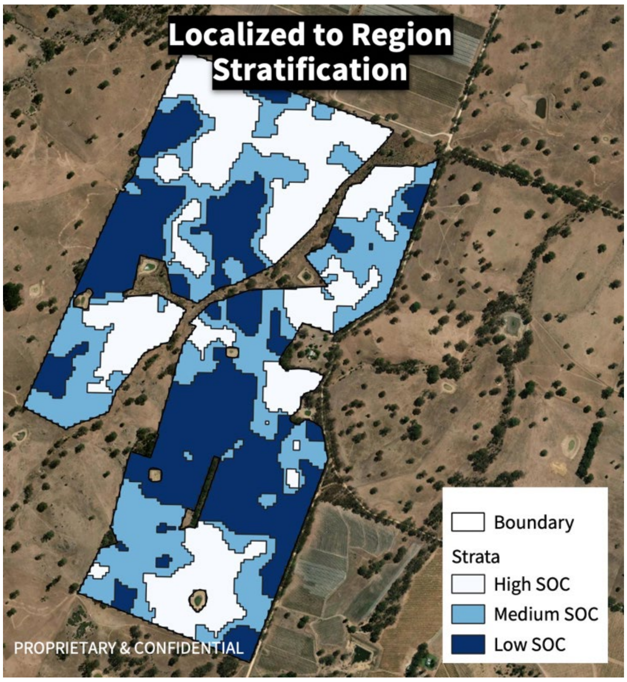
| Grower, CEA | Physical Sampled SOC Percent (%) | LOOC-C SOC Percent (%) | Cloud Agronomics Model SOC Percent (%) | Cloud Agronomics Localised SOC Percent (%) |
|---|---|---|---|---|
| **Nottle, 2** | 1.2 | 1.0 | 1.3 | 1.1 |
| **Evans, 3** | 1.7 | 1.3 | 1.6 | 1.7 |
| **Hall, 2** | 1.1 | 1.1 | 1.3 | 1.3 |

| | | | | |
|---|---|---|---|---|
| **Average Percent Error** | – | 10.7% | 9.5% | 7.8% |

## 4.3 Using a hybrid model approach to improving stratification of CEAs

As illustrated in Fig. 18 below, the Cloud Agronomics model generated initial sampling strata for each CEA in Phase 2 sampling using just the regionally localized model, and this would be used for the T0 initial baseline soil sampling following the 2021 Soil Carbon Methodology

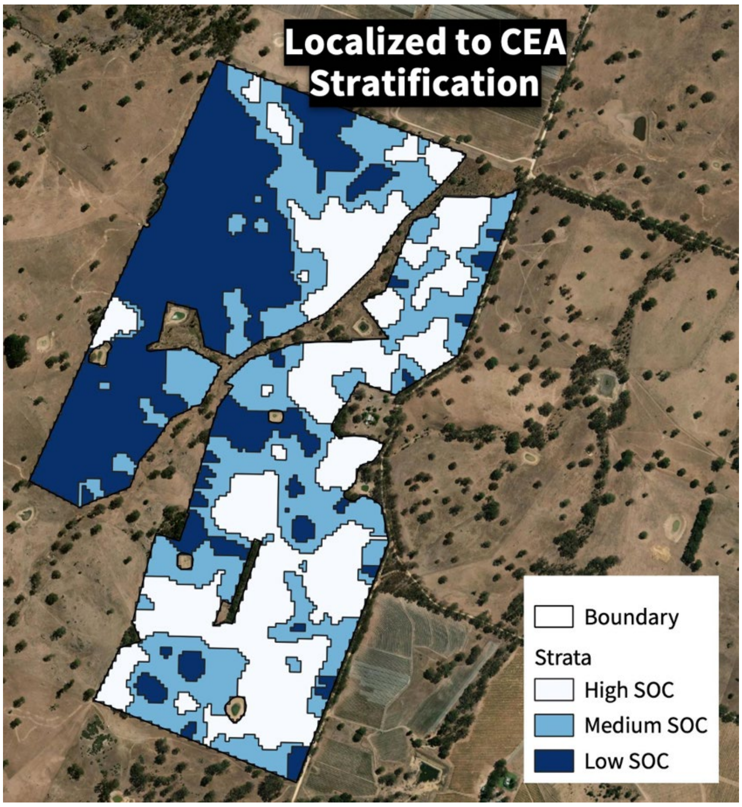
**Fig. 18. T0 stratification of a CEA ahead of baseline sampling**




Once the soil sample results were integrated back into the Cloud Agronomics model, a second version of the sampling strata was created using the model localized to the CEA. This is illustrated in Figure 19 below, and would be used for T1 soil sampling carried out in following years.

Under the current methods of calculating discount factors in relation to the 2021 Soil Carbon Methodology, the accuracy of stratification at T1 re-baseline sampling has a significant impact on the confidence that the Clean Energy Regulator has in the results, and the discount factor that's applied in terms of the % of carbon credits that are issues to the landholder.

**Fig. 19. Stratification using the localized Cloud Ag model of a CEA ahead of T1 baseline sampling**

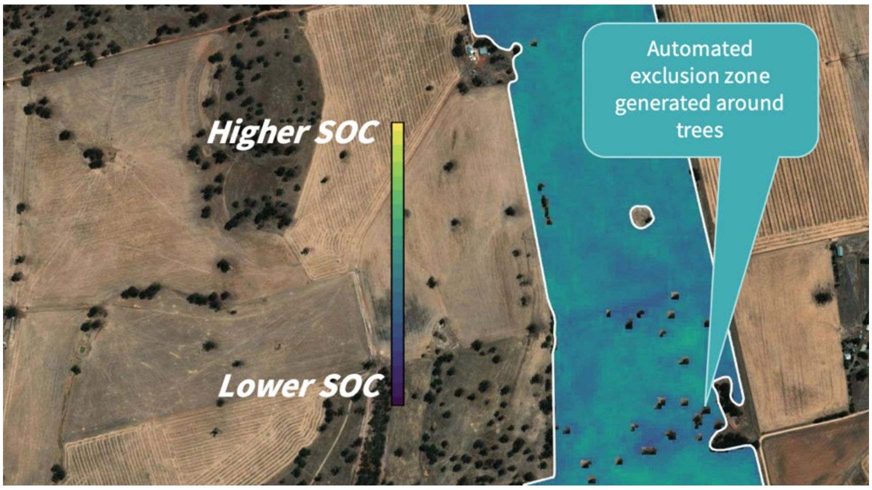



**Other key learnings**

One of the main challenges that the Cloud Agronomics team overcame was Greenness Artifacts, and the effect of trees being present in the CEA which would skew the carbon prediction upwards for that 10m x 10m SOC quantification area

The team developed a method for automated exclusion zone generation, in order to reduce misprediction on trees as illustrated in Figure 20 below:

**Fig. 20. Automated exclusion of trees in a CEA**




# 5. Conclusion

The project has focused on using a data driven machine learning model approach to directly predict SOC at 100 points per Ha. The Cloud Agronomics model used remotely sensed data and other spatial data layers as its inputs. The model has been trained with physical soil sample data, and then further localised against specific geographies using the targeted Phase 2 soil sampling data. This localisation data has been weighted so that the model most accurately captures the SOC variability at either the per CEA or regional level as appropriate.

## 5.1 Key findings

- The results support the case that using a low number of physical soil samples to localise a RS/ML model is significantly more accurate and cost effective than using the current minimum of 9 samples alone to quantify SOC.

- Based on the validation CEAs, a significant performance gain was observed when the model was localised against just 6 soil samples per CEA.

- There are diminishing returns with respect to accuracy when the model was localised against 9 samples per CEA.

- The project has demonstrated that leveraging remotely sensed data is a key component of accurate SOC quantification, but that it is a part of a broader data driven challenge that requires other spatial covariates (including physical climate and weather proxies, topography and edaphic variables) as well as physical soil samples to localise the model against. This contrasts with it being a purely remote sensing problem, typically using measurements from a single sensor which assumes a strong physical basis for the relationship between SOC content and remote sensing.

- It is likely to be that decreasing the number and spatial density of physical soil samples required for accurate SOC quantification that is going to be the biggest driver towards achieving the National Soil Carbon Innovation Challenge stretch goal of $3/ha.

- As highlighted in 8.1 of the Appendix, the project has also identified some of the key challenges that exist with the Schedule 2 'Measure-Model-Measure' approach in the current 2021 Soil Carbon Methodology; namely that when it comes to the bias correction method that the Clean Energy Regulator uses, it doesn't take into account that the Cloud Agronomics model is making a spatially explicit measurement at a resolution of 10m2

## 5.2 Benefits to industry

- The focus of Cloud Agronomics on reducing the density of sampling as the key driver to reducing the costs, and scaling the adoption of soil carbon quantification is in contrast to many other technologies that are only attempting to reduce the cost per sample, and leaving the requisite number of samples unchanged – as operationally challenging prospect

- The project has identified two compelling avenues to reducing the requirements for physical sampling, and significantly decreasing the costs for red meat producers:

  - Reducing the number of samples required to localise the model on each CEA to 6 or less

  - Achieving a position where only regional calibration CEAs are required in order to achieve the required level of confidence in SOC quantification at a CEA level across a whole target geography.

- Further to the point above, putting in place a network of regional calibration CEAs would enable quantification of soil carbon across livestock paddocks at a national scale with the required level of confidence to be used as a performance metric for the Australian Beef and Sheep Sustainability Frameworks

- The data driven approach that Cloud Agronomics model takes is sensitive to changes in temperature, rainfall and land management. An important objective outlined in the recommendations below is to be able to attribute observed changes in SOC content to specific measurable causes such as management practice changes, which is a fit with the technical approach the project is taking

- This MLA CN30 project has supported the Cloud Agronomics successful application for the 'National Soil Carbon Innovation Challenge – Development and Demonstration' round, which will enable the 2$^{nd}$ and 3$^{rd}$ points of the recommendations in Section 6 below to be accomplished

# 6. Future research and recommendations

The project has initially validated the RS/ML approach that Cloud Agronomics are taking, and it has highlighted three next steps that are key to achieving an outcome for the red meat industry to hit the CN30 targets

- From Cloud Agronomics learnings in the US market, **the Australian red meat industry should be aiming by the end of 2024 to develop a data set of 10,000 samples distributed across livestock grazing lands**. Achieving this critical mass of data would enable the localisation of nationwide RS/ML SOC models would underpin both a baseline peer review published metric for the Australian Beef and Sheep Sustainability Frameworks. It will also support the red meat supply chain to have a baseline in place that demonstrates an industry wide commitment to working towards CN30 from a soil carbon perspective, as well as delivering on the CN30 SOC targets. This is further outlined in Appendix 8.2.

- **Produce historical predictions of SOC and relate this to previous farming practice changes in order to demonstrate and quantify the impacts that farm management changes have made on paddock-level SOC stocks**. Once an RS/ML model has been localised, Cloud Agronomics will use historical remote sensing observations of the CEA to run the model at points in the past. For certain CEAs which have undergone farming practice changes within the last 5 years, Cloud Agronomics have proposed to produce a 5-year annual time series of SOC measurements. Then, the SOC time series will be cross-correlated with time series of farming practices on the target CEAs. Examples of practice changes include switching to no-till, cover cropping, increased stubble retention, and time-controlled grazing. Other statistical analyses will be performed in order to summarise which farming practices, and which practice changes, have had the greatest directional impact (both sequestrative and emissive) on SOC stock trends. Results will be compiled into a comprehensive report or research paper and delivered along with a set of recommendations on effective practice changes for increasing SOC – the objective being to increase the confidence of producers looking to also adopt these additional practice changes in order to increase their soil carbon levels.

- **Work with the Department of Innovation and Science and the Clean Energy Regulator to develop a set of recommendations and/or a supporting module for a future Soil Carbon Method which details best practices for applying and validating data driven machine learning SOC quantification approaches.**

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# 8. Appendix

## 8.1 Cloud Agronomics submission to the Department of Industry, Science, Energy and Resources re: Draft 2021 Soil Carbon Methodology

Cloud Agronomics submission to the Department of Industry, Science, Energy and Resources re: Draft 2021 Soil Carbon Methodology

To Whom It May Concern:

I am writing in response to the request for consultation for the 2021 Soil Carbon Method under the Emissions Reduction Fund. I am the Chief Scientist for Cloud Agronomics, Inc., a United States company focused on the quantification of soil organic carbon in agricultural land and pastures worldwide using ground-truthed remote sensing models. We are presently working with public and private customers to deliver soil organic carbon quantification in New South Wales, Victoria, South Australia and Queensland under the 2021 methodology.

We view the 2021 methodology as a positive development for carbon quantification and carbon markets in Australia under the management of the Clean Energy Regulator. We also believe that the methodology developed under the Emissions Reduction Fund has the potential to drive innovation in carbon quantification outside Australia as a precedent-setting document. We are therefore motivated to describe two issues that, after a thorough review, we believe require clarification or modification in the methodology.

1. The mechanism of bias correction

The 2021 methodology puts forward a bias correction approach that, with a small number of physical validation samples, may result in undue statistical uncertainty given the spatial variability of soil organic carbon. Our approach uses remote sensing and statistical methods to generate modelled estimates of soil organic carbon at the high spatial resolution, capturing this variability at a resolution as low as 10m. This results in 100 unique measurements of soil organic carbon per hectare (as each hectare contains 100 square pixels of 10m by 10m in size). At the size of a 100Ha CEA, our approach would produce 10,000 unique measurements of soil organic carbon.

Spatially explicit measurements like ours create opportunities for validation and bias correction that do not appear to have been anticipated by the draft methodology. Changing or clarifying the methodology to accommodate spatially-explicit bias corrections and validation is likely to strengthen the measurement of soil organic carbon in Australia. For example, Equation 85 in the draft methodology documents a mean bias-adjusted modelled soil organic carbon stock for the CEA by computing the difference between the mean modelled soil organic carbon stock for the CEA and the extrapolated bias for the model. The equation implies that the bias adjustment is applied to the mean modelled soil organic carbon stock for the CEA. However, when spatially explicit measurements are available, a more rigorous way to calculate the mean bias-adjusted modelled soil organic carbon stock for the CEA is to compute the regression relationship between modelled soil organic carbon stock for modelled elements (i.e. pixels) and validation physical samples collected within those modelled elements. Importantly, this regression characterizes bias associated with the model, whereas a comparison of mean values within strata (as currently defined by the methodology) characterizes both model bias and sampling variation. Because strata are not spatially homogeneous and the 2021 methodology permits as few as 3 samples to be collected within each stratum, sampling variation will be present in the mean soil organic carbon stock for the CEA. Failure to eliminate the impact of sampling variation on bias correction will result in two different kinds of errors:

Type I error: Wrongly concluding that the model is biased when it is unbiased.

Type II error: Wrongly concluding that the model is unbiased when it is biased.

Notably, each of these errors will result in incorrect determination of net abatement under the 2021 methodology. The direction of the impact is difficult to anticipate—it could sometimes result in the conclusion that carbon has been sequestered when it has not, and at other times could support the conclusion that no carbon has been sequestered when it has. Either way, the impact of this error will be to undermine confidence in carbon quantification because modelled output may not align with measurements.

We emphasize that the problem here is not caused by model-based measurement methods. It is due to genuine spatial variation in soil organic carbon stocks and the difficulty of obtaining a reliable estimate of the true mean soil organic carbon stock within a CEA using a small number of physical samples.

Extending the methodology to also allow spatially explicit validation would greatly reduce the potential impact of this problem. By comparing modelled estimates of soil organic carbon to estimates from dry combustion of physical soil samples at the same locations, the impact of spatial variation is nearly eliminated. By assuming that the modeled bias is consistent across CEAs in a project area (which is already an assumption of the 2021 methodology), it becomes possible to perform a bias adjustment that is not undermined by spatial variation in soil organic carbon stocks.

2. Calculation of the extrapolated variance of soil organic carbon stock for the CEA

We express a similar concern regarding the calculation of the extrapolated variance of the soil organic carbon stock for the CEA (Equation 86), which includes, among other terms, the coefficient of determination for the modeled carbon stock estimate. We understand this term to be defined by Equation 102, which describes the correlation between stratum-level measured and modeled mean SOC. Because stratum-level mean SOC is derived from physical samples, it contains both true variation and sampling variation and suffers from the same issues described above. For methods that produce spatially explicit measurements of soil organic carbon, it would be appropriate to allow the coefficient of determination to be calculated using the relationship between modeled elements (pixels) and physical samples collected within those modeled elements because such a comparison greatly reduces the impact of spatial variation in estimates soil organic carbon stocks. This ultimately will boost confidence in the methodology and is likely to prevent the Type I and Type II errors documented above.

There may be other places within the 2021 draft methodology that could benefit from considering whether spatially explicit measurements are available and whether calculations should be spatially explicit as opposed to mean-based. We encourage the Clean Energy Regulator to consider the impact of this issue throughout the 2021 draft methodology. Spatially-explicit validation is a cornerstone of forest carbon quantification, including the validation of the NASA Global Ecosystem Dynamics Investigation, the only current spaceborne mission focused explicitly on the measurement of carbon density inland ecosystems from space1,2. Please do not hesitate to contact me if I can be of assistance. Cloud Agronomics has performed internal data analysis and statistical simulation to document the issues described above. We would be happy to share this with the Clean Energy Regulator to help develop the most rigorous standards for soil organic carbon quantification in Australia.

Thank you for helping accelerate the global adoption of robust, verified soil carbon accounting through this first-of-its-kind methodology. We look forward to your response.

Sincerely,

James R. Kellner, PhD
Chief Scientist, Cloud Agronomics Inc.

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## *8.2* Cloud Agronomics – Project proposal '*Enabling the massive scaling up of soil carbon quantification'*

<u>Summary of project</u>

The project will work with 1,000 livestock producers, taking 10,000 soil cores, and will baseline 1mi Ha of pastureland that producers are committing to build soil organic carbon (SOC) on, with the data being lodged with the Integrity Systems company (ISC) for the benefit of producers and the industry collectively working towards CN30.

This project is the key step in the industry proving out the massive scalability of a novel approach to the rigorous quantification of SOC that fuses together remotely sensed data from space, calibrated with physical soil cores, and combined with other geospatial data layers to make it profitable for livestock producers to make management changes that drawdown carbon from the atmosphere into their soils.

The project directly supports achieving the CN30 roadmap target of producers using soil carbon sequestration methods to increase soil carbon on 30% of improved grazing lands, and achieving the CN30 target of $8/ha quantification by 2024, and also creating a pathway to achieving the federal government's stretch target of $3/ha.

The project will pioneer the ability to track historical changes in SOC levels, and this can be mapped against how previous practice changes have impacted SOC levels. The objective is to use this data to prove out the benefits of making management practice changes such as switching to time controlled grazing, and drive their widespread adoption.

For many livestock producers, being locked into selling their carbon credits as offsets to 3rd party emitters isn't the right strategic decision, as it's likely to remove their ability to become carbon neutral. This project is proving out an additional pathway for producers to work in alignment with processors and brands, to decarbonise the red meat supply chain through insetting carbon that is sequestered in farmers soils.

Project Objectives and desired outcomes

1. Demonstrate that the projects novel technical approach, combined with the benefits of scaling both the area of land quantified and the amount of geo-referenced soil cores used as a calibration dataset, results in the substantial decrease in the spatial density of soil cores that are required to rigorous quantify SOC across a carbon estimation area. The reduced requirement for physical sampling is the driver that will accelerate achieving the CN30 roadmap target of $8/ha by 2024.

2. Create a globally leading dataset of soil samples lodged with ISC for the benefit of producers, and support the industry achieving CN30. 10,000 soil samples across 1mil Ha will provide:

    - Sufficient land area under study to serve as basis for peer review (see 3).
    - Sufficient land area and historical dataset to demonstrate effectiveness of time based functionality to provide predictive capability for farmers to assess ROI.

3. Publish a peer reviewed paper from the project which helps to inform the development and direction of the next Australian Soil Carbon Methodology (likely to be 2024/25) so that it enables livestock producers to baseline and lodge the carbon estimation area of their farm using a combination of remotely sensed data calibrated against regional physical soil coring data fused with other geospatial data layers.

4. With the 1m Ha of improved pastureland baselined in the pilot project, based on a realistic target sequestration rate of 200kg of soil carbon per year, the project will be contributing 730,000 tonnes of $CO_2$-e per year towards the CN30 target (over 1% of the overall emissions footprint of the industry)

5. Demonstrate that commercial alignment can be achieved between farmers, processors and brands to collectively benefit from decarbonising in the red meat supply chain. The project is creating value for livestock producers by supporting them to rigorously and cost effectively quantify their soil carbon levels and track changes over time. Enabling farmers to prove out that they're lowering the overall emissions footprint of their farm, and are working towards/achieving carbon neutrality. These benefits of farmers sequestering soil carbon are then passed onto the processors and brands by enabling them to report that they are

reducing their Scope 3 emissions from supplier producers, creating a case study of decarbonising the red meat supply chain that follows Science Based Target Initiative best practice principles.

6. As a part of achieving point 5 above, a pilot program will be delivered in partnership with Trust Provenance to align key stakeholders (farmers / processors / retailers) to demonstrate that they are collectively working to decarbonise the red meat supply chain using soil carbon as a starting point

   - Work with a small group of farmers supplying to Gundagai Meats to baseline their current soil carbon stocks, and also identifying the management practices that they are undertaking to optimise their soil carbon/soil health.

   - Trust Provenance integrate with the GS1 barcode system, and a CN30 soil carbon sustainability flag will be put against the GS1 Global Location Number for each property.

   - By integrating with the GS1 standards and Gundagai Meats the CN30 soil carbon sustainability flag will be passed through processing so that it's linked to the barcode on the Gundagai Lamb retail product.

   - As a part of working in collaboration with Temasek to demonstrate the decarbonisation of supply chains, the sustainability flagged product will be exported to a retailer in Singapore.

   - The team will work with ISC to scope out adding a soil carbon sustainability flag against a producers PIC#, and subsequently how to pass this flag onto existing sustainability reporting systems like the Australian Beef Sustainability Framework.

   - Case study content will be created by the Perennial PR team for all collaborators in the project to use (farmers / Gundagai Meats / MLA / ISC / Trust Provenance / Perennial)

7. Deliver ground-breaking functionality which enables changes in SOC to be tracked and displayed against a historical timeline, and map this against previous practice changes in order to be able to demonstrate and quantify the impacts that farm management changes have made at a regional level of granularity. Publish this analysis in order to increase the confidence of producers looking to also adopt these additional practice changes in order to increase their SOC levels, and provide a robust scale of the likely sequestration that they'll see.

8. The project creates the data structure and the opportunity for the transactional relationship to evolve between red meat processors/brands and their supplier farmers around a 'differentiated sustainable product' in the red meat supply chain, whilst enabling the market to set its own pricing and commercial model.

Background of Proposed Work and Significance

The project is the extension of the initial Module 8 “Space Derived Remote Sensing of Soil Organic Carbon” (P.PSH.2103) which is a part of the CN30 Carbon Storage Pathways program

The proposed work has been driven by the convergence of a number of factors which are enabling the red meat industry to be at a point where soil carbon drawdown can be massively scaled up following the project.

- Schedule 2 ‘Measure-Model-Measure’ of the recently released 2021 Soil Carbon Methodology, developed with input from Cloud Agronomics, is aligned with the technical approach that Perennial are taking, and provides a pathway to work with DISER and the Clean Energy Regulator to develop a future methodology post this project that achieves the federal government target of $3/ha SOC quantification.

- Cloud Agronomics have successfully closed their Series A capital raise, and the board wants to commit a significant part of the proceeds to build on the positive partnership that has been created with the CN30 program, and use this investment to create a pathway to scale up the carbon drawdown into soils across all of Australia’s grazing land by overcoming the most substantial hurdles with farmers’ interest at the center.

Through the Series A round, Temasek have become an investor in Cloud Agronomics, and are keen to be a collaborator in the Cloud Agronomics module. Temasek are the national investment vehicle for Singapore, and are one of the worlds largest investors in the agrifood supply chain. The CN30 module is aligned with the structural trends guiding its long term portfolio construction – Digitisation, Sustainable Living, and the Future of Consumption. Singapore represents a sophisticated and lucrative export market for Australian red meat valued at $220m in 2020, and Temasek will be actively involved in the extension project through the pilot to export Australian red meat with sustainability credentials to the Singapore market.

The project will deliver a significant positive impact for the red meat industry by validating the economies of scale that can be achieved through reducing the density of physical soil sampling required as a critical mass of data is achieved, enabling the CN30 roadmap target pf $8/ha by 2024.

From a value proposition perspective, the project will also deliver the functionality and data to producers to demonstrate that historical changes in SOC that have been driven by practice changes amongst early adopters. The objective is to be able to increase the confidence of the mainstream majority of farmers to adopt additional practices designed to build their SOC levels and increase their overall ROI

The project will also work collaboratively with the red meat value chain (farming groups, industry bodies, livestock management tools, processors and brands) to create a farmer focused value proposition that supports and incentivises them to go through the process of baselining their lands SOC levels, and lodging their farms data with ISC. As well as this being a key facilitator for Cloud Agronomics it will also support other SOC quantification researchers in the CN30 Carbon Storage Partnership.

Extension pathway

The project will work with 1,000 livestock producers to baseline their SOC, and capture the data on the land management strategies that they're adopting. The Perennial team have already been successfully working with a number of livestock industry groups (e.g. Barossa improved Grazing, Upper North Farming Systems, Monaro Farming Systems), and these groups are going to be a key component of communicating a farmer centric value proposition for baselining soil carbon, and lodging the data with ISC, and also the ERF if that's the right route for them to take.

The project will also collaborate with other key stakeholders in the red meat value chain such as processors and brands, so they can use the project to align with any environmental sustainability goals they have, and provide options for livestock producers to inset carbon credits that they generate into their red meat supply chain.

The value proposition for livestock producers is to provide them with SOC baselining that meets the 2021 Soil Carbon Methodology, and specialised support to complete the necessary steps for lodging the data with ISC.

By initially lodging data with ISC, with the option of also lodging under the ERF, farmers will retain the flexibility to decide what is the right option for them at the point in time in the future that they've earned credits, and this could be to decide to inset them against their own supply chain, or selling the credits to a 3rd party as a part of an offset transaction.

Through being able to use historical remotely sensed data to identify changes in SOC over time in paddocks where new management practices have occurred, the project will also help overcome one of the other major barriers to adoption in terms of livestock producers not having a clear ROI in terms of making management practice changes aimed at increasing SOC levels.

The Cloud Agronomics team have already been actively collaborating with the key farm management platforms (AgriWebb / MAIA Grazing) to recruit their users for calibration and validation soil sampling, and they are initially sharing paddock boundaries to assist with the creation of Carbon Estimation Areas. The project will build on this core communications pathway to recruit the initial target producers that are innovative and data orientated.

In terms of the adoption outcomes, the project has an objective of baselining and lodging an initial 1m Ha of improved grazing land. Based on the assumption of an average rate of soil carbon sequestration of 200kg per Ha per year, this will generate over 730,000 tonnes of $CO_2e$ per annum towards the CN30 target.

Method to achieve objectives

The additional functionality to identify changes in SOC levels against time will be technically developed by the data science team at Cloud Agronomics, and will leverage the initial soil carbon quantification model that has been localised for Australian conditions.

The research team will overlay this spatial change data against known paddocks that have previously undertaken management practice changes designed to increase SOC levels, such as implementing time controlled grazing or multi-species planting. This work will validate the changes in SOC that have occurred compared to paddocks where no additional practices have been implemented, and the results of this work will be peer reviewed and published.

- The project will work with key stakeholders (farming systems groups / farm management platforms / agronomy groups / meat processors and brands) in order to sign-up producers to have their current SOC levels baselined and lodged with ISC, with the costs being covered by the project.

- Producers will work with Cloud Agronomics and the FarmLab platform to select cadastral boundaries, draw CEAs, generate sampling strata and a randomised sampling plan following the 2021 soil sampling protocol

- The FarmLab software will be used to manage the physical sampling process and interface with the labs to receive back geo-referenced soil carbon data

In the initial phase of the project the number of physical soil cores will start at a level commonly seen across soil carbon projects. The objective being to build up a critical mass of localisation data in that geography so that the number of physical samples per farm can be reduced. Blind validation CEAs will also be created in each geography to prove out that the Cloud Agronomics model was able to rigorously identify in paddock variability, and has accurately quantified the SOC levels using only remotely sensed data and a low number of physical soil samples from the validation CEA to localise against.

The initial objective is to prove out that Cloud Agronomics can accurately quantify soil carbon with uncertainty that meets requirements for ACCU issuance with less than half the samples typically required to achieve this result.

The final stage of the project is to demonstrate that the Cloud Agronomics approach can reach the CN30 roadmap target of $8/ha, being in a position to be scaled up to apply to the entire 70m Ha of improved grazing pastureland, and is on a pathway to achieving the federal government's stretch target of $3/ha

Cloud Agronomics will liaise with the methodology development team at DISER and the Clean Energy Regulator throughout the project. The results will be peer reviewed and published, with the objective of it informing the development of the next Australian Soil Carbon Methodology (likely to be in 2024/25) with the objective of the Cloud Agronomics approach to SOC quantification being fully utilised as a part of the methodology at this point.