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Carbon monitoring in soil - Proof of Concept

A testcase for multiple fields in the United States

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DRAFT REPORT

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Summary

From both the private and governmental sector there is an increasing interest in *carbon credits* that can be used to offset emitted carbon. Soils constitute the largest terrestrial storage of organic carbon and can play a role in mitigating climate change. Soil management practices on arable soils can increase soil organic carbon storage, and have co-benefits such as increased soil fertility and resilience to climate change. A key obstacle in the development soil-derived carbon credits is the lack of a reliable and affordable method to ascertain increases in soil carbon stocks over time. NMI presents a Proof-of-Concept (PoC) for a robust, cost-effective and scalable method which can ascertain carbon stock at a farm-level and even field-level. The protocol has been tested across a number of arable fields in the Iowa and Arkansas (United States). We show that this method is effective in ascertaining the carbon stock using both satellite and field-derived data. Soil C stocks was estimated robustly with a deviation around 5% on farm level, and 5 – 10% on field level. A key asset of this method is that it can rapidly be scaled up for other areas across the globe.

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Summary and conclusions

In the context of mitigating climate change, there is increasing interest in increasing the carbon stocks held in arable soils. The Rabobank requested the NMI to perform a Proof of Concept to quantify the carbon stocks of a series of arable fields in Iowa and Arkansas farms.

The carbon stock was estimated for all (non-)contiguous field sizes (10-64 hectares) on a 10x10 grid based on field measurement and machine learning models. Estimated field-level C stock ranges between 17 and 55 ton carbon per hectare. Deviation of soil C stocks estimates (as evaluated with coefficient of variation) was around 5% on farm level and 5 – 10% on field level. The method can discern high levels of spatial heterogeneity in carbon stock within and between fields. Specific areas which are marked by e.g. high C stocks can be clearly identified. This detailed quantification can be an asset for the verification of carbon stocks in the framework of carbon offsetting. The minimum field for which the carbon stocks could be robustly assessed was 10 hectares at a sampling rate of 0.5 sample per hectare. Thus, a ten hectare field would require five samples.

NMI combines the strengths of both satellite-derived data as well as field-derived measurements to estimate the carbon stocks. Stratified sampling method cLHS facilitated effective selection of optimal measurement locations, while use of handheld scanner with NIR spectroscopy enabled to measure many soils at low cost. Furthermore, use of effective covariates in the machine learning models (e.g. the satellite data and global SOC predictions) enabled to discern local variation of C stock. In future, as calibration dataset for the machine learning model increases, even less samples will be needed to obtain robust C stock estimates.

We conclude that the NMI method can be applied robustly, that it attains consistent results and that the method is rapidly scalable.

1 Introduction

1.1 Relevance of soils in framework carbon markets

In the context of mitigating climate change there is an increasing demand for *carbon credits* across a wide range of industries. Considering the economic and political developments (Sikora, 2020), this development is likely to persist. Presently, the demand for carbon credits outpaces the supply. Farmers can potentially play a role in this market by increasing their soil carbon stocks and thus mitigate climate change. This can be done by increasing the amount of soil organic matter (SOM) in soils. This increase can have additional co-benefits such as increases in soil fertility and increases in resilience against climate change (Smith et al., 2020; Ros, 2021). Presently, the main roadblock for a cost-effective implementation of *carbon farming* is the development of a scalable and robust method that can ascertain carbon stock increases over time which can be converted to *carbon credits*.

1.2 State of the Art methods carbon stock assessments

Combing strengths of both satellite and field-based data

In order to attain carbon stock estimates, sometimes only satellite-based data are used (Köchy et al., 2015), or only field-derived data (Nussbaum et al., 2014). Few however, combine both the strength of both external (satellite) with field-based (wet-chemical or nearby sensing) analysis (Fujita et al., 2021). In this PoC we use both all available satellite data (>50 covariates, being publicly available) as well as field-derived data. By combining these resources we can attain robust estimates.

Effective and efficient sampling

Soils are marked by high spatial variability, and this is reflected in soil carbon stocks (Van der Voort et al., 2016). In order to capture this variability and produce accurate stock estimates, it is necessary to develop a statistically robust sampling design (Ros, 2019). To further capture the variability with depth (e.g. due to rooting depth impacts), the IPCC recommends sampling up to 30 cm depth. If no pre-analysis is done, a high sampling density is needed (e.g. every 10 meters, Van der Voort et al., 2016). This can be costly and time consuming. However, with pre-analysis and robust statistical inferences these samplings can be strongly reduced.

A combination of direct measurements (at the point or field scale) and modelling (at larger spatial scales) can greatly help defining the efficacy of land management practices in enhancing soil carbon. In this PoC, an analysis is done to develop an optimal sampling protocol which uses as few field-measurements as possible whilst capturing the highest level of variability. The same protocol has already successfully been tested for three Dutch farms with contrasting land use and soil properties (Fujita et al., 2021).

Robust machine-learning methods

Multivariate statistics and machine learning methods can be valuable to extract patterns from data and then leverage that to predict data (e.g. carbon stocks). However, various methods (e.g. linear regression, partial least squares, random forest) each have their own advantages and disadvantages. Therefore in this PoC, we used a suite of multivariate and machine learning methods (see 2.4) to model the carbon stocks. Using model assessment criteria (e.g. residual mean squared error, RMSE), the optimal model was selected. This automated selection is part of the developed method. This way, our results are robust and not biased by any method in particular.

1.3 Objective

The goal of this project is to provide a Proof of Concept to use the NMI Carbon Stock method to robustly determine the carbon stocks in the fields located in Iowa and Arkansas. The results encompass the following aspects.

1. Carbon stock per field on a 10x10 meter resolution
2. Visualisation of the spatial variability over the fields and variability assessments of the underlying data
3. Assessment of the minimum size of fields for an accurate result

This goal is attained using both satellite and field-based data, robust sampling protocols and state-of-the-art machine learning approach.

We want to stress that the C stock estimation of the original method (described in Fujita et al., 2021) is focused on arable farms and encompasses the variation of carbon within and among fields. Field based maps illustrating the spatial variability within fields have additional value for the evaluation and planning of management options to boost soil carbon levels.

2 Material and Methods

2.1 Sample Locations

The sample locations locate between 35 to 41.3 ° latitude and -92.0 to 91.6 ° longitude, found in the USA states of Arkansas and Iowa. The land use of all fields is agricultural. In Iowa, the fields are characterized as a silty loam to a silty clay loam. The parent material is Pleistocene loess, and there is a small slope varying between 0-1%. In Arkansas the soils are also classified as silt loam but they're partly located in a hilly area (>10% slope). The parent material is also loess with occasional glacial deposits. Both soils are identified as Alfisols.

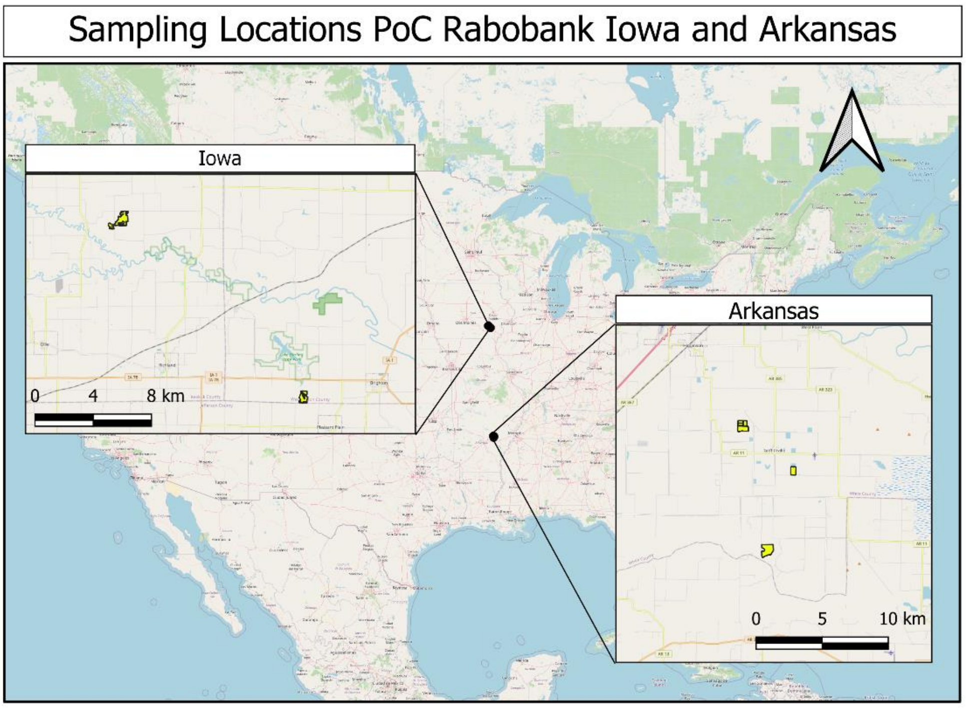

Figure 2-1. Overview Sampling Locations PoC fields. Background map OpenStreetMap.

2.2 Sampling protocol

Covariates for (potential) sampling points

To select optimal sampling locations, we made optimal use of available satellite and open soil data to select key covariates. This section describes how the data was selected and instrumentalized. For the sampling scheme for each farm, the fields are divided in a grid of 10 meter resolution. Each of those units is a potential sampling location. See Appendix 6.1 for example maps of these potential sampling points. For all these potential locations covariates have been collected that might be related to the spatial variation in soil C levels from open source available data sources.

For each potential sampling point, a series of covariates were collected. These covariates were selected given our earlier evidence from developed machine learning models reflecting spatial variation in soil organic matter levels. See full list in **Fout! Verwijzingsbron niet gevonden.** in the Appendix.

The private and open source (soil) data for the United States include:

- Global soil map of ISRIC ('SoilGrids')
- Information on slope and elevation (Digital Elevation Map)
- Sentinel1 and Sentinel2 Mosaic data

All information is stored in a raster format, and globally available. Satellite data is processed to calculate several indices (incl. VSM, TVI, and SATVI). In total, 47 covariates were retrieved for each potential sampling point.

Prior to the analysis for each farm, covariates were excluded when the variable is available for less than 99% of the potential sampling points (i.e. >1% is missing value). Subsequently, missing values were imputed with the median values of the variable. These missing values occur in only in a few cases and imputation is needed to avoid the removal of valuable covariates due to single missing data points. It has little impact on the stratification algorithm used.

Optimal sample location selection using cLHS

Using as few measurements as needed is the key for a robust carbon stock assessment procedure because it significantly reduces the overall cost. Presently**, the required sampling density is one sample per two hectares,** being extrapolated from the Dutch pilot study where this density was required to reach the desired precision in farm-level C stock estimates (Fujita et al., 2021).

Sampling locations should be selected carefully so that it can effectively capture the variation of soil properties of the area in question. We use conditioned Latin HyperCube Sampling to determine the optimal location of sampling points (Figure 2-1). With cLHS a subset of strata are selected using a stratified random procedure based on the multivariate distribution of the covariates (Minasny & McBratney, 2006). This will ensure that strata that are closely related to each other will not be measured both, making the sampling efficient to estimate a spatial trend. Earlier studies have shown its benefits above simple randomized and random stratified sampling methods (Fujita et al., 2021).

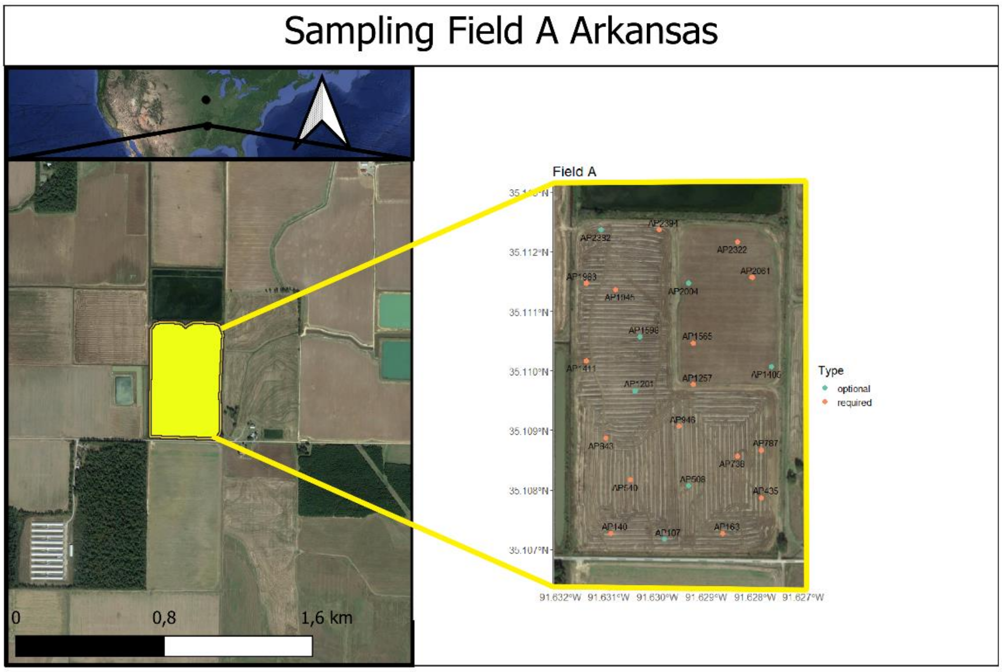

Figure 2-2. Visualization of the application of cLHS empowered selection of sampling location.

Using HandHeld sensor

The HandHeld scanner forms the optimal trade-off between sampling speed, low cost and accuracy. Diffuse reflectance NIR spectroscopy has extensively been applied for analyses in very diverse fields including, agriculture, geology and soil science. In soil science, numerous studies have demonstrated that the NIR spectral range combined with a multivariate calibration method (or any machine or deep learning calibration) could be used as a non-destructive rapid analytical technique to simultaneously estimate several soil properties (including soil organic carbon) in a very short time. Using these NIR sensors it is possible to take a lot more soil samples for SOC analysis within a field at the same time for low costs. Assuming a well-designed calibration and validation procedure, the accuracy of NIR measurements are comparable with wet-chemistry analysis whereas the precision is usually higher. The HandHeld scanner of Agrocares has been selected since it is one of the best sensors currently available.

Field sampling protocol

NMI uses optimal sampling strategy to capture the maximum amount of variability whilst reducing the amount of samples needed. For each farm, a field analyst went to the cLHS selected sampling locations (Figure 2-1). The sampler was presented with obligatory and optional (Figure 2-1) sampling locations, where the obligatory were derived via the cLHS algorithm and the optional sampling points were selected optimizing sampling area (for the case the sample taker had time left). In each sampling location, the sampler noted the XY-coordinate (via a supporting carbon-app coupled to the HandHeld-scanner) and collected a soil sample of 0-30 cm depth. Each of the soil samples was transported to the laboratory and mixed in a bucket and measured with the AgroCares HandHeld scanner. This approach proved more time-efficient than mixing and measuring in the field (the common sampling approach), a solution triggered by the actual weather conditions and sampling time available. **The NMI sampler required 15-30 minutes per hectare to do the sampling**. The sampling protocol is further described in Fujita et al. (2021).

2.3 Carbon stock calculation

Estimation of point-level C content

To estimate soil carbon stock of farms, soil organic carbon (SOC) content of every point (of 10 x 10m resolution) need to be first estimated. For that, we built prediction models based on the 205 measurements of SOC (%) determined by the HH scanner and covariates. Here we choose to use the difference between the scanner-measured SOC and the SOC of a generic, globally applicable SOC prediction model as target variable of the prediction model. The rationale of using the deviation as target variable is that the HH scanner can capture local heterogeneity of SOC and thereby it can fine-tune the global estimates of SOC (which is available for the whole world but not accurate enough). This also has a benefit that the model remains sensitive to a small number of new local training dataset. This is because, as the calibration dataset is extended, the model tends to focus on generic patterns and give on average a good prediction but fails to make accurate predication on individual farm or field level. If we train the deviation of the locally measured SOC from the global, then the model can be fine-tuned for the local heterogeneity while preserving the generic patterns of SOC. Thus, NMI can continue to capture small scale variability even when upscaling the approach.

We used the soil map of ISRIC ('SoilGrids') as our first estimate of SOC since it presents the outcome of a globally trained SOC prediction model (https://soilgrids.org/). SoilGrids offers estimates of SOC of different depths on 250 x 250 m resolution. The SOC content of 0-30 cm was calculated from the SOC content of 0-5cm, 5-15cm, and 15-30 cm, weighted by the depth of the three soil layers. Subsequently, we computed the difference between the HH scanner measured SOC and the predicted SOC from SoilGrids.

There are different algorithms to fit data. We tested different algorithms and chose the best among them. Tested algorithms were: linear regression, partial least square regression, ridge regression, lasso regression, elastic net regression, decision tree, and random forest regression. In addition, we also tested different transformations (log-transformation, box-cox transformation, and no transformation) of the target variable. The resulting 21 combinations of the methods (algorithms x data transformation) were compared with 10-fold cross validation, by randomly splitting the 205 sampling points into 10 subsets. The method which achieved the smallest RMSE value of the testing sets was chosen. That was: the random forest regression model for box-cox transformed target variable.

Subsequently, SOC (%) of 0-30 cm depth in every grid point was predicted with the random forest regression model, built on all 205 measurement points as training dataset.

Estimation of farm-level C stock

Soil carbon concentration of top 30 cm (g C kg^{-1}) was converted to a carbon stock (g C $100m^{-2}$) by multiplying the soil C content (g C kg^{-1}) with the bulk density (kg m^{-3}), the depth of the soil (m) and the area of the grid cell (100 m^2).

The bulk density was estimated from soil organic matter content and clay content based on a well-known empirical relationship built on a large dataset of Dutch agricultural soils (Fujita et al., 2021). Soil organic matter content was estimated from soil C content, using the conversion factor of 0.5, the most popular conversion algorithm globally.

The formula of bulk density estimation is as follows:

$$BD = cf \cdot BD_{clay} + (1 - cf) \cdot BD_{sand}$$

$$cf = \min\left(1, \frac{Clay}{25}\right)$$

$$BD_{clay} = 1000 \cdot (a_1 \cdot OS^4 + a_2 \cdot OS^3 + a_3 \cdot OS^2 + a_4 \cdot OS + a_5)$$

$$BD_{sand} = 1000 \cdot \frac{1}{b_1 \cdot OS + \ b_2}$$

$$OS = \frac{1}{0.5} \cdot soilC \cdot 10^{-3} \cdot 10^{2}$$

where *BD* is the bulk density (kg m^{-3}), *OS* is the soil organic matter (%), *soilC* is the soil C content (g C kg^{-1}), a_i and b_i are empirically derived coefficient values (Fujita et al., 2021).

Finally, farm C stock (in unit of ton C) was calculated as sum of soil C of all grids located within the farm.

HandHeld scanner and error propagation

Error propagation is key for the penultimate accurate assessment of carbon stocks, and we also propagated the error associated with the field measurements. The AgroCares HH scanner was used in the field measurements to determine soil organic C levels.

Based on previous studies where datapoints were externally validated on a few thousand independent sample locations all over the world, we conservatively assume that the measured SOC value of HH sensor is associated with an error of +-30% error rate (1 x standard deviation, SD) for a single SOC measurement (in reality, this error is scale dependent).

For the quantification of the actual C stock, this study strongly depends on the soil organic carbon levels determined by the HH scanner. Therefore, we quantified the effect of the HH scanner error on C stock estimate with Monte Carlo simulations. Model was trained for the same 205 measurement dataset but with a random error of HH scanner (mean 0%, SD ±30%) on the measured SOC, and farm-level C stock was calculated with the model. This procedure was repeated for 100 times, and the uncertainty range of the farm-level C stock was quantified.

3 Results

3.1 Carbon stocks

In this section the carbon stock per farm, field and the carbon stock density on a 10x10 meter grid will be detailed.

Carbon stocks per farm

The carbon stock per farm is shown in Tabel 2-1. Arkansas has much higher C stock (5059 tC) than Iowa (2630 tC), due to their larger surface area as well as higher concentration per hectare. The coefficient of variation (CV; standard deviation divided by mean), a metric to evaluate the variability, is 4.3% for Iowa and 5.0% for Arkansas (see Figure 6.3 in Appendix). This is comparably low level of variation as the former similar study in Dutch farms (Fujita et al., 2021), indicating that the method used can make robust estimates of farm-level C stock.

Table 3-1. Overview of carbon stocks per farm. Abbreviation tC is short for ton (1.000 kg) of carbon. The tC range indicates farm-level C stock uncertainty range (5th and 95th percentiles) associated with HH scanner error.

Farm	Area (ha)	C Stock (tC)	tC per hectare	tC range
Arkansas	143.0	5059	35.4	32.8-38.7
Iowa	95.2	2630	27.6	25.4-29.6

** the total stock is estimated from the total grid area rather than total polygon area.*

Carbon stocks per field

The carbon stocks per field are summarized in Table 3-2. The ton carbon (tC) per hectare ranges from ~17 to ~55. The highest stock is found in Arkansas (field B) whereas the lowest is found in field E. The CV of field-level C stock ranges between 5.4% and 9.4%, slightly higher than that of farm-level C stock estimates but still below the critical boundaries established by most accreditation protocols (Ros, 2021). If a higher accuracy is needed on field level, then the sampling density needs to be increased.

Table 3-2. Overview of carbon stocks per field. Abbreviation tC is short for ton (1000 kg) of carbon. The tC range indicates field-level C stock uncertainty range (5th and 95th percentiles) associated with HH scanner error.

Field	Farm	Area (ha)	C stock (tC)	tC/ha	tC/ha range
A	Arkansas	23.4	469	20.1	18.0-22.4
B	Arkansas	64.4	3509	54.5	50.7-60.5
C	Arkansas	10.9	206	18.9	16.6-21.6
D	Arkansas	14.0	280	20.0	17.7-22.4
E	Arkansas	30.4	530	17.4	15.8-19.4
F	Iowa	31.7	688	21.7	19.7-24.4
G	Iowa	53.4	1635	30.6	28.0-33.1
H	Iowa	10.1	294	29.0	24.5-33.6

** the total stock is estimated from the total grid area rather than total polygon area.*

Carbon stocks density on a 10x10 meter grid

The model shows the carbon density on a 10x10 meter grid for all fields.

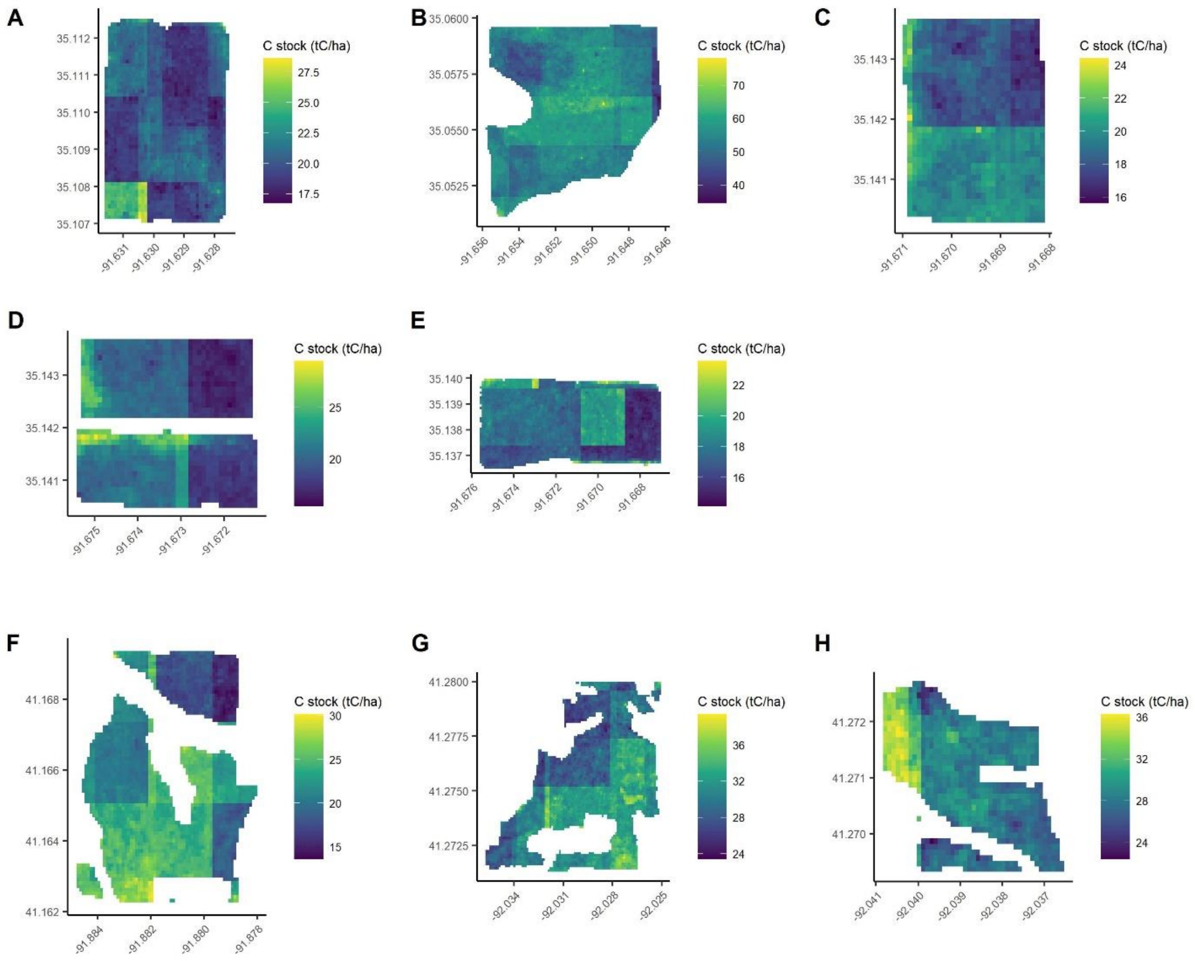

Figure 3-1. Overview of carbon stocks for fields. Note the total area in fields varies from 10-64 hectares. Note, legends differ per field.

3.2 Spatial Variability

We see significant spatial heterogeneity both within fields as well as between fields. Figure 3-2 shows the range of carbon stock values that can be found within the individual fields on a 10x10 grid. Field B shows high internal variability, which is in line with the high variability in the field measurement of carbon within this field.

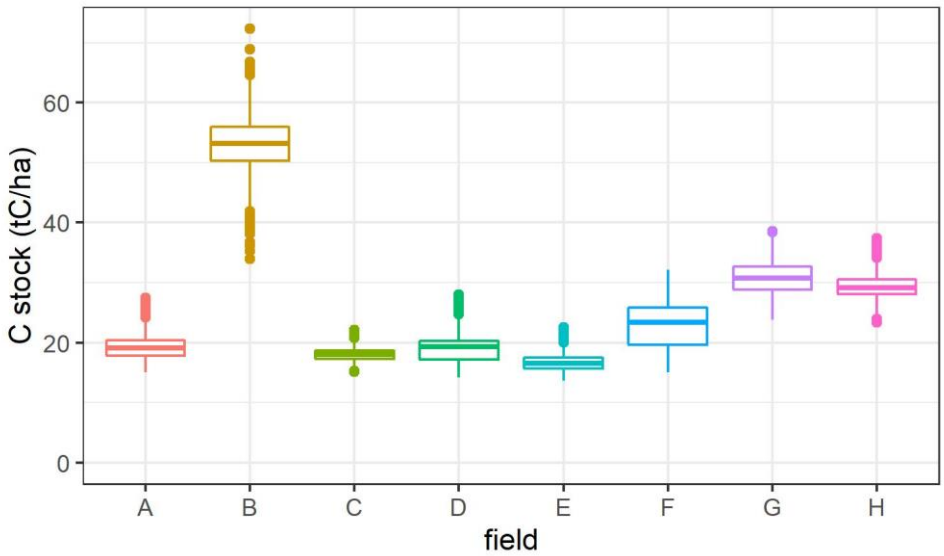

Figure 3-2. Overview of the variability of carbon stock within specific fields. The box represents the 75th up to 25th percentile range, the line the median. The error bars indicate the 1,5 interquartile range above and below the 75th and 25th percentile ranges. Points indicate outliers.

3.3 Sampling area size

With a sampling density of 0,5 samples per hectare, the smallest field size included in this study is ten hectares. This translates to five samples on a ten hectare field. We tested whether this sampling density leads to a robust field-level C stock estimate, using repeated random sampling with varying sampling density for 100 times each. Coefficient of variation (CV%) in predicted field-level C stock was used to assess the model precision under different sampling density (i.e. the lower the CV, the better). The results showed that the CV levels off when the sampling density increases till ca. 0.5 per hectare, even for the small fields (C, H) (Figure 3-3). This indicates that **a field size of 10 ha is sufficient to achieve robust estimate of field-level C stock**, given the sampling density of 0.5 sample per hectare.

Potentially, robust estimates for smaller fields would also be achieved by increasing the sampling density. It should be noted that the required sample number or field size depends highly on the field properties (such as the spatial heterogeneity in covariate values within the field, similarity of covariate values compared to other fields in the calibration dataset). Further tests are needed to provide definitive answers for the required minimum field size.

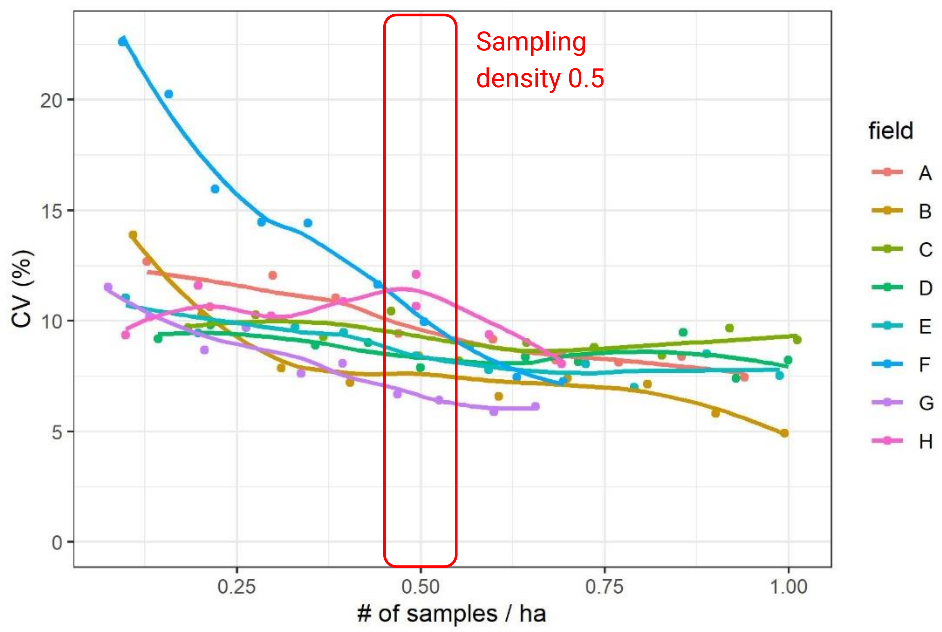

Figure 3-3.The coefficient of variation (CV%) in predicted field-level C stock versus the amount of samples per hectare taken. The CV is a measure of model precision, the lower the better. The CV levels off around 0.5 sample/ha, even for the smallest field (10 ha).

4 Conclusion and outlook

In this report we have provided robust carbon stock estimates for a range of fields in Arkansas and Iowa, in the USA. For the Arkansas farm, the average is ~35 ton carbon per hectare, for Iowa it is ~28. The carbon stocks in the individual fields range between ~17 to ~55 ton carbon per hectare. We also show that our method captures intra-field variability and that it is therefore detailed enough to capture changes in carbon stock over time. The minimum field size needed for robust estimates is 10 hectares with a sampling density of 0.5 samples per hectare. The method presented here is robust, precise and scalable for other carbon sequestration projects across the globe.

As an outlook, we would like to highlight that a number of avenues that can be explored to further expand the reach of the method. First, we can test how fast and to what degree we can reduce the sampling density (now 0.5 samples/hectare) when we measure larger fields or fields with low degree of heterogeneity. Furthermore, we could explore if one always needs to take the entire 30 cm (more time consuming) or of the top 10 cm or even top 5 cm would also suffice (less time consuming). We might also explore the use of the handheld predictions for the dry bulk density rather than the use of generic pedotransfer-functions for bulk density, in particular since these bulk density estimates might differ within and among fields. Last but not least, we could test a larger range of individual field sizes, focusing specifically on smaller fields <10 hectares, which have not been included yet in this study.

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6 Appendix

6.1 Overview of cLHS sampling selection approach

Figure 6-1 shows the area of Field A, potential sampling points on a 10x10 grid, the cLHS seleced sampling points and the resulting carbon stock map.

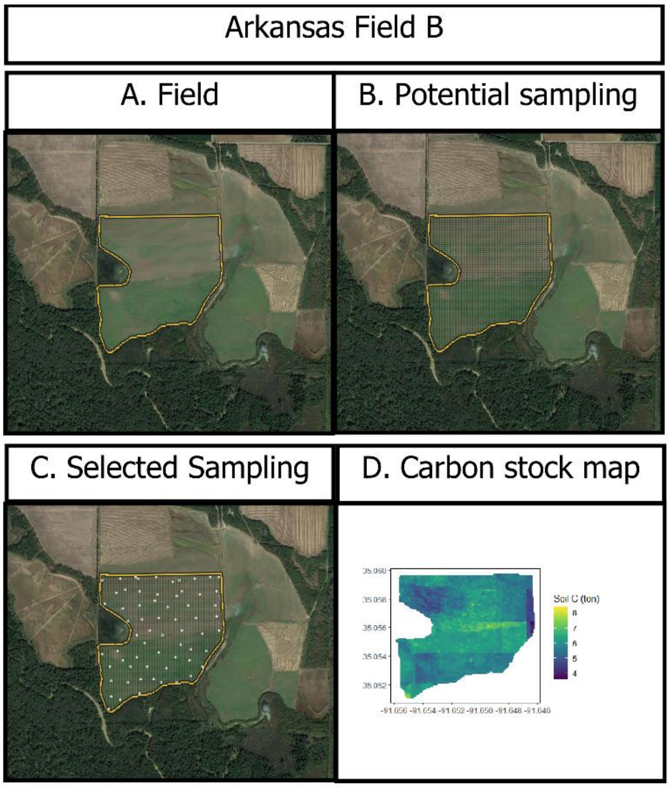

Figure 6-1. Visualisation cLHS sampling technique. Window A shows Field B in Arkansas, window B shows potential sampling locations, window C the selected sampling locations, and window D the resulting carbon stock estimates.

6.2 Precision of estimated farm C stock

Using the Monte Carlo approach, the uncertainty on the estimated C stock per farm has been estimated for scenarios that vary in sampling density. This is done for prediction models that are build on data from the selected farm only (scenario "farm") as well for the situation that measurements from the other farm are also used for calibration (scenario "all"). For the exact procedure to estimate this CV, we refer to the method described by Fujita et al. (2021). In both cases, a sampling density of around 0.5 samples per hectare gives a precision of around 5% of the estimated C stock.

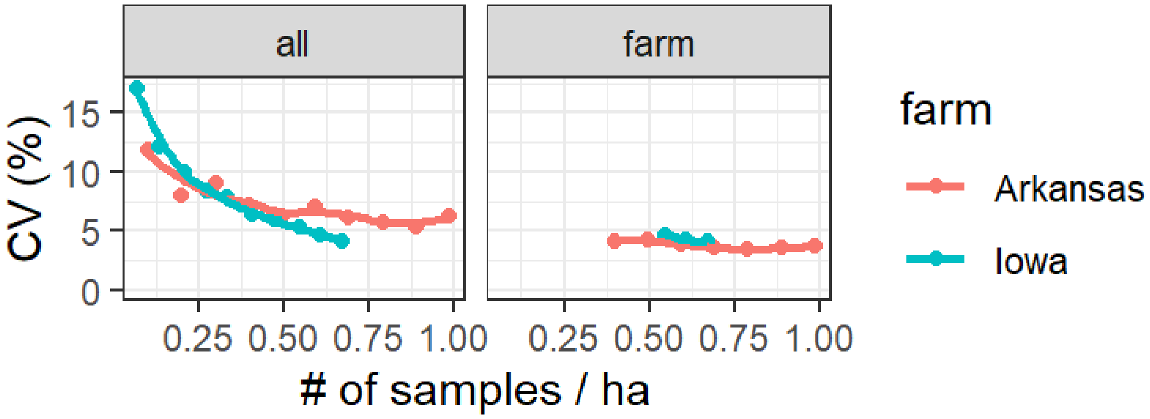

Figure 6-22. The Coefficient of Variation (CV, %) of the carbon stock for the two farms in Iowa and Arkansas. The CV of the carbon stock that uses data from the previous field campaigns (scenario "all") reaches the threshold of 5% around a sampling density of 0.5 samples per ha.

6.3 Overview of covariates

Complete overview of all covariates is shown below. Covariates for which >1 % was unknown (NA) were removed. This concerned s2_TVI_7_2020 and s2_TVI_10_2019. Finally, 45 covariates were used to optimally predict carbon stocks.

Table 6-1. Overview of used covariates in models.

Variable	Number of unknowns (%)	Resolution
s2_TVI_4_2019	0.6	10m
s2_TVI_4_2020	0	10m
s2_TVI_4_2021	0	10m
s2_TVI_7_2019	0	10m
s2_TVI_7_2020	16	10m
s2_TVI_7_2021	0	10m
s2_TVI_10_2019	35.6	10m
s2_TVI_10_2020	0	10m
s2_B11	0	20m
s2_SATVI	0	20m
s2_BI2	0	10m
sg_bdod_0_5_mean	0	250m
sg_bdod_15_30_mean	0	250m
sg_bdod_5_15_mean	0	250m
sg_cec_0_5_mean	0	250m
sg_cec_15_30_mean	0	250m
sg_cec_5_15_mean	0	250m
sg_cfvo_0_5_mean	0	250m
sg_cfvo_15_30_mean	0	250m
sg_cfvo_5_15_mean	0	250m
sg_clay_0_5_mean	0	250m
sg_clay_15_30_mean	0	250m
sg_clay_5_15_mean	0	250m
sg_nitrogen_0_5_mean	0	250m
sg_nitrogen_15_30_mean	0	250m
sg_nitrogen_5_15_mean	0	250m
sg_phh2o_0_5_mean	0	250m
sg_phh2o_15_30_mean	0	250m
sg_phh2o_5_15_mean	0	250m
sg_sand_0_5_mean	0	250m
sg_sand_15_30_mean	0	250m
sg_sand_5_15_mean	0	250m
sg_silt_0_5_mean	0	250m
sg_silt_15_30_mean	0	250m
sg_silt_5_15_mean	0	250m

Variable	Number of unknowns (%)	Resolution
elevation	0	10m
slope	0	10m
aspect	0	10m
vsm_4_2018	0	20m
vsm_4_2019	0	20m
vsm_4_2020	0	20m
vsm_7_2018	0	20m
vsm_7_2019	0	20m
vsm_7_2020	0	20m
vsm_10_2018	0	20m
vsm_10_2019	0	20m
vsm_10_2020	0	20m

soil for life

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