Exploring the behaviour of the ACCU Scheme 2021 Soil Carbon Method

Queensland Government

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Executive Summary

In the Australian Carbon Credits Unit (ACCU) Scheme, the soil carbon method (measurement-only approach) is based on soil sampling at baseline, T_0, and a subsequent sampling round, T_1, using a statistical design and analysis. To provide conservative crediting, credits are awarded for soil organic carbon (SOC) increases based on an estimated 60% exceedance value (i.e. the data show a 60% chance that the actual change in SOC between T_0 and T_1 is greater than the credited change). It is not clear in the method determination what happens when the data from a project lead to a negative value for the estimated 60% exceedance value. The work in this report explores the expected behaviour of crediting that results from the method if such a scenario leads to zero credits being issued (rather than to negative credits). Under this assumption, we ran simulation tests to (i) investigate the behaviour of expected crediting that results with different underlying SOC change, SOC spatial variation, and sampling intensity and (ii) compare alternative strategies for designing projects. Results demonstrate that when the spatial variation of SOC is large and the temporal change of SOC small, the method can produce anti-conservative crediting and give the largest expected crediting with the least permitted soil sampling points. Results also show that a design approach that splits the land into multiple projects, each project a single CEA, can give close-to-guaranteed crediting, which might make it an attractive strategy to proponents. These features of the soil method are potentially problematic, and care should be taken to ensure that they do not get used to provide large crediting in the absence of real SOC increases.

Contents

Key points

- The soil carbon method (measurement-only approach) is based on soil sampling at baseline, T_0, and a subsequent sampling round, T_1, using a statistical design and analysis, and awards credits for SOC increases based on an estimated 60% exceedance value (i.e. the data show a 60% chance that the actual change in SOC between T_0 and T_1 is greater than the credited change).
- A consequence of this exceedance value is that if the SOC has not changed between T_0 and T_1, then a project should always have at least a 40% chance of being credited, even with no actual change.
- When the 60% exceedance value is larger than zero, credits are issued; when the 60% exceedance value is less than zero, it is not clear in the method determination, but to the best of our knowledge, zero credits are issued (rather than negative credits)
- Under this assumption, we ran simulation tests to (i) investigate the conservativeness of the soil method (measurement-only approach) and (ii) compare alternative strategies for designing projects.
- The method provides conservative crediting (considered here as an expected crediting that is smaller than the actual change in SOC) when the spatial variation of SOC is small and there is an actual temporal increase in SOC. As a rough guide here, this means a standard deviation of measurements within a CEA of <10% of the actual SOC (i.e. a coefficient of variation of <0.10) and increases of >5% relative to the initial SOC. In this case having more sampling points gives smaller uncertainty discounts and greater expected crediting (with an upper limit of the actual SOC change).
- When the spatial variation is larger however, the soil carbon method can produce anti-conservative crediting (an expected creditable SOC change that is larger than the actual SOC change; or equivalently, an expected number of ACCUs that is larger than the actual CO_2-equivalent change), particularly when the actual change in SOC is small. Again, as a rough guide this means a standard deviation of measurements of >25% of the actual SOC. In this case although increasing the number of sampling points again decreases the uncertainty discount, it can also reduce the chance of selecting sampling points that give an estimated large increase or large decrease in SOC. Since decreases in SOC are not penalised (there is no negative crediting when the estimated change is negative), increasing the number of sampling points can in some circumstances lead to a reduction in the expected crediting.
- We compared alternative strategies for dividing up land for applying the soil method: 1. a single project with a single CEA, 2. a single project split into multiple CEAs, 3. multiple projects, each a single CEA. The first strategy allows the least sampling effort to meet method requirements (9 samples), which can give the highest expected crediting in situations of large spatial variation and small actual SOC change. However, the third strategy (with more samples, 9 per project, required to meet minimum requirements) can give similar expected crediting, but with a higher probability of being credited when there is no actual SOC change. This close-to-guaranteed crediting could make it an attractive strategy to proponents.
- If a proponent only expects a small actual change in soil carbon but large spatial variation of SOC, then it is advantageous for them to:
    - Split the carbon farming area into multiple single-CEA projects and
    - Sample each project at minimum requirements
- These features of the soil method are not desirable, and care should be taken to ensure that they do not get used to provide large crediting in the absence of real SOC increases. Possible future updates to the method could look again at minimum sampling requirements or at a more conservative probability of exceedance, perhaps depending on the SOC increase expected from an activity within a given time.
- Given that the Integrated Farm and Land Management (IFLM) method (under development) proposes using aspects of the soil method in its crediting calculations, this work will also be relevant for a better understanding of how the IFLM method addresses conservativeness.

1 Introduction

Soil carbon and potential to sequester carbon through management change.

Soil carbon has seen attention over the past decades due to its potential for increased carbon storage that could compensate for global emissions of greenhouse gases by anthropogenic sources (Minasny et al., 2017). The adoption of best management practices can potentially restore some of the soil organic carbon (SOC) that has been lost since the clearing of native vegetation, improve agricultural practices and ecosystem services, and sequester atmospheric carbon dioxide (Smith et al., 2008; Lal et al., 2018). Temporal changes in SOC are driven by a combination of factors, including land use/management practice, ecosystem conditions and climatic variation (Stockmann et al., 2013). However, the high spatial variation and slow changes in SOC make robust quantification of its changes—that is cost-effective and provides a statistical assessment of uncertainty—challenging (Smith et al, 2020; Paustian et al., 2019; Stanley et al., 2023).

Carbon market

The Australian Carbon Credit Unit (ACCU) Scheme is designed to credit landholders who implement management changes that result in increased carbon sequestration in the landscape or decreased emissions of carbon dioxide or other greenhouse gases into the atmosphere. The compliance of ACCU Scheme methods against Offsets Integrity Standards is assessed to ensure the continued integrity of the scheme. The Offsets Integrity Standards (https://www.dcceew.gov.au/sites/default/files/documents/erac-information-paper-offsets-integrity-standards.pdf) include a list of six standards, all of which must be satisfied by methods:

1. Additionality: A method should result in carbon abatement that is unlikely to occur in the ordinary course of events (disregarding the effect of the Act).
2. Measurable and verifiable: A method involving the removal, reduction or emissions of greenhouse gases should be measurable and capable of being verified.
3. Eligible carbon abatement: A method should provide abatement that is able to be used to meet Australia's international mitigation obligations.
4. Evidence-based: A method should be supported by clear and convincing evidence.
5. Project emissions: Material greenhouse gas emissions emitted as a direct result of the project should be deducted.
6. Conservative: Where a method involves an estimate, projection or assumption, it should be conservative.

The last of these, conservativeness, is the focus of this work.

Soil method

One of the ACCU Scheme methods is titled "Estimating soil organic carbon sequestration using measurement and models method", herein referred to as the 2021 soil carbon method or just the soil method (https://cer.gov.au/schemes/australian-carbon-credit-unit-scheme/accu-scheme-methods/estimating-soil-organic-carbon-sequestration-using-measurement-and-models-method). The method credits landholders if they undertake new land management activities that are expected to increase soil carbon, with crediting based on measurements of that increase. The method provides a list of eligible activities, including for instance establishing, and permanently maintaining, a pasture where there's previously no or limited pasture, or using legume species in a cropping or pasture system. Measurement of the changes is based on data collected using a statistical sampling design and a corresponding statistical analysis.

Conservativeness of the soil method

Conservativeness is built into the 2021 Soil Method (measurement-only approach) through an uncertainty discount, based on a statistical analysis of measured SOC stocks of soil samples collected at baseline (before implementation of management changes, T_0) and a subsequent sampling round (T_1). The statistical approach estimates the change in SOC between T_0 and T_1 and its associated uncertainty, and credits are awarded based on a 60% exceedance value (a value slightly smaller than the estimated change, which the statistical analysis determines that there is a 60% chance that the actual change in SOC will be larger than). While this is conservative in the sense that given that set of sampled data, the awarded credits are more likely than not to be smaller than the actual change, it doesn't necessarily mean that the expected crediting (over all possible sets of sampling points) is smaller than the actual SOC change. For instance, consider an actual SOC change of zero; if the randomly selected sample points for T_0 and T_1 happen to show a large increase in SOC, then credits might be awarded. Therefore, the expected crediting can never be less than zero, since there is no requirement to pay back when SOC decreases are measured, so in this situation, conservative crediting (based on an expected crediting interpretation, rather than a probability of crediting interpretation) can never happen.

Questions and outline of this work

In this work, we use a simulation study to investigate the conservativeness of the soil method with different assumptions about the underlying spatial variability of soil carbon and its change through time due to the actions of the project, and with different numbers of soil samples collected to estimate the change and its uncertainty. First, some brief details of the soil carbon method (measurement-only approach) are set out, then a simulation study is used to explore the potential behaviour, and finally an illustration of how this might apply in a real soil carbon project is shown.

We aim to address the questions:

1. How is the expected crediting of projects impacted by the variation of SOC stocks, the temporal change of SOC stocks and the sampling strategy? When can we expect conservative crediting?
2. How do different approaches for splitting up land for soil carbon farming differ in their expected crediting?

2 Background: The 2021 Soil Method (measurement-only approach)

The 2021 soil method (measurement-only approach) sets out sampling requirements and a statistical analysis for estimating (with uncertainties) soil carbon changes between two sampling rounds, one at the start of the project, T_0, and another subsequent sampling round, T_1. The method includes the following requirements:

- A project should be divided into one or more carbon estimation areas (CEAs).
- For each sampling round, each CEA should be divided into at least three strata.
- From each stratum, at least three soil sampling points must be randomly selected.

The division of CEAs into strata can be done based on any information the proponent has about the variation of soil carbon. It could be based on previous soil data collected from the CEA, it could be based on other existing maps that help split the CEA into strata that have similar soils, or it could be based on the landowner's knowledge of the variation, for instance, knowledge of different management histories within the CEA. The strata can be re-designed for each sampling round, so for instance the T_0 data could be used to map the initial soil carbon and help re-stratify a CEA for the T_1 sampling round.

Equations in the method determination state how the soil carbon percentage and bulk density data from each sampling point should be used to calculate the soil carbon content (for 0-30 cm or deeper) for those points on an equivalent soil mass (ESM) basis (e.g. so that the data at each soil sampling location represents the soil carbon stock, in t C / ha, contained in the top 3900 t soil / ha).

2.1 Illustration of the statistical method to estimate SOC change and its uncertainty and calculate ACCUs

Although the method is based on stratified sampling and associated statistical analysis, in this section we illustrate the main concepts of the method based on simple random sampling (i.e. a CEA is not stratified, and sampling points are selected entirely at random from the entire CEA). In our simulation studies (described in Section 3 with results in Section 4), the stratified sampling approach is used for investigating the behaviour of the method under different assumptions about the variation, change and sampling intensity.

Suppose we have sampled 10 points from a CEA at time T_0 and another 10 points at time T_1 and calculated the SOC on an ESM basis for all 20 sampling points. An illustration of some simulated data are shown in the first two histogram plots of Figure 1. These data were simulated from normal distributions based on mean SOC stocks for T_0 and T_1 of 40 t C / ha and 42 t C / ha (i.e. a 5% increase), and standard deviations of 10.0 t C / ha and 10.5 t C / ha for T_0 and T_1 (i.e. 25% of the actual SOC mean for each sampling round). Also marked on the two histograms are the means of the measured data for each time (41.0 t C / ha and 48.2 t C / ha, marked as circles) and one standard error of the mean (2.4 t C / ha and 2.8 t C / ha; i.e. representing uncertainty about the estimated mean) either side of those means (as horizontal bar lines). In the soil method, these data are used to estimate the difference in SOC between times T_0 and T_1, the uncertainty of which is calculated using the standard errors from T_0 and T_1 and represented using a t distribution. This uncertainty in the estimated difference is shown in the probability density plot, the third plot of Figure 1, centred on the estimated mean SOC difference (7.1 t C / ha here, marked as the circle on the plot). However, crediting in the soil carbon method is not based on this central value; rather the crediting is based on the 60% exceedance probability value (6.2 t C / ha), indicated by the vertical line in the plot, where the shaded area to the right of the vertical line represents 60% of the probability distribution (i.e. given this set of data, there is a 60% chance that the actual change in SOC is greater than this value of 6.2 t C / ha). Note that the difference between the central value estimate of the change (7.1 t C / ha) and the 60% exceedance value (6.2 t C / ha) can be referred to as the uncertainty discount. If the number of samples collected is increased, then we would expect that this discount becomes smaller as the uncertainty associated with the estimated SOC change becomes smaller. Note also how even though the actual soil carbon stocks for T_0 and T_1 (for simulating the data) were assumed to be 40 t C / ha and 42 t C / ha, the measured soil carbon (simulated from normal distributions, representing measured values at the randomly selected sampling points) gave an estimated increase of 7.1 t C / ha (from 41.0 t C / ha and 48.2 t C / ha), and crediting based on the 60% exceedance value was for 6.2 t C / ha, quite a bit higher than the actual change in this single simulated example.

We will refer to the 60% exceedance SOC change as the uncertainty-discounted SOC change, as calculated in the method determination. Note that if uncertainty-discounted SOC change is positive, it is assumed here that credits would be issued, while if it is negative, it is assumed that zero credits would be issued (rather than there being an issuance of negative credits); we will refer to the resulting value as the creditable SOC change, defined as:

$$Creditable\ SOC\ change = \begin{cases} Uncertainty\text{-}discounted\ SOC\ change & \text{if } Uncertainty\text{-}discounted\ SOC\ change > 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{(Eq 1)}$$

This is the key assumption in this work, that negative values of the uncertainty-discounted SOC change are awarded zero credits, and we explore the behaviour of the soil method under the assumption that this is the case. In the method, this is converted to ACCUs by multiplying by 44 / 12 (to convert tonnes of carbon to tonnes of CO_2-equivalent), however, this conversion is not done in this work, to retain changes in units of SOC.

Note also that for a first resampling event (T_1), the soil method applies a 25% temporary discount to any calculated credits. This discount is not considered in this work, since it is not applied to subsequent (T_2 and beyond) sampling rounds, for which the difference between T_0 and T_2 stocks is estimated and credited. A further discount of 25% is also applied in practice as a risk-of-reversal buffer and permanence discount. This is also not applied here, since they are designed for purposes other than conservativeness; this also allows straight comparisons with actual SOC changes. Results for the expected creditable SOC change should be interpreted with this in mind.

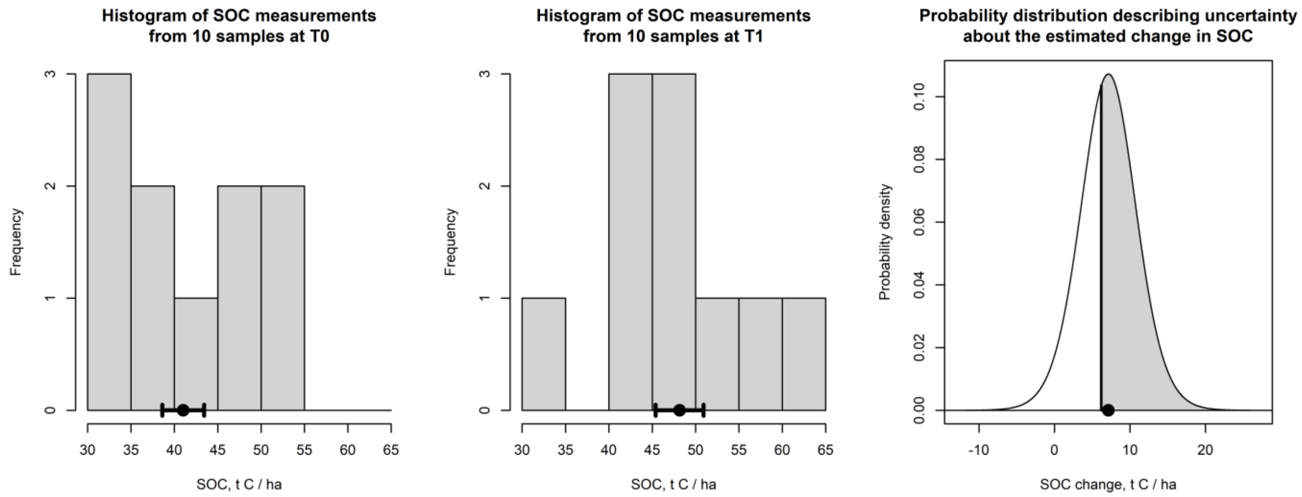

Figure 1 An illustration of soil data for estimating the change in SOC between two sampling times, T_0 and T_1. The first histogram shows 10 SOC data collected at T_0, with their mean indicated by a circle and on standard error either side of that mean by the horizontal bar lines. The second shows the same for 10 SOC data collected at T_1. The final probability density plot represents the uncertainty about the estimated difference in mean SOC between T_0 and T_1, with the estimated difference indicated by the circle and the 60% exceedance value by the vertical line, with the shaded area to the right of that line representing 60% of the probability distribution.

The simulated data in Figure 1 illustrated the basics of the soil carbon method, but in the setting of simple random sampling. As noted, the soil carbon method stipulates that each CEA should be split into at least three strata. This should have the effect of producing estimates of SOC and SOC change that have smaller standard errors and uncertainty discounts than for the case of simple random sampling, though the logic of the statistical analysis is the same: estimate the mean SOC and its standard error for T_0, estimate the mean SOC and its standard error for T_1, then put these together to estimate the change in SOC, its uncertainty, and the uncertainty-discounted SOC for crediting.

3 Methods: Simulation study details

3.1 Simulations set up

In this work, we use a simulation study to test the conservativeness of the soil method with different assumptions about (i) the underlying spatial variation of soil carbon, (ii) the temporal change of soil carbon, and (iii) the sampling strategy/number of soil samples collected. The parameters that are used to set up the simulation study are as follows.

3.1.1 Starting SOC stock

The starting actual SOC stock over the CEA is $A\,S_0$ t C, where A is the area of the CEA in hectares; i.e. if the soil from the entire CEA was collected and analysed without measurement error, the total carbon stock would be $A\,S_0$ t C. We will report all results on a per-hectare basis, for easier comparison with simulation parameters, so from here on will refer to S_0 (t C / ha) as the initial SOC stock.

Just a single value of $S_0 = 40$ t C / ha is used in the simulation tests throughout this work. This represents an average SOC stock for cropping soils in Queensland, for instance Page et al. (2012) reported a mean SOC stock for 0-30 cm of 38 t C / ha (and range of 15-75 t C / ha) from sampling 179 cropping paddocks from commercial farms across the state.

Due to other factors in the setup of the simulations, results (expected SOC stocks, changes and credits) for a starting stock of $b\,S_0$ would be obtained by multiplying the S_0 results by b.

3.1.2 Spatial variation of SOC stocks

The spatial variation within the CEA (and measurement error) result in measurements of the SOC stock (in t C / ha) at sampling points varying about the actual initial (T_0) SOC stock, S_0; we will use a base map and random sampling of points within strata to represent this variation, as described in Section 3.2. The base map will be used to generate a starting SOC stock map with a given mean (S_0) and a standard deviation of $c\,S_0$, where c represents the coefficient of variation. Setting up the simulations this way means that CEAs with a larger SOC stock would also be expected to have greater spatial variation of SOC stocks. We refer to this as the spatial variation, though note that this also includes sampling and measurement errors, and the standard deviation is that for simple random sampling from points within a CEA.

A range of values for the coefficient of variation, c, (governing the spatial variation of SOC stocks) within the CEA are tested in this work: $c = 0.01, 0.05, 0.10, 0.25, 0.50$. From the dataset analysed in Page et al. (2012), there were 8 paddocks for which multiple soil cores, collected from different locations within a 25-m quadrant in a paddock, were analysed separately for their SOC contents (note, individual core data not presented in Page et al., 2012). For each of these 8 paddocks, we calculated a mean and standard deviation of the measurements and used these values to calculate a coefficient of variation for each paddock. These 8 coefficients of variation ranged from 0.07 to 0.26 with a mean of 0.13. The CEAs (and strata within CEAs) used in the soil method will typically be much larger than these quadrants (0.06 ha), and therefore the spatial variation in practice is likely to be considerably larger than the average of 0.13. Elsewhere, data from farms in Southern California (Stanley et al., 2023), where samples were collected along 50-m transects, showed coefficient of variation values for SOC stock in 0-15 cm of between 0.20 and 0.26 (7 different paddocks), and for 15-30 cm of between 0.15 and 0.41. All this considered, perhaps the most realistic value from our set of simulation parameters for representing a real example is $c = 0.25$, with the values of $c = 0.01, 0.05$ overly optimistic.

3.1.3 Temporal change of SOC stocks

The temporal change in SOC stocks is here represented by defining the actual SOC stock, S_1, for a subsequent resampling time, T_1, by multiplying the initial actual SOC stock by a factor to represent an r% increase. For example, for an $r = 5\%$ increase, the initial SOC stock is multiplied by 1.05, while for an $r = 10\%$ increase, the initial SOC stock is multiplied by 1.10.

The range of values considered for r in this work are $r = 0, 5, 10, 20$. Data from Jones et al. (2014), where long-term cropping sites in Queensland (2 farms, 10 paddocks in each) were sampled before being converted to pasture and then resampled 20 years later showed an increase in the average SOC (for an ESM of 4000 t soil / ha, representing a nominal depth of 0-30 cm) of 14%, from 24.5 t C / ha to 27.9 t C / ha.

The increase that any particular change in land management as permitted under the soil carbon method (e.g. introducing legume species into a cropping system) will depend on many factors, including what that change is, the management history of the site, the pre-clearing SOC content, and the length of time between sampling rounds. The range of values in the simulations should cover broadly what might be expected of a realistic soil carbon project, at least over the early stages of 25-year period.

3.1.4 Number of sampling points

The number of sampling points per stratum must be at least 3 for the soil method, which together with a requirement of at least 3 strata per CEA leads to a minimum of 9 samples for a CEA for each sampling round. We assume that the number of samples, n, for T_1 is equal to the number of samples for T_0, and investigate increasing numbers of samples from $n = 9$ to $n = 60$ in increments of 3.

3.2 Simulated data

Raster maps representing the spatial variation of carbon stocks for T_0 and T_1 were generated for this work by extracting values from the SOC baseline map of Viscarra Rossel et al (2014). (Note that this map represents a predicted value of the SOC for each pixel location, rather than a simulated value from a distribution that includes uncertainty at each location; hence, prediction maps such as this are smoother than would be expected if soil samples were collected and measured for each pixel location.) First, that map was cropped to a 5-km x 5-km (2500-ha) area, with south-west corner at longitude 145, latitude -28; this is referred to as the base map (Figure 2, left-hand side). Next, the values in the cropped map were rescaled to give a map, M_0, for the SOC at T_0 with prescribed mean and standard deviation (S_0 and $c\,S_0$, based on parameters described in Section 3.1). This was done by subtracting the base map mean, dividing the values by the base map standard deviation, multiplying by the required standard deviation, then adding the required mean. Then the map for T_1, M_1, was generated by applying the prescribed temporal increase to all pixels in M_0 (i.e. multiplying the SOC at T_0 for all pixels by $(1 + r/100)$). This gave a way to generate spatial data with controlled variation and temporal change, albeit with the same temporal change (as a percentage) everywhere. Figure 2 (right-hand side) illustrates a map of SOC values generated from the base map; it has the same spatial pattern as the base map, but with mean 40 t C / ha, and standard deviation 10 t C / ha (i.e. $c = 0.25$).

For each stratum (see Section 3.3) and sampling time (T_0 and T_1), data are simulated by randomly generating the required number of locations from within the stratum and extracting the data from the T_0 and T_1 maps for those locations. Given this set of data, the equations of the soil method are applied, with Equation 1 then used to give the creditable SOC change that would arise based on that particular set of sampled data. This process is repeated 1000 times, each time with a new set of randomly generated sampling locations, to give 1000 sets of outputs from the method equations and the resulting creditable SOC change (Equation 1). To summarise these 1000 equally likely simulations, we calculate expected values (means). For the creditable SOC change, this expectation gives an indication of the total amount of SOC change the scheme should expect to credit for under any given scenario (disregarding the permanence period and risk-of-reversal discounts). We also calculate the proportion of those 1000 simulations that gave rise to positive values for the uncertainty-discounted SOC change and hence positive credits, to give a probability of crediting under that scenario. A step through of this procedure, for any given values of S_0, c, r and n, is as follows:

- Step 1: Transform the values in the basemap to have a mean of S_0 and standard deviation of $c\ S_0$ to give a map of the actual SOC for T_0, M_0
- Step 2: Multiply all of the values in the T_0 map, M_0, by $(1 + r/100)$ to give the map of the actual SOC for T_1, M_1
- Step 3: Subsample map M_0 at n locations and map M_1 at another n locations, with locations split equally between the three strata (see Section 3.3) and sampled randomly within those strata
- Step 4: Apply the equations of the soil method to calculate the uncertainty-discounted SOC change (60% exceedance value) that results from this set of subsampled data
- Step 5: Apply Equation (1) to calculate the creditable SOC change that would result from this set of subsampled data. The zeroing of negative values when calculating ACCUs for a soil project is something that happens based on a single set of soil data and their resulting uncertainty-discounted SOC change, hence it is applied here in the process, to each simulated set of project data. (Note that in a real project, this value would then be multiplied by 44/12 and other discounts to calculate the ACCUs that would be awarded; these steps are not applied here, for reasons noted in Section 2.1.)
- Step 6: Repeat Steps 3-5 1000 times to build a distribution of the soil method outputs and the resulting creditable SOC change
- Step 7: Calculate the expected value for each of these outputs, and the proportion of those 1000 simulated datasets that gave rise to positive values of the creditable SOC change

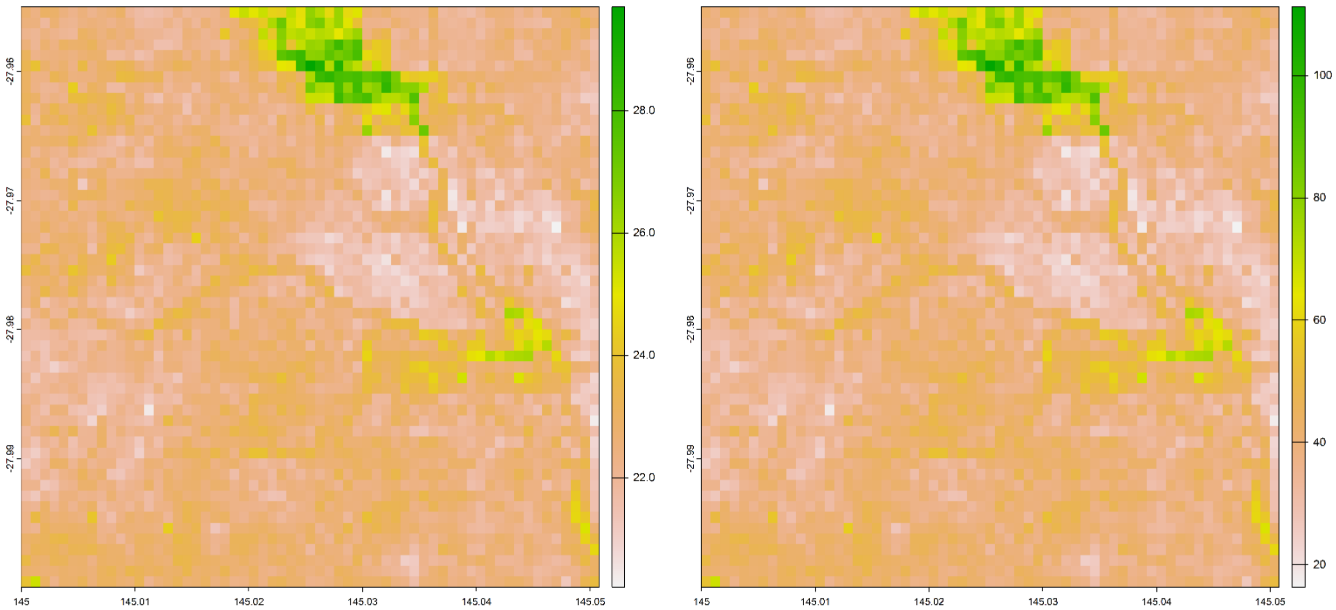

Figure 2 The base map (t C / ha), extracted from the SOC baseline map of Viscarra Rossel et al (2014), and an illustration of a generated map for SOC at T_0 with mean 40 t C / ha and standard deviation 10 t C / ha (coefficient of variation of 0.25).

3.3 Stratification

A first and basic approach to stratify the area into three strata for sampling was to split the area into three equal-area horizontal bands. This approach might be expected to capture some of the variation, due to the spatial auto-correlation in the soil data. Compact equal-area strata (Walvoort et al., 2010) provides a better stratification design in the absence of other information to guide stratification, but was not used here.

A second stratification approach was compared, representing a stratification that better captures the variation. To design strata for this optimistic stratification, the data from the base map were split into three strata, with the pixels in the top 1/3 of SOC values forming the first stratum, the next 1/3 forming the second stratum, and the smallest 1/3 of SOC values forming the third stratum. (Note, this use of underlying data to design strata is not possible in practice, it is used here to represent an optimistic stratification.)

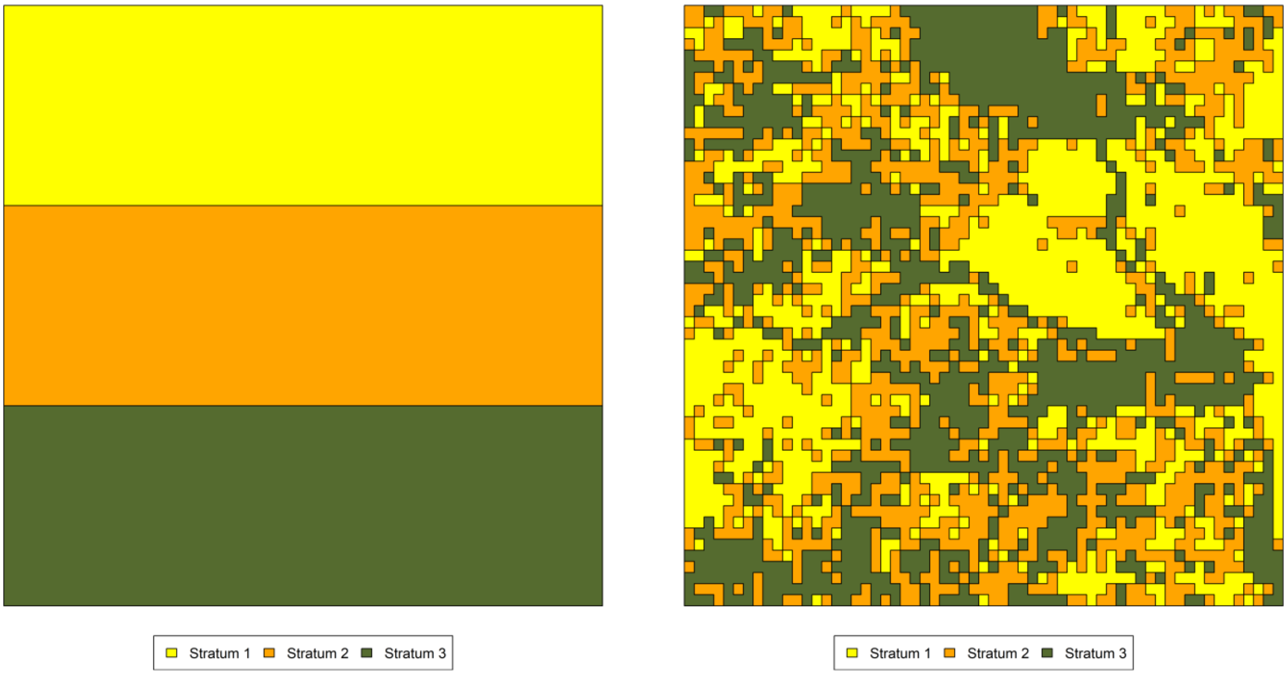

Figure 3 Strata based on the two stratification approaches applied in this work. The left-hand plot is the basic approach based on three horizontal bands, while the right-hand plot is an overly optimistic approach, in which the base map is used to design the three strata.

3.4 Alternative designs of soil carbon projects

The simulation tests described in Sections 3.1 and 3.2 considered a soil carbon project that consisted of one CEA. However, given a block of land where carbon farming is being considered, there are multiple options for how to split this land up into projects and CEAs. Figure 3 illustrates three possible options. Scenario 1 in the figure represents the case we have looked at, one project consisting of one CEA. In Scenario 2, the area is still considered as one project, but split into four CEAs. In Scenario 3, the area is split into four projects, each consisting of a single CEA. The figure depicts a situation where there is an actual increase in SOC in the north-east block (marked in green), and decreases of similar magnitude in the other three blocks (grey); this actual change (an overall decrease in SOC) is the same for all three scenarios. In Scenario 1, samples are collected for T_0 and T_1 and used to estimate the uncertainty-discounted SOC change. If this is larger than 0, credits are issued. In Scenario 2, samples are collected from all CEAs for T_0 and T_1, the uncertainty-discounted SOC change calculated for each CEA, those four values are added together, and if the final result is larger than 0, then credits are issued. In Scenario 3, samples are again collected from all CEAs for T_0 and T_1, the uncertainty-discounted SOC change calculated for each CEA (i.e. each project); however, any of those CEAs that have a negative value for the uncertainty-discounted SOC change will not get credited, while any that have a positive value will be credited. Thus, in the hypothetical of the four blocks of the carbon farming area having equal magnitudes of SOC change, with only the north-east block being positive (i.e. an overall negative change), the first two scenarios are likely to end up with no credits, while the third scenario is likely to lead to credits for the positive change in that north-east block.

We run a second set of simulations to compare these alternative designs. These simulations are based on a similar set of assumptions to generate data to those described in Sections 3.1 and 3.2. The simulations use the same total number of sampling points for the three scenarios, starting with n = 9 for Scenario 1 and n = 36 for Scenarios 2 and 3 (with four CEAs, this would be the minimum number of samples for the method), up to n = 120. In all scenarios, these points are split evenly between all CEAs and all strata.

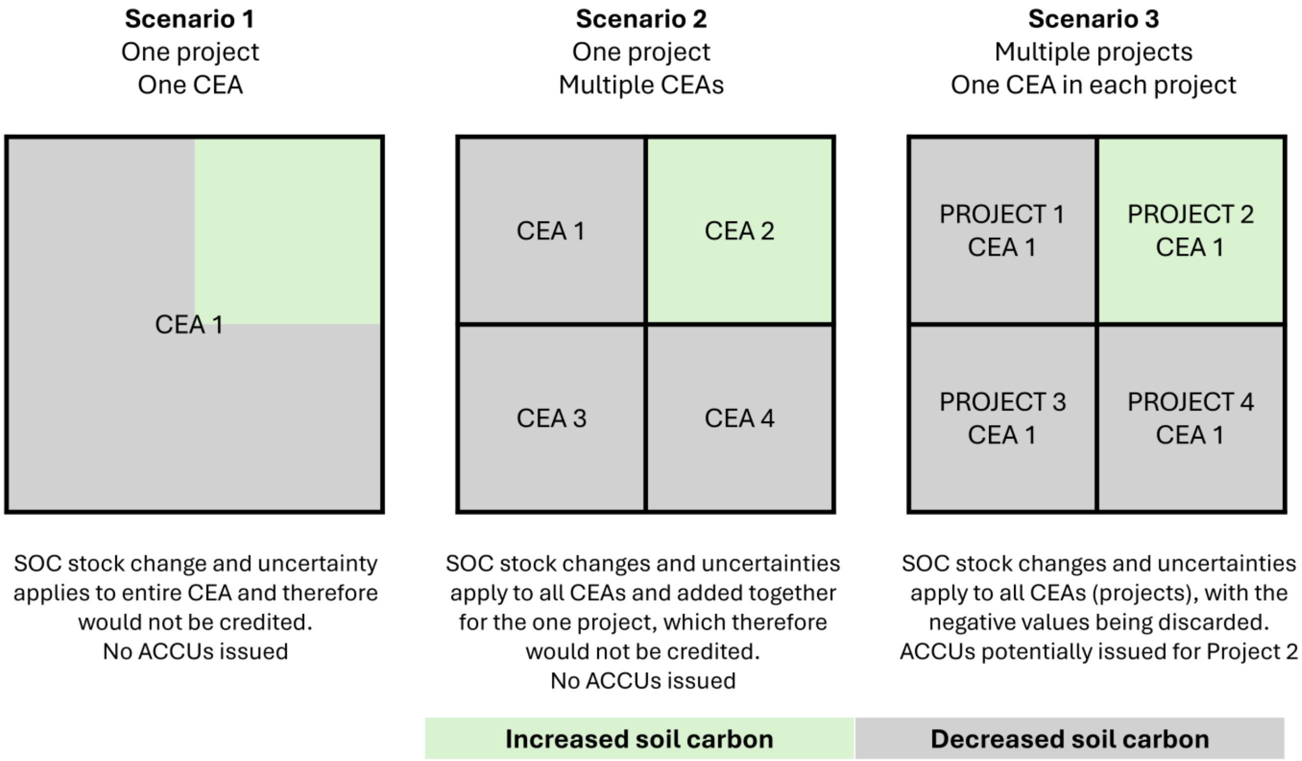

Figure 4 Three scenarios for splitting up a block of land into projects and CEAs for soil carbon farming

4 Results

4.1 Estimated changes in SOC and crediting with different simulation parameters

The first four rows of Figure 5 show the mean (over the 1000 simulated datasets) for each of four output variables: the estimated SOC change (top row), the uncertainty discount (second row), the uncertainty-discounted SOC change (third row), and the creditable SOC change (fourth row). The final row of plots shows the probability of a project being credited (the proportion of the 1000 simulated datasets for which the crediting was greater than zero). The four columns of plots represent different temporal changes in SOC used to simulate the data ($r = 0, 5, 10, 20$ % increase relative to the initial actual SOC stock, S_0). The five coloured lines (green, cyan, yellow, orange, red) represent the spatial variation as a coefficient of variation ($c = 0.01, 0.05, 0.10, 0.25, 0.50$). For easier comparison with simulation parameters, all results are presented on a per-hectare basis.

Some observations from the results in Figure 5 are as follows:

Estimated SOC change

- The estimated SOC change (first row) shows expected behaviour, with expected values (over the 1000 simulated datasets) always close to the SOC change used to simulate the data. This provides a bit of a sense check for the simulations.

Uncertainty discount

- The uncertainty discount (second row) shows expected behaviour, with greater sampling effort being rewarded by smaller uncertainty discounts. This occurred for all simulation set ups (large and small spatial variation, no temporal change to large temporal change).

Behaviour when there is no temporal change

- When data are simulated based on no underlying temporal change, the probability of being credited is always around 0.4 (first column, bottom row). This is a result of crediting being based on the 60% exceedance probability. This means that even in the absence of any real change, 40% of projects should still expect to be credited, irrespective of their sampling strategy (x-axis) or the underlying variation (different colours).
- When there is no actual change in SOC, the uncertainty-discounted SOC change (first column, third row) is always less than zero. This is because in this situation, the data are simulated with identical underlying means for T_0 and T_1, so the expected difference between T_0 and T_1 is 0, and when the uncertainty discount is applied (to give the 40th percentile of the estimated difference), the result is negative. (It should be noted that this is an average over all simulated datasets, and that a negative value does not result from every single simulation.)
- The creditable SOC change (per hectare) when there is no actual change in SOC (first column, fourth row) is always largest for the smallest number of samples (i.e. nine here), and is largest when the spatial variation is high (red line). This is because if there is no actual change in SOC, then we must rely on chance to return a set of data that give rise to ACCUs being credited. This chance is highest if we collect as few as possible data, and the magnitude of the crediting is largest if there is a lot of variation.

Behaviour when there is temporal change

- In all cases where the actual SOC change was an increase (columns two, three and four), the probability of being credited (bottom row) shows an increase with increasing number of samples. When the spatial variation is large (red lines), the probability of being credited is lowest, while when the spatial variation is very small (green lines), the probability of being credited is close to 1 even for a very small number of samples (n = 9). This behaviour is as would be wanted from a method, in that greater sampling effort results in a resulting smaller uncertainty of estimated SOC change, which is rewarded through a greater chance of being credited.
- In the case of an actual 5% increase (second column) and based on the low spatial variation situations ($c = 0.01, 0.05$; green and cyan lines), the creditable SOC change (per hectare) shows a small increase as the number of samples is increased (from 1.9 to 2.0, and from 1.8 to 1.9). This behaviour is again as would be wanted from a method, with greater sampling effort rewarded. However, based on the high spatial variation situations ($c = 0.25, 0.50$; orange and red lines), the creditable SOC change shows a decrease as the number of samples is increased (from 2.3 to 1.7, and from 3.5 to 2.0). Thus sampling effort is not rewarded, behaviour that might not be as expected for a method. This happens because when the spatial variation is large, with a small number of samples there is a chance of sampling locations being selected that happen to show a large change in SOC (positive or negative), whereas with more sampling locations, this chance is reduced. Since negative values of the uncertainty-discounted SOC change give a creditable SOC change of zero and zero ACCUs (rather than resulting in negative ACCUs), the average crediting over all simulations can be larger than the actual SOC change. When the creditable SOC change is greater than the actual change in SOC, it represents a situation of anti-conservative crediting. With a 5% actual SOC increase, the high spatial variation simulations showed anti-conservative crediting for all tested values of n.
- Similar general behaviour can be observed with a larger actual SOC change of 10% and with the largest spatial variation (column three, row 4, red line), though for the largest actual SOC change of 20% (column 4), the expected creditable SOC change was smaller than the actual change even for all n (i.e. conservative), even with the largest value of the spatial variation.
- Note, the scheme-wide buffer discount of 25% (for risk of reversal and permanence period) has not been applied to the creditable SOC change in these simulations. This discount would take some of the simulated situations from anti-conservative to conservative crediting (e.g. 5% increase, $c = 0.25$, n = 9). However, as noted before, these discounts are specifically for issues other than conservativeness related to uncertainty in the estimated difference arising because of sampling variation, and so are not applied here. The pattern of incentivizing sampling at minimum method requirements in these situations remains the same as shown and as discussed above, whether or not these discounts are applied.

The general features remarked on here were reasonably insensitive to the choices of stratification design and location for extracting the base map (see Supplemental Material for results based the optimistic approach to stratification and based on a base map from a different location)

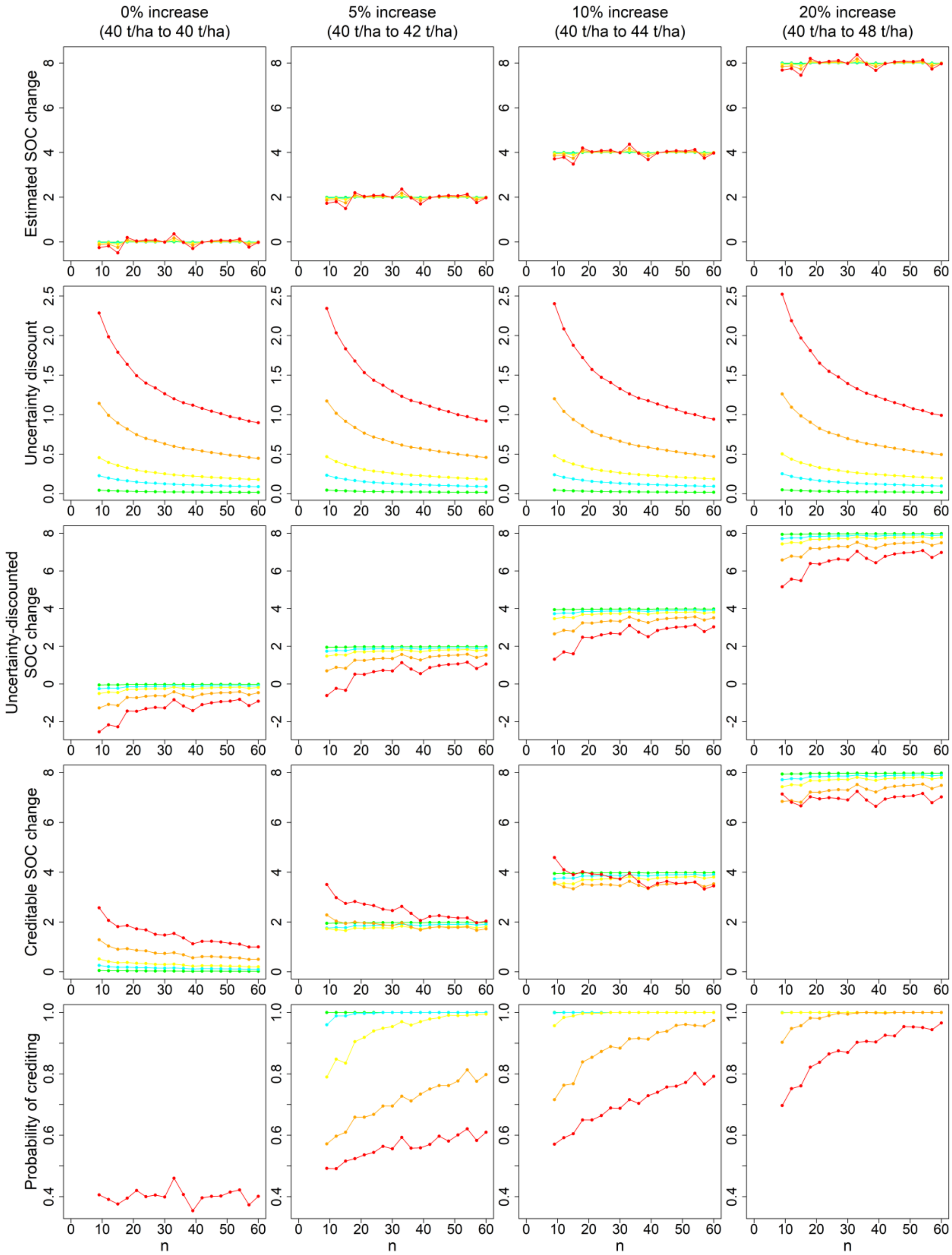

Figure 5 The per-hectare estimated SOC change (top row), uncertainty discount (second row), uncertainty-discounted SOC change (third row) and creditable SOC change (fourth row), and probability of being credited (bottom row) from the simulation study (means over 1000 simulations), based on the basic stratification approach. For each point, data are simulated based on a different set of parameters. The x-axis in each plot shows n, the number of simulated data for each sampling round, T_0 and T_1. The five coloured lines in each plot show data simulated with different coefficients of variation (spatial variation): c = 0.01 (green), 0.05 (cyan), 0.10 (yellow), 0.25 (orange), and 0.50 (red). For all cases, the actual SOC content for T_0 is assumed to be 40 t C / ha. The four columns represent different temporal change in SOC used to simulate the data T_1: no change from T_0 (first column), a 5% increase (second column), a 10% increase (third column), and a 20% increase (fourth column).

4.2 Conservativeness of the method

We can use the simulation results from Section 4.1 to give a point of conservativeness for each situation (i.e. set of simulating parameters, Table 1). That is, for a given percentage increase in SOC ($r = 0, 5, 10, 20\%$ increase from an actual baseline SOC of 40 t C / ha) and spatial variation (coefficient of variation $c = 0.01, 0.05, 0.10, 0.25, 0.50$), we can find the number of sampling points which gives an expected creditable SOC change that is larger than the actual SOC increase. For instance, for the 5% increase situation and with a coefficient of variation of $c = 0.25$, the creditable SOC change (Figure 5; fourth row, second column, orange line) starts off above the actual SOC increase of 2 t C / ha (anti-conservative), and drops below 2 t C / ha (i.e. becomes conservative) for 15 samples and above; thus 15 samples is the point of conservativeness for this situation. For other situations (e.g. all situations with no actual change), there is never a point of conservativeness, while others still (e.g. all situations with an actual increase of 20%) are always conservative (i.e. even with 9 samples, the expected creditable SOC change is less than the actual change in SOC). Note that although the situation with 5% increase and 0.50 coefficient of variation gave a result of 'Never', if *n* were to be increased further (beyond the maximum of 60 samples used here), this situation would get to a conservative result at some point.

Table 1 Sampling point of conservativeness for different situations for the actual increase in SOC and for the standard deviation of measurements. 'Never', shaded red, represents a situation for which all values of n gave anti-conservative results (i.e. expected creditable SOC change exceeded the actual increase in SOC); 'Always', shaded green, represents a situation for which all values of n gave conservative results (i.e. expected creditable SOC change was always less than the actual increase in SOC); a number, shaded yellow, represents the number of samples collected at T_0 and T_1 above which results were always conservative

		Actual increase in SOC			
		0% (40 to 42 t/ha)	5% (40 to 44 t/ha)	10% (40 to 44 t/ha)	20% (40 to 48 t/ha)
Coefficient of variation, *c* (spatial variation)	0.01	Never	Always	Always	Always
	0.05	Never	Always	Always	Always
	0.10	Never	Always	Always	Always
	0.25	Never	15	Always	Always
	0.50	Never	Never	21	Always

4.3 Alternative designs of projects

Figure 6 shows the creditable SOC change (mean over 1000 simulations) for the three scenarios of alternative project designs (Scenario 1 = one project, one CEA: green; Scenario 2 = one project, four CEAs: blue; Scenario 3 = four projects, one CEA per project: red). In the top row of plots (very low spatial variation), there is no evident difference between the three scenarios (there are small differences but not evident at the scale of the plot), with all three giving a creditable SOC change that is very close to the actual SOC change. In the bottom row of plots (very high spatial variation), Scenario 3 generally gives the highest creditable SOC change for any given total number of sampling points for a round, particularly when there is a small or no actual change in SOC.

In the case of no actual change, a coefficient of variation of $c = 0.25$ and a total of 36 sampling points (the minimum sampling requirement for Scenarios 2 and 3), Scenario 3 gave a creditable SOC change (per hectare) of 1.1, while Scenarios 1 and 2 gave expected numbers of 0.7 and 0.4. With these simulation parameters, as the number of sampling points is increased, the expected crediting decreases (i.e. in the case of no actual change and large variation of measurement, it is advantageous to split your carbon farming area into multiple projects and sample at minimum requirements). With Scenario 1 (one project, one CEA), a smaller number of sampling points is permitted (a minimum of 9 points per round); the expected crediting at this minimum requirement was 1.3, larger than the expected crediting of Scenario 3 at minimum sampling requirements. Although this is larger than the expected crediting for Scenario 3 at minimum requirements (1.1), the probability of being credited (Figure 6) under Scenario 3 is larger (0.89 for Scenario 3 at minimum sampling requirements, compared with 0.41 for Scenario 1 at minimum sampling requirements); therefore Scenario 3 might provide a more attractive option for setting up a soil carbon project (from the perspective of a proponent wanting to maximise their expected crediting while having a low risk of not being credited).

The situation of a coefficient of variation of c = 0.25 and a 5% increase in SOC also favoured Scenario 3, with a creditable SOC change of 2.2 from 36 sampling points (i.e. greater than the actual change of 2 t/ha, representing anti-conservative crediting), compared with 2.3 from Scenario 1 at 9 sampling points, but coupled with a higher probability of being credited (0.99 compared with 0.57). This situation also showed (for all Scenarios) decreasing expected credits as the number of sampling points is increased (i.e. favourable to sample at minimum requirements).

Further to the creditable SOC change, we can look at the probability of being credited under the three scenarios (Figure 7). Agreeing with earlier analysis (Figure 5), the probability of being credited under Scenario 1 with no actual change in SOC was always around 0.4 (due to the 60% probability of exceedance). However, the probability of being credited was quite a bit higher under Scenario 3, where even with no actual change the probability was around 0.9. In this case of no actual change, the value of around 0.9 is again due to the 60% probability of exceedance, which can be used to calculate a theoretical probability value of $1 - 0.6^4$=0.87 for the probability of being credited, where the power of 4 is due to splitting the area into four projects.

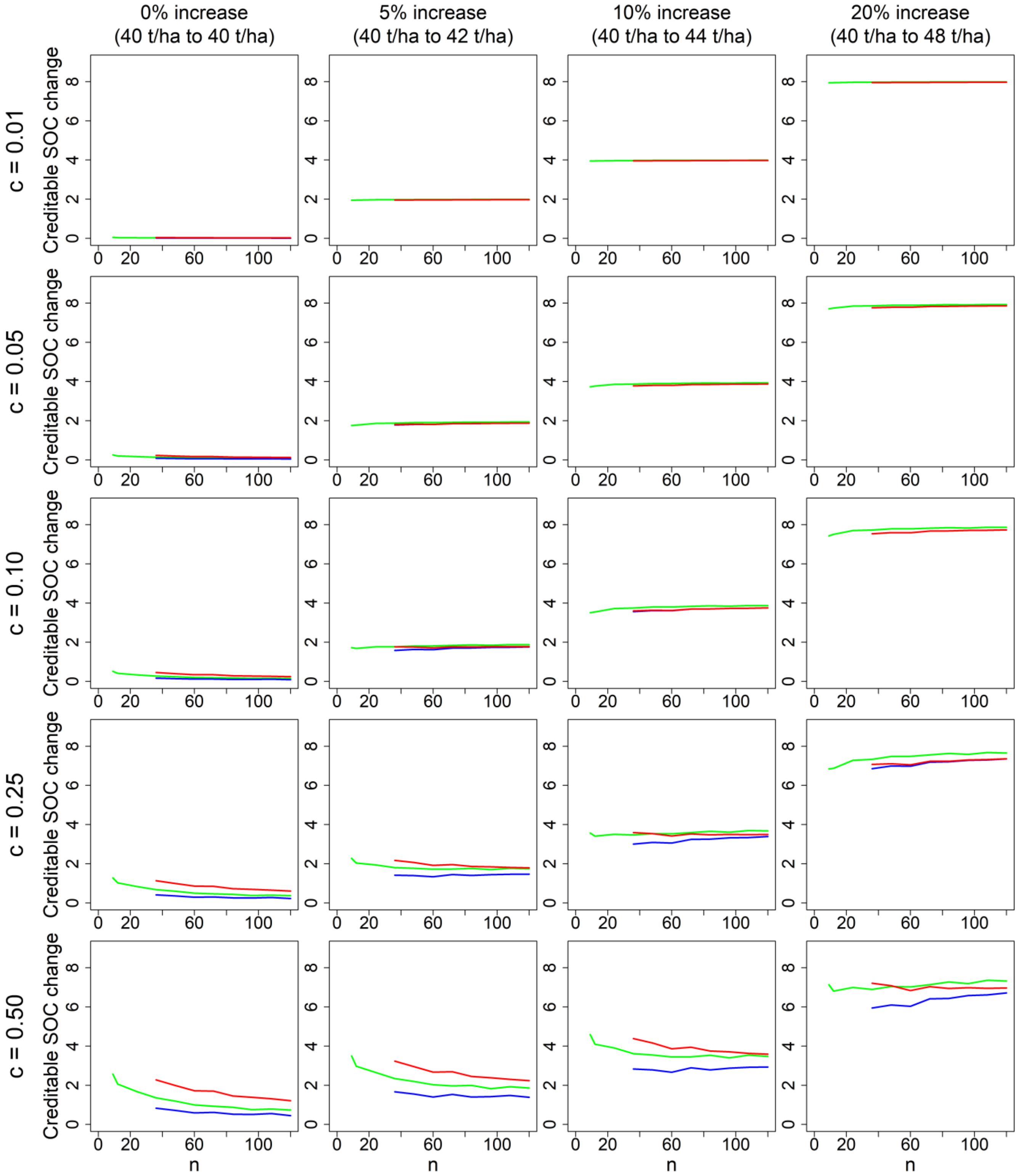

Figure 6 The creditable SOC change (mean over 1000 simulations) per hectare awarded (in a simulation study) under the three scenarios set out in Figure 4 (Scenario 1: green; Scenario 2: blue; Scenario 3: red).

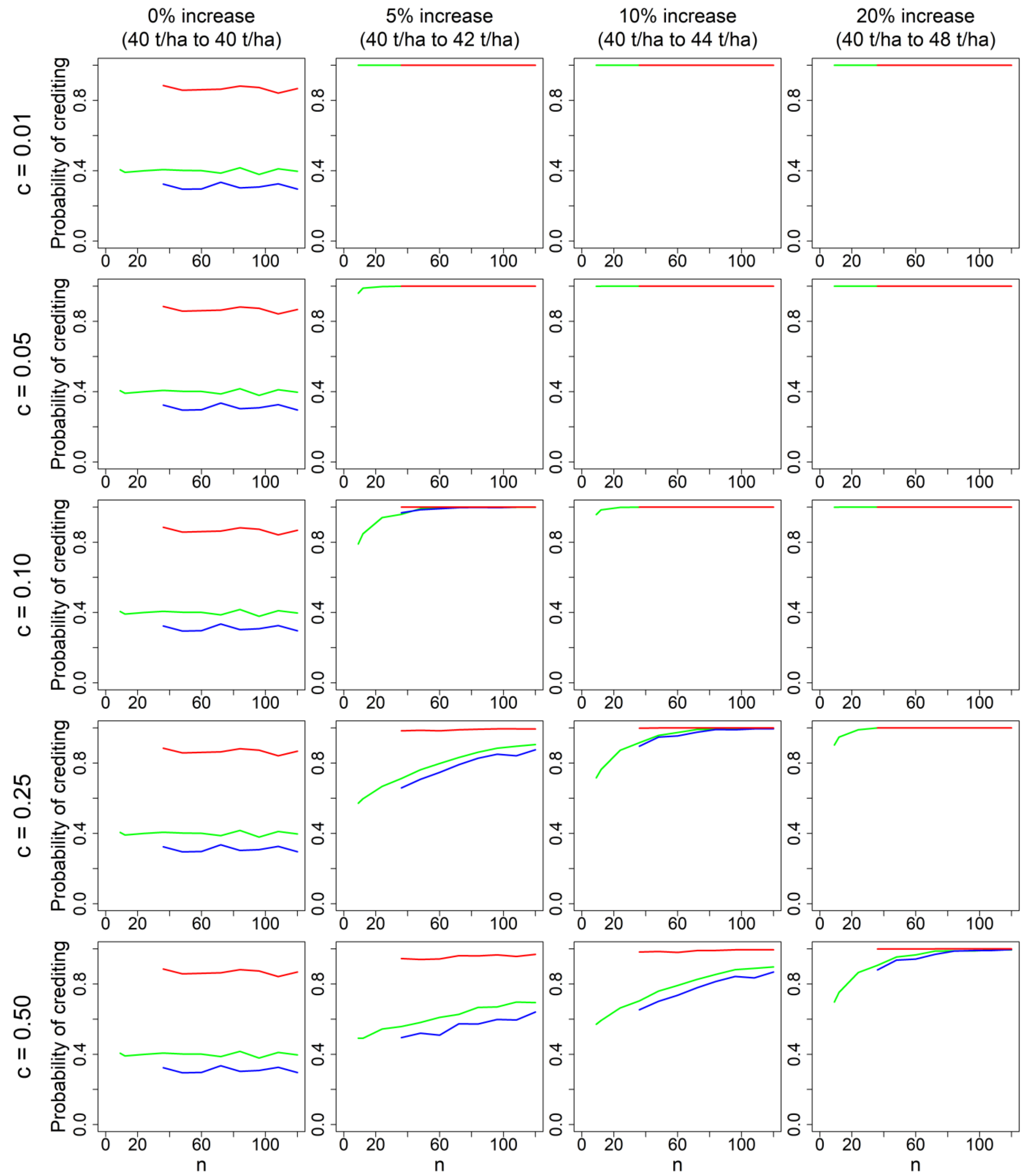

Figure 7 The probability of being awarded ACCUs (in a simulation study) under the three scenarios set out in Figure 4 (Scenario 1: green; Scenario 2: blue; Scenario 3: red).

5 Discussion

The results in this work should flag some potential issues with the soil method, which should warrant further investigation in future and some discussion here.

5.1 Sampling requirements

The soil method is based on a statistical sampling design and analysis that aims to reward more intensive sampling effort by smaller estimation uncertainties, smaller uncertainty discounts, and a resulting larger expected crediting. However, in cases where the spatial variation of SOC stocks is large and the actual temporal change of SOC is small, although the more intensive sampling gives smaller uncertainties and discounts, it also gives smaller expected crediting. This occurs because when estimated (uncertainty-discounted) SOC changes are negative, zero credits are issued and to the best of our knowledge, there is no negative crediting.

The simulation results demonstrated that for the situations with a 0.25 coefficient of variation (a realistic situation based on data from Page et al. 2012 and from Stanley et al., 2023), conservativeness was reached at 15 samples per sampling round for a 5% increase in SOC. Therefore, for that situation, from the perspective of the proponent, it is advantageous for them to sample as few points as possible in order to maximise their expected creditable SOC change and number of ACCUs, which would give an expected creditable SOC change larger than the actual increase in SOC.

To limit the impact of this anti-conservative behaviour (if the issues raised here are considered to represent a material risk), it might be worth considering changes to the minimum sampling requirements of the method, or use an alternative to the 60 percent exceedance value, for instance a 75 percent exceedance value. These choices could possibly depend on the expected temporal change for an activity (possibly depending on the expected temporal change for an activity within a certain timeframe). However, it should be noted that while such changes would reduce the situations in which anti-conservative behaviour arises, there would always remain a possibility of crediting in the situation of no actual change, and without ‘negative crediting’ when a project measures a negative change, it would be impossible to entirely eliminate anti-conservative behaviour in this situation.

It should be noted that we have not considered here whether or not the behaviour of the method and its resulting crediting represents a material risk. We have explored and presented the behaviour; whether this behaviour represents a material risk requires further expert and policy interpretation.

The simulations also confirmed the expected behaviour of the method in the absence of any actual SOC change, with a probability of being credited of 0.4 in this case, arising because crediting is based on the 60% exceedance value (the uncertainty-discounted SOC change).

Results have been presented on a per-hectare basis and as creditable SOC change throughout this work. For a 2500-ha CEA, in the situation of no actual change, a starting SOC stock of 40 t C / ha with coefficient of variation of 0.25, the total expected crediting at minimum sampling requirements (9 samples per round) would be a creditable SOC change of 3200 t C (1.3 t C per hectare) which converts to a total of around 11800 ACCUs (around 4.7 ACCUs per hectare).

5.2 Design of projects

The results from comparing different ways of dividing land into multiple projects suggest that this is another issue that warrants scrutiny, with it being advantageous (from a project proponent’s perspective) to split land into multiple projects in order to maximise the expected crediting, for a given number of sampling points. With land split into multiple projects, this also offers the benefit of providing almost guaranteed crediting, since SOC decreases for projects are not penalised, while the projects that show increases are credited. It might be worth considering including rules in the soil method to credit averages over multiple projects where land has been split into multiple projects rather than multiple CEAs of the same project, so that crediting will be more likely to be conservative.

5.3 Other issues

The work here has focused on the behaviour of the method based on two-point estimates of SOC change, applying the measurement-only approach. However, even if crediting for the two-point estimate was guaranteed to be conservative (i.e. expected crediting smaller than the actual two-point SOC change), this does not attribute that change to management actions. Other work (Mitchell et al., 2024) has highlighted issues with the additionality of the soil method, since credited changes can be due to natural climate variation (e.g. low soil carbon after a long dry period, higher soil carbon expected after wetter periods, better plant growth and more carbon input into the soil) as well as due to management changes. That work recommended extending the minimum measurement period for credit issuance to five years, and including sense-checks of estimated SOC changes based on science-based ‘reasonable bounds’ for expected gains. While it should be noted that the impact of climate variation on additionality is a separate issue to the those around conservativeness investigated in our study, their recommended changes might also go some way to reducing the impact of the issues raised in this work around anti-conservative crediting in situations with small expected SOC gains.

5.4 Limitations

The 2021 soil method includes other features not investigated here. One is the permission to use raster maps to explain some of the spatial variation within strata, using a model-assisted estimation method to estimate the SOC stock and its uncertainty within CEAs that have been sampled. The findings from the current work might have some relevance for the model-assisted approach (for instance, if a map fails to capture the spatial variation within strata, the model-assisted method might be expected to behave similarly to the measure-only approach).

Further to the model-assisted approach, the method also permits a model-measure extrapolation approach, where maps of SOC stock predictions are calibrated using sampled CEAs, and applied to predict stocks for T_1 (and for later sampling rounds) for CEAs that have not been sampled at T_1, applying an extrapolation penalty to increase the associated variance and the uncertainty discount. This approach also has not been considered in the current work.

A regression approach has been considered in past versions of the soil method to fit a linear model through SOC stock data from three or more sampling rounds. It has been suggested that this might be more robust to short-term changes in SOC driven by climate variation (rather than management changes). We haven’t run simulations to look at the impacts of sampling strategies on regression estimates, though we might expect similar general findings to be relevant. For instance, sampling at minimum requirements when there is large spatial variation and small temporal change might be expected to give the largest expected crediting.

The analysis presented in this report has used ‘simulated data’ in the form of maps of ‘known’ maps of the underlying SOC variation (with specified mean and variance), for baseline (T_0) and a subsequent resampling round (referred to as T_1 here), with these maps subsampled (as would be in a soil project) to give data. The subsampled data were used to apply the soil method formulae and calculate the (non-negative) creditable SOC change; this subsampling and set of calculations was repeated to build distributions of outputs, before calculating expected values of those outputs (including the creditable SOC change) over all sets of subsampled data. We tested the robustness of findings to some assumptions about the ‘known’ underlying variation, with similar general findings, although certainly the exact numbers for expected creditable SOC change (and the resulting expected number of ACCUs) would be different. The main conclusions to be drawn from our analysis are around the behaviour of crediting with different assumptions about the spatial variation and temporal change of SOC and with different numbers of samples and designs of projects. This has pointed to a subset of situations (small temporal change, large spatial variation) where the method can behave in a way that might seem counter-intuitive (largest expected crediting with smallest number of samples), but which is understandable given that negative crediting of soil projects does not occur. The aim of this report is to explore and communicate these behaviours, such that any potential loopholes might be addressed. However, this should not be interpreted as an indication of method-wide anti-conservativeness; projects under the soil method will be employing a range of different activities in many different starting conditions with different potential to sequester carbon and different ‘actual’ temporal change and spatial variation of SOC, and the full range of likely projects might be needed when considering method-wide conservativeness.

6 Concluding remarks

The soil method is designed to reward more intensive sampling and the resulting smaller prediction uncertainties by smaller uncertainty discounts and increased expected crediting. However, in some cases (small actual change in SOC, large spatial variation of SOC), this does not happen, and the greatest expected crediting can occur with sampling at minimum requirements for the method (3 strata, 3 sampling points per stratum). The results in this work should flag some potential issues with the soil method, which should warrant further investigation, including the splitting up of land for carbon farming into multiple projects rather than a single project with multiple CEAs. If the behaviour presented in this work is deemed to be a 'material risk', then potential changes to the method to reduce the level of anti-conservativeness in certain situations could include changes to minimum sampling requirements or to discounting. This could include for instance, setting alternative minimum sampling requirements (possibly depending on the expected temporal change for an activity), or using an alternative to the 60 percent exceedance value, for instance a 75 percent exceedance value (again, possibly depending on the expected temporal change for an activity). Whether or not such changes are required would need expert and policy interpretation of results and is beyond the scope of the current work.

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8 Appendix

Results from the second (optimistic) stratification approach, demonstrating similar features to the initial (basic) approach.

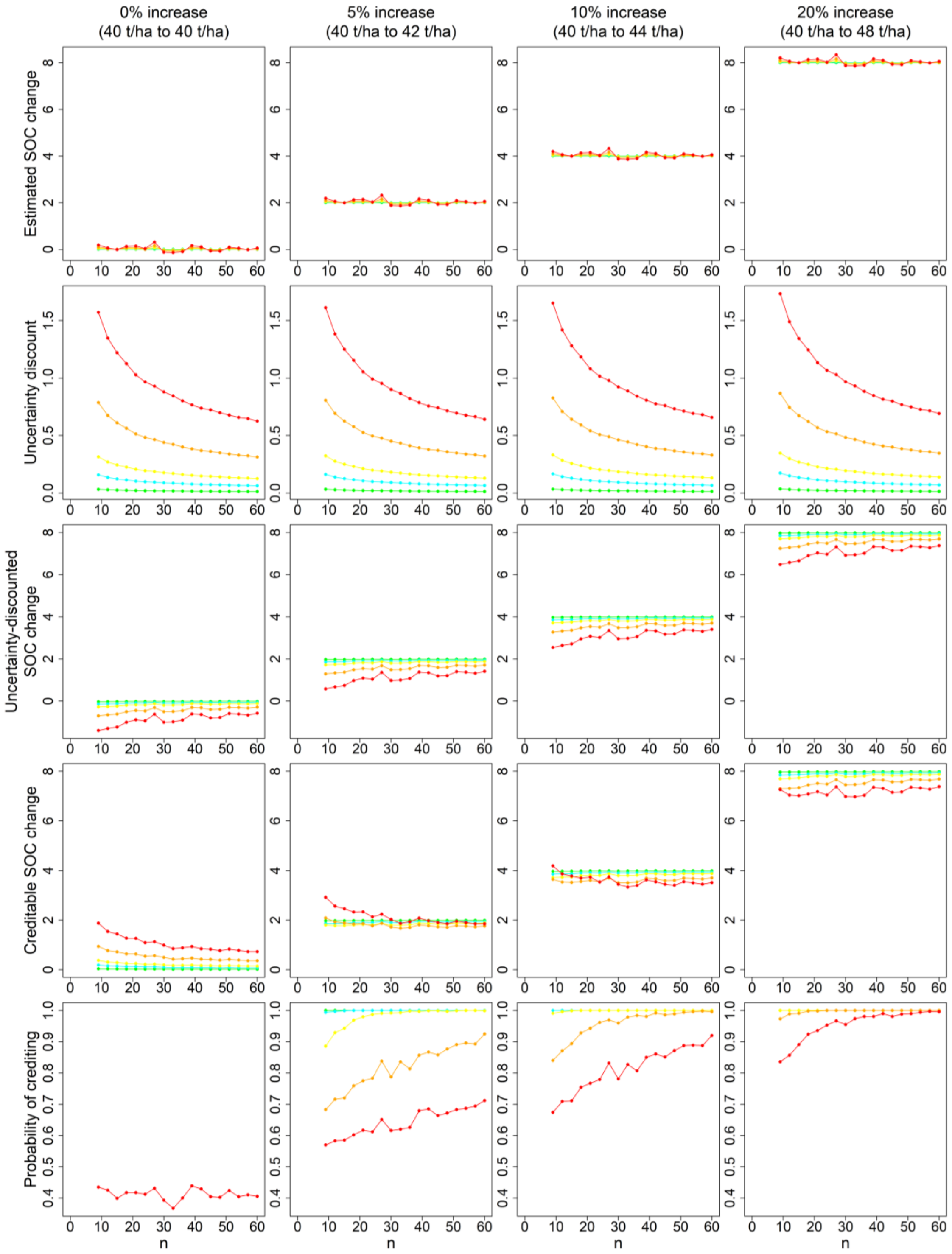

Figure 8 The per-hectare estimated SOC change (top row), uncertainty discount (second row), uncertainty-discounted SOC change (third row), creditable SOC change (fourth row), and probability of being credited (bottom row) from the simulation study (means from 1000 simulations), using the optimistic stratification approach. For each point, data are simulated based on a different set of parameters. The x-axis in each plot shows n, the number of simulated data for each sampling round, T_0 and T_1. The five coloured lines in each plot show data simulated with different coefficients of variation (spatial variation): c = 0.01 (green), 0.05 (cyan), 0.10 (yellow), 0.25 (orange), and 0.50 (red). For all cases, the actual SOC content for T_0 is assumed to be 40 t C / ha. The four columns represent different temporal change in SOC used to simulate the data for T_1: no change from T_0 (first column), a 5% increase (second column), a 10% increase (third column), and a 20% increase (fourth column).

Results from the second location (south-west corner at longitude 145, latitude -27) for extracting the base map, demonstrating similar features to the first location.

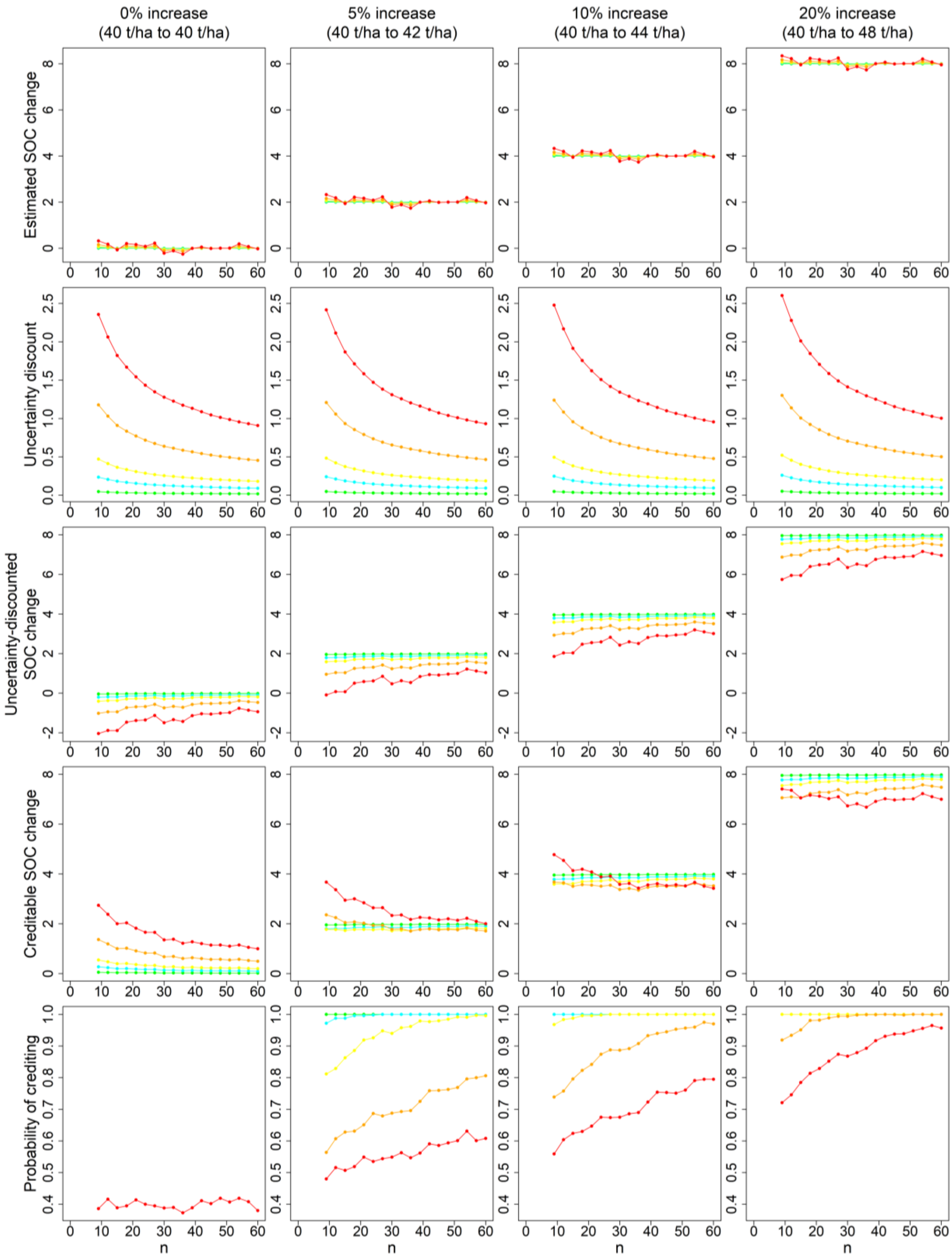

Figure 9 The per-hectare estimated SOC change (top row), uncertainty discount (second row), uncertainty-discounted SOC change (third row), creditable SOC change (fourth row), and probability of being credited (bottom row) from the simulation study (means from 1000 simulations), using the basic stratification approach but with the second location for the base map. For each point, data are simulated based on a different set of parameters. The x-axis in each plot shows n, the number of simulated data for each sampling round, T_0 and T_1. The five coloured lines in each plot show data simulated with different coefficients of variation (spatial variation): c = 0.01 (green), 0.05 (cyan), 0.10 (yellow), 0.25 (orange), and 0.50 (red). For all cases, the actual SOC content for T_0 is assumed to be 40 t C / ha. The four columns represent different temporal change in SOC used to simulate the data for T_1: no change from T_0 (first column), a 5% increase (second column), a 10% increase (third column), and a 20% increase (fourth column).