Carbon*Plus*

Methodology for GHG and Co-Benefits in Grazing Systems v1.0

Regen Network Development, Inc

Authors:	Gisel Booman, PhD- Head of Science
	Ned Horning- Principal *Scientist*
	Sam Bennetts - *Applied Scientist & GIS Developer*
	Sophia Leiker - former *Geosp. Env. Res. & Project Analyst*
	Ron Steinherz - former *VP Product*
Version:	1.0
Last updated:	12/05/2023
Contact:	registry@regen.network/
	https://www.regen.network

Table of Contents

1. Methodology Overview

1.1. Scope

The Carbon*Plus* Methodology for Grazing Systems is intended to provide a holistic assessment of multiple ecological state indicators for grasslands under the practice of prescribed grazing. It can be used by Project Developers and other stakeholders to obtain estimates of Soil Organic Carbon (SOC) stocks within a project area, track changes in SOC stock over time to generate Carbon Credits, and measure additional ecological co-benefits such as animal welfare, ecosystem health, and soil fertility.

The Methodology is intended to assist Project Developers in applying a measurement-based soil organic carbon approach focused on maximizing the accuracy of the estimation of the changes in SOC stocks through time, while minimizing sampling efforts and costs. Soil sampling coupled with remote sensing data or spatial interpolation methods will be used to calculate SOC stocks at different points in time. Soil samples will also be used to assess soil fertility while remote sensing data and peer reviewed literature will enable an assessment for ecosystem health.

The main ecological health indicator assessed in this methodology is:

- CARBON SEQUESTRATION
    - Soil Organic Carbon (SOC) stocks and CO_2 equivalents (CO_2e)

Additional Co-Benefits assessed are:

- SOIL FERTILITY
    - pH
    - Macronutrients
        - Nitrogen, Phosphorus, Potassium
    - Other Soil Cations:
        - Calcium, Magnesium, Potassium, Sodium, Aluminum

- ANIMAL WELFARE
    - Measured using standards aligned with the project area locale

- ECOSYSTEM HEALTH
    - Ecosystem Vigor
        - Normalized Difference Vegetation Index (NDVI)
    - Ecosystem Organization
        - Woody vegetation landscape metrics
        - Protected perimeter of wetlands and watercourses
    - Ecosystem Resilience
        - Bare Soil Estimation (BSI)

1.2. Minimum skills required from the Monitor

This Methodology requires that the Monitoring Team has the following skills and experience:

- Soil sampling experience
- Moderate to strong quantitative spatial analysis and remote sensing skills (e.g. GIS, Google Earth Engine, geostatistics)
- Some experience in GHG accounting and in environmental monitoring. A professional in the area of agronomics, environmental science, soil science or biology is recommended.

1.3. A Measurement-based Soil Organic Carbon Methodology

Several steps are required to estimate the long term changes in soil organic carbon stocks within a project area:

1. Develop a soil sampling plan for the project area according to Section 3.1.
2. Sample collection and preparation
3. Laboratory analysis of soil samples
4. Estimation of SOC stocks for the project area using GIS
5. Converting SOC stocks to CO_2 equivalent stocks
6. Calculating the change in CO_2e stocks between monitoring periods

A general schema for the measurement-based approach to estimate changes in SOC stocks is presented in Figure 1. SOC stocks measured in the first sampling round (i.e. the Baseline), are compared to those calculated in subsequent sampling rounds to quantify changes in carbon stocks after project commencement.

This methodology entails two main alternative approaches for estimating carbon stocks. The first one is an innovative approach based on using sample data coupled with satellite remote sensing data to generate statistical models to estimate the changes in SOC stocks through time. The second approach uses spatial interpolation.

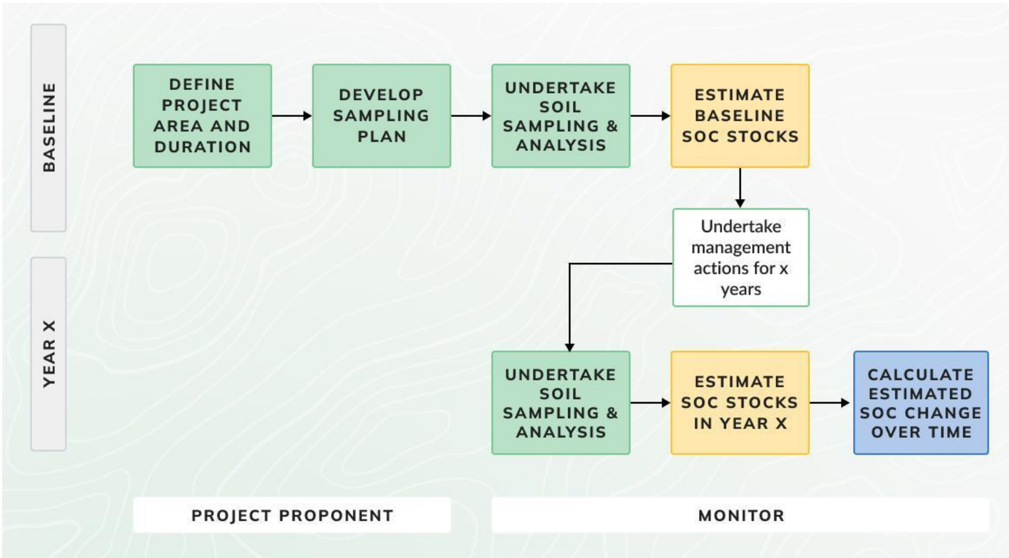


Figure 1: Main Steps for assessing changes in SOC stocks within a project area.

1.4. Co-Benefits

The co-benefits are intended to allow for a holistic assessment of the project area beyond carbon sequestration. The soil fertility, ecosystem health, and animal welfare metrics are chosen based on their widespread use as known, reliable indicators sensitive to the changes in ecological state. The co-benefits will be monitored following the same frequency as the SOC monitoring.

1.4.1. SOIL FERTILITY INDICATORS

Chemical indicators such as pH, macronutrients, soil cations and Cation Exchange Capacity values can be used to assess changes in soil function and are sensitive to variations in management[1]. Thus, chemical indicators will be ranked according to local benchmarks for the project region and project soils (see Section 4).

1.4.2. ECOSYSTEMS HEALTH

Ecosystem health is assessed holistically through the use of context-dependent indicators of ecosystem vigor, organization and resilience (see Section 5).

[1] NRCS USDA Soil Health

1.4.3. ANIMAL WELFARE

The American Veterinary Medical Association[2] defines Animal Welfare as the means by which "an animal is coping with the conditions in which it lives. An animal is in a good state of welfare if (as indicated by scientific evidence) it is healthy, comfortable, well-nourished, safe, able to express innate behavior, and if it is not suffering from unpleasant states such as pain, fear, and distress. Good animal welfare requires disease prevention and veterinary treatment, appropriate shelter, management, nutrition, humane handling, and humane slaughter." Animal welfare evaluations are often locale specific. Regional guidelines and variations should be taken into account during the evaluation (see Section 6).

2. Project Boundary

2.1. Spatial Boundaries

The spatial boundary encompasses all land on which the *Project Proponent* will undertake the *Proposed Activity*. Spatial boundaries defining the project area should be provided by the *Project Proponent* with any parcels or stratification schemes defined. Acceptable polygon data formats include ESRI shapefile OGC GeoPackage, KML/KMZ and GeoJSON.

2.1.1. MASKING FOR GRASSLANDS AREA

To ensure proper estimation of soil organic carbon stocks, any man-made objects such as roads or buildings, as well as any land cover types not included within the bounds of the *Proposed Activity*, such as woody vegetation, water bodies, riverine areas, must be excluded. A mask representing grasslands **under the practice of prescribed grazing** must be provided since this will be used to calculate the amount of carbon sequestered. This mask can be created using GIS and remote sensing tools, land cover algorithms, visual inspection or any other method chosen by the *Monitor* or *Project Proponent*.
The Net area of Grasslands should then be calculated in GIS based on the number of hectares within the mask.

2.2. Temporal Boundaries

The Crediting Term is the finite length of time for which a Project Plan is valid, and during which a project can generate credits. This methodology adheres to a 10-year Crediting Term. The monitoring scheme within the Crediting Term of a project should adhere to the following guidelines:

- The Project Initial Monitoring Date is the date when the baseline sampling round is performed and acts as the starting date of the 10-year Crediting Term.

- The minimum number of sampling rounds for a 10-year crediting term is three (3).

[2] AVMA: Animal Welfare: What Is It?

- Sampling rounds at the beginning of the first year (baseline) and during the last year of the project are mandatory.
- The minimum duration between soil sampling rounds is ten (10) months.
- The end date of the Crediting term will correspond to the date of the last sampling round, and must fall 10 years after the Project Initial Monitoring Date +/- five (5) months.
- The maximum time between sampling rounds is five (5) years.

The examples below outline acceptable soil sampling timelines during the 10-year crediting period.

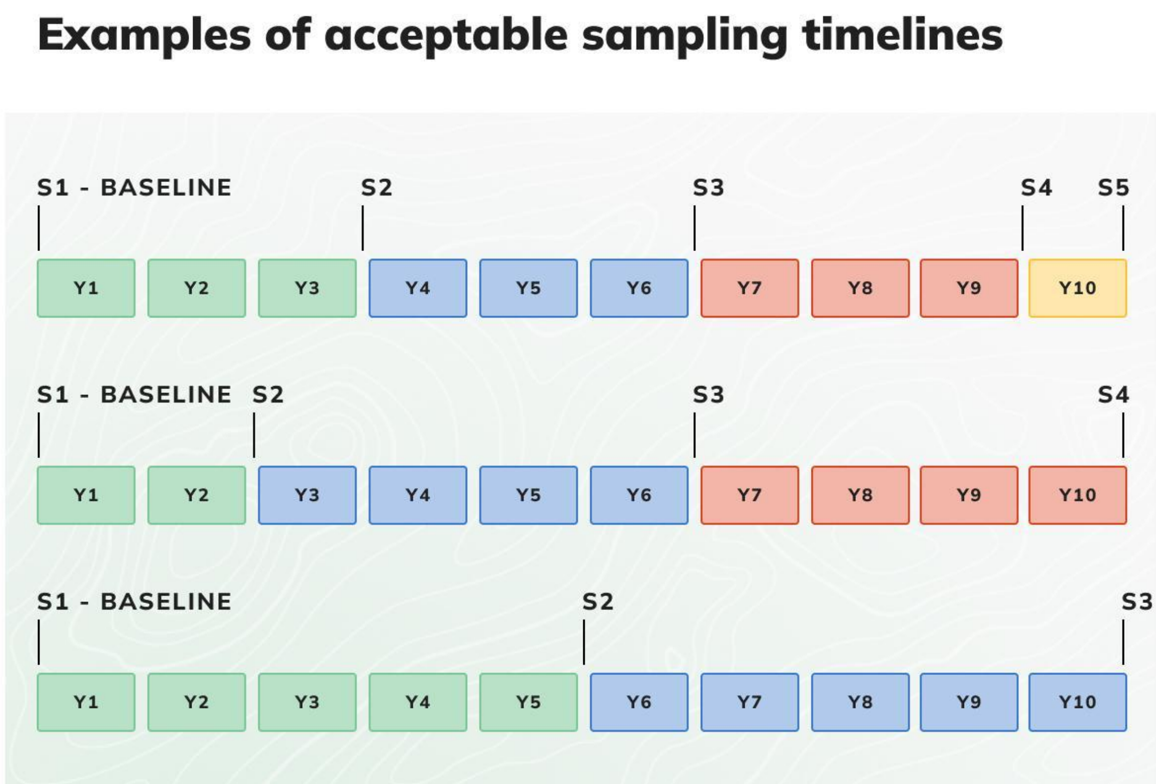


Figure 2: Examples of acceptable sampling timelines. Each crediting period is shown in a different color. The first sampling round is the baseline sampling, which sets "time zero" for the 10-year crediting term of a project. The last sampling round must happen at the end of the 10-year term. Number of years between consecutive sampling rounds is flexible, as long as no longer than five (5) years pass between consecutive sampling rounds.

> *Note: The schema described above can be modified if an extreme climatic event or disaster is declared for the area of the project, in which case please contact the RND Science Team (science@regen.network).*

3. Calculating the Carbon Sequestration and Net GHG Reduction

3.1. Collection of Data

3.1.1. SAMPLE SIZE

The sample size is defined here as the number of samples necessary to detect significant levels of change in the soil organic carbon between sampling rounds. Traditional SOC quantification methods (i.e intensive sampling[3]) often require a much larger sample size than the satellite calibration or spatial interpolation approaches described herein.

The RND Science team developed a specific online calculator for the satellite calibration and interpolation approaches (see Section 3.1.1.1.), to ease the estimation of the sample size for the soil sampling plan. The minimum number of samples provided by the calculator for a project must be met to achieve a reliable and statistically valid level of rigor. Nonetheless, more comprehensive approaches based on previous sampling and/or GIS analysis are preferred if feasible, in which case a brief description along with a valid scientific reference to the specific approach to estimate the sample size should be cited in the report.

Monitoring periods where the number of samples falls below the minimum provided by the RND online calculator could result in a deviation. In this case please contact the science@regen.network.

3.1.1.1. SAMPLE SIZE ESTIMATION FOR SATELLITE CALIBRATION AND SPATIAL INTERPOLATION

Both for the satellite calibration and the spatial interpolation approaches, **the number of samples needed for the soil sampling plan is the same**, and can be calculated by using the Carbonplus Grasslands Sample Calculator V1.0. The Calculator only requires two inputs: the net grassland area in hectares (ha) of the Project, and the level of landscape variability. It then provides a minimum and an optimal number of sampling points for the project.

More detailed information about the underlying concept and equations of the Calculator can be found in the document The RND inc. CarbonPlus Grasslands Sample Size Calculator- Explanatory Document- V 1.0.

Main steps for estimating the sample size:

1. Load the online Carbonplus Grasslands Sample Calculator V1.0
2. Enter the net grassland area (ha) of the Project, as calculated in Section 2.1.1.
3. Determine the Landscape Variability Class:

[3] Conant, R. T., Smith, G. R., & Paustian, K. (2003). *Spatial Variability of Soil Carbon in Forested and Cultivated Sites. Journal of Environment Quality, 32(1), 278.* doi:10.2134/jeq2003.2780

All else equal, areas with higher variability are going to require more samples than areas with less variability[4]. The Landscape Variability Class of the project can be determined according to a set of landscape characteristics, qualitatively assessed by a local expert (ideally an agronomist, biologist or similar background professional with access to the land). Observations from the land stewards should also be taken into consideration. Table 1 can be used as a survey to classify the project area. The final Landscape Variability Class of the project area will be defined as follows:

- **Low Variability:** If at least 4 proxies are ranked as Low, and not more than 1 proxy ranked as high.
- **Moderate Variability:** If at least 3 proxies are ranked as Moderate, and not more than 1 proxy ranked as high.
- **High Variability:** At least 2 proxies are ranked as High.

4. Set the final sample size between the minimum and the optimal numbers provided by the calculator:

   For a given grasslands area and Landscape Variability Class, the Carbonplus Grasslands Sample Calculator V1.0 provides for a **minimum** and an **optimal** sample size:

   - **The *minimum number* is the lowest sample size allowed**. It should still allow for reaching the minimum accuracy of 50%, if best practices in sampling, geolocating and lab analysis are followed, but still could imply large discounts (up to 50%) in the final credits. It also carries a larger risk of not hitting the 50% uncertainty threshold.
   - **The *optimal number* should be preferred, in particular for the first sampling round**, as it lowers the chance of having significant uncertainty discounts (see section 3.6.4.). Having more samples also enables adjusting the sampling size for the following sampling rounds to the desired level of uncertainty and sampling costs.

The *Project Proponent* should analyze trade offs between risks, final revenues, potential uncertainty discounts and sampling costs and define a sampling size that could be somewhere between the minimum and the optimal range.

If prior soil sampling results indicate that lower sampling intensity than the minimum stated by the calculator is sufficient to achieve the minimum accuracy, then exceptions can be considered under the appropriate justification. In this case, please contact the RND Science Team (science@regen.network).

---

[4] Herrick et al., 2009. Volume II: Design, supplementary methods and interpretation. Monitoring Manual for Grassland, Shrubland and Savanna Ecosystems.

Note: The RND Science team highly encourages stratification to achieve better accuracies from the amount of samples estimated by the RND online calculator. Please refer to section 3.1.2 for more information about the stratification process.

Table 1: survey for determining the Landscape Variability Class of the project area.

VARIATION IN SOIL CARBON	LANDSCAPE CHARACTERISTICS
HIGH	• Steep slopes (>20%) are present • More than 3 Soil Types (suborder level) • Diverse vegetation assemblages • Adjacent/ crossed by a waterbody • Large area (> 1,500 ha) • The management history of parcels largely differs. This applies not only for the implementation of regenerative management, but also in the level of intensity of the previous land use. Some areas may have been more degraded than others, and thus the starting point for each parcel differs greatly.
MEDIUM	• Moderate slopes (between 5 and 20%) across a majority of the project area • 2-3 soil types (suborder level) • Similar vegetation assemblages, variable herbaceous species in different areas • Not adjacent to a water body • Medium sized area (500 - 1,500 ha) • In some areas regenerative grazing management has been implemented before others. The land use history of the different parcels has been similar despite differences in stock density, frequency of rotation or dates of implementation. The previous land use was similar across paddocks/ parcels.
LOW	• Flat area (slopes of less than 5%) across a majority of the project area • 1 soil type (suborder level) • Uniform herbaceous vegetation (e.g. open grassland, same species across study area) • Not adjacent to a water body • Small area (< 500 ha) • The same management history has been implemented across the entire project area.

Design considerations:

- It is a good practice to avoid undersampling at the design stage, not only to compensate for any high variance or outliers, but also to prevent a situation at the analysis stage where the required reliability was not achieved and additional soil sampling efforts would be required. The need for additional soil sampling would be expensive, time-consuming, and inconvenient.

- It is highly recommended that several cores (min. 10) are extracted at each sampling location, in order to improve the total accuracy of the results. These subsamples shall be composited per point or analyzed separately. Compositing reduces the sampling cost, but a separate analysis would allow detecting any outliers coming from sample handling or lab analysis. Both options are accepted.

> *Note: If the project does not meet the Minimum Sample Size requirements, or in the case of following the Optimal number of samples but still not achieving the 50% accuracy, please contact the RND Science Team (science@regen.network).*

3.1.2. STRATIFICATION

In statistics, stratified sampling is a technique used to partition the population into subgroups, or strata, based on similar characteristics. Stratified sampling can help reduce the number of samples needed to measure soil fertility by segregating the landscape into subregions which share similar biophysical characteristics. Less samples are needed because the samples collected are representative of soil characteristics across the entire strata.

> *Note: The RND Science team highly encourages stratification to achieve better accuracies from the amount of samples estimated by the RND online calculator in section 3.1.1.1.*

When to stratify?

Stratification is always recommended as it tends to increase the accuracy of the results. Stratification should be applied particularly if:

A. The spatial boundaries provided include a large number of parcels and there is a need to aggregate similar parcels.

B. The parcels provided by the *Project Proponent* have high variability of soils, moisture, vegetation cover, hydrologic conditions, management history or other variables that might be affecting SOC in the topsoil.

How to stratify?

Variables highly correlated to soil organic carbon can be used as proxies to divide the project area into strata. This approach will help establish a sampling plan which covers the full range of percent SOC values, thus providing more accurate stock estimates. Some variables found to be good proxies to spatial variability of SOC at the field scale[5] include:

- **Topographic:** elevation, slope, aspect, erosion, terrain ruggedness Index (TRI) and the multi-resolution valley, bottom flatness index (MrVBF)
- **Land Use / Land cover (LULC):** Vegetation cover, above ground biomass, land management history

[5] Modeling and Stratification Technology Report for the ESMC. Lawrence et al., 2022

- **Satellite Imagery:** Multispectral satellite bands (e.g. Sentinel-2, Landsat TM), NDVI , BSI, NDWI, Tasseled Cap
- **Hydrologic:** topographic wetness index (TWI), catchment area and stream power index (SPI)
- **Pedologic:** soil types, clay content
- **Other:** pH

The project area can be re-stratified at each soil sampling round as improved quality of information becomes available, however at least the minimum number of sample locations estimated by the online calculator must remain consistent between sampling rounds. Additional sampling locations must be recorded as specified in Section 3.1.3.

The monitoring report must specify the methods and variables used to define strata. A geospatial file defining stratified zones used for each sampling round must be provided with each report. Also, any additions or any changes in the sampling points between sampling rounds must be clearly reported.

Useful Resources:

- cLHS - Conditioned Latin Hypercube Sampling[6] [7]
- QuickCarbon Stratifi[8]
- Equal-range stratification[9]
- k-means [20] [10]
- A thorough review of variations on these methodologies authored by Biswas and Zhang (2018)[11].
- Methods to optimize sampling for spatial interpolation[12] [13]

3.1.3. ASSIGNING SAMPLE LOCATIONS

- Soil sample locations must be determined prior to any soil sampling performed.

---

[6] White. 2019. cLHS - Conditioned Latin Hypercube Sampling
[7] Minasny and McBratney. 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information
[8] QuickCarbon Stratification Tool
[9] Hengl et al. 2003. Soil sampling strategies for spatial prediction by correlation with auxiliary maps [20]
Viscarra Rossel and Brus. 2018. The cost-efficiency and reliability of two methods for soil organic C accounting
[10] Brus et al. 1999. A sampling scheme for estimating the mean extractable phosphorus concentration of fields for environmental regulation
[11] Biswas and Zhang. 2018. Sampling Designs for Validating Digital Soil Maps: A Review
[12] Peter Diggle and Søren Lophaven. "Bayesian geostatistical design." Scandinavian Journal of Statistics 33.1 (2006): 53-64
[13] Heuvelink, Gerard BM, Dick J. Brus, and Jaap J. de Gruijter. "Optimization of sample configurations for digital mapping of soil properties with universal kriging." Developments in soil science 31 (2006): 137-151

- Unless a spatial optimization of sample location is followed, geolocations for soil sampling points must be selected at random. GIS tools, such as the QGIS "random points inside polygons tool", can be useful for creating random sampling points.
- If stratification was used, at least three sampling locations must fall within each strata to ensure underlying variations in soil organic carbon are represented.
- Sample locations must remain consistent between sampling rounds, though if sample locations differ, it is crucial to record the GNSS coordinates for the newly sampled locations, as well as specify and justify the changes in the sampling locations between rounds in the report.
- There are various approaches to establishing sample locations using a traditional sampling framework. Please reference the resources provided in Section 3.1.2. and select a sampling plan that is appropriate for the project location, variability and expected analysis approach .

It is recommended that a visual inspection is done based on updated satellite imagery or on the field prior to sending the sampling plan, so that any points that look hard to access or falling over or close to trees, shrubs, roads or other features, are manually moved within a 20m radius from the original geolocation.

3.1.4. EXTRACTING SAMPLES

It is important that samples used for soil carbon quantification follow proper sample collection and preparation procedures. Improper collection or preparation of soil samples can result in substantial errors, which can render the results of expensive sampling rounds unusable and compromise the integrity of the results.
Regen Network provides the following recommendations and requirements to collect soil samples:

1) Prior to core extraction, clear the sample location of living plants, plant litter and surface rocks.
2) The minimum sampling depth for SOC and BD is 30 cm. Justification must be provided if sample depth is shallower than 30 cm. It is recommended to go deeper than just 30cm in the soil profile.
3) The sampling depth must be the same at all sample locations. Where the nominated sampling depth cannot be reached due to bedrock or impenetrable layers, the sampling point should be moved to a better spot within a 20m radius and the new geolocation point must be recorded.
4) The sampling depth must be consistent between all sampling rounds (i.e if samples are collected at 30cm depth for the baseline, samples must also be collected at 30cm for following sampling rounds).
5) A GNSS receiver with a minimum accuracy of 4 meters must be used to record the sampling point in the field. The GNSS model must be reported in the monitoring report. If the minimum accuracy of 4 meters requirement is not met by the device, the Monitor should explore options like the point averaging method to improve accuracy.
6) For soil carbon and soil fertility parameters from the topsoil layer (0-30cm depth), it is a requirement that at least 3 subsamples are collected and composited at each sampling

point, although it is recommended that 10 or more subsamples are extracted at each sampling point (i.e. within the 4m radius) to generate the composite samples.

7) When deeper soil layers are also sampled (i.e. deeper than 30cm), a separate set of samples will be extracted at each sampling point for the deeper depth. Compositing several samples per point for the deeper layer is still recommended, although it might be unfeasible under certain conditions of soils and/or due to limitations from available tools and resources. At least one sample must be taken from the deeper layer at each sampling point to be analyzed for SOC and bulk density, and for soil fertility when it corresponds, matching the same sampling points (30%) selected for the topsoil layer sampling.
8) For bulk density, only one core at each sampling point would suffice, following recommendations in section 3.2.1.1. and 3.2.1.2. The sampling depth must match the depth from the soc% samples. If deeper soil layers are sampled, take separate cores for the topsoil layer (0-30 cm) and for the deeper soil layer (30-x cm),
9) For bulk density, it is NOT recommended to use small core samplers or rings (less than 5 cm in diameter) because they might compress the sample within. A diameter of 7.62cm (3-inch) would be ideal.
10) Samples must be taken at least 10 meters away from any tree, shrub, structure, or body of water, as well as from any animal paths. If there´s any modification in the original geolocation of the samples, the new geolocation must be recorded.
11) Report the day, month and year for each sample collected within the given sampling round. We recommend writing several labels per sample, including at least one paper strip with pencil (graphite) to be included within the sample bag.
12) Please contact your lab for in-depth recommendations for soil sampling and handling, considering the requirements from this Methodology. Usually, each laboratory has specific soil sample collection instructions.
13) Please check in advance if the benchmarks that would be used for soil fertility for your project match the sampling depth for SOC and BD. Otherwise, you will need to generate separate samples for soil fertility at each sampling point for the depth that matches your local benchmarks (see whole section 3.2.1. below)
14) It is a requirement that all sampling rounds occur at least 6 months after the application of non-synthetic fertilizer.

15) Regen Network´s Science team strongly advocates that users choose a laboratory that is certified in their local area, or a part of a land-grant institution, and keep the same laboratory and analysis throughout the project lifetime.

There is a useful list of the data that will be needed for the reports in Supplement 3 of this Methodology, that should be reviewed in advance to the sampling round.

3.2. Sample Analysis

3.2.1. WHAT TO MEASURE?

To quantify SOC stocks, there are mainly two ways to account for the spatial and temporal variability of bulk density: the Fixed Depth (FD) approach, and the Equivalent Soil Mass approach

(ESM) [14, 15]. This Methodology follows the Fixed Depth approach as the default. The Equivalent Soil Mass (ESM) approach can be alternatively implemented, in which case the exact procedure for infield measurements, sample analysis and calculations of stocks must be well documented in the report, and follow robust scientific references. The chosen approach must be consistent across all sampling periods, including the baseline.

Following the FD approach, three metrics are required to quantify the SOC stocks: SOC concentration (i.e. %), bulk density, and sampling depth (eq. 6, section 3.3.1.2). Under this Methodology, sampling depth must be constant for all samples and vintages, and both percent SOC and bulk density must be measured from every soil sample, at every point in time.

Additional metrics to assess soil fertility are required from a smaller subset (30%) of the total number of samples. In the case of stratification, there must be a representative number of this 30% pool of samples from each strata.

- **All soil samples must be analyzed for:**
    1. Percent soil organic carbon
    2. Bulk density
    3. Gravel content, when soil has >10 % gravel or the stones are >2 cm [16]

- **30% of the samples randomly chosen, will be also analyzed for:**
    1. pH
    2. Macronutrients
        a. Phosphorus
        b. Potassium
        c. Nitrogen (at least one of the following)
            i. Total Nitrogen
            ii. Nitrate Nitrogen
            iii. Ammonium Nitrogen
    3. Soil Cations: at least three (3) of the following:
        a. Calcium
        b. Magnesium
        c. Potassium
        d. Sodium
        e. Aluminum

Important: Please check in advance to the sampling date whether there are local benchmarks that could be used for the chosen soil fertility indicators for the same depth of the SOC sampling. In some cases, the information available might correspond to samples collected at a different depth

[14] Wendt, John & Hauser, S.. (2013). An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. European Journal of Soil Science. 64. 10.1111/ejss.12002.
[15] FAO. 2019. Measuring and modeling soil carbon stocks and stock changes in livestock production systems: Guidelines for assessment (Version 1). Livestock Environmental Assessment and Performance (LEAP) Partnership. Rome, FAO. 170 pp.Licence: CC BY-NC-SA 3.0 IGO.
[16] Coughlan, K., Cresswell, H., & McKenzie, N. (2002). Soil Physical Measurement and Interpretation for Land Evaluation . CSIRO PUBLISHING

(e.g. 20 cm) and thus the samples for soil fertility would need to be collected separately, matching the depth of the benchmarks.

Additional local parameters that are relevant to the project location and management activity can be included in the soil fertility assessment. Benchmarks for these indicators must be clearly indicated. More details on this process can be found in Section 4.

In terms of which analytical procedures should be followed for each parameter, we will defer to the local experts to choose the best options within the local possibilities. We recommend that standard and well accepted procedures are followed in order to avoid avoidable errors and potential negative criticism about the credits.

> *Note: It is required that the same analytical procedures and service laboratory are used across all sampling events, to reduce additional errors from calibration bias or changes in the analytical techniques. Exceptions are allowed under strong justification: i.e. the laboratory shuts down, or stops providing the service.*

3.2.1.1. BULK DENSITY

Bulk density quantification may require the collection of a separate set of soil samples at each sampling point. The depth of sampling for bulk density must match the depth of sampling for the SOC%.
The volume of the sample will be calculated based on the number of cores (in the case of a composite sample per sampling point), the diameter of the coring device used, and the sampled depth (Equation 4). This volume can be used in the Soil Bulk Density equation below (Equation 5) to calculate bulk density. Check that units are appropriately converted to cm to ensure accurate bulk density measurements.

$$Total\ Soil\ Volume(cm^3) = number\ of\ cores * \pi * (Core\ Radius)^2 * Sample\ Depth \qquad \text{(Eq.4.)}$$

$$Soil\ Bulk\ Density\ (g/cm3) = \frac{Dry\ Soil\ Weigh}{Total\ Soil\ Volume} \qquad \text{(Eq. 5.)}$$

3.2.1.2. GRAVEL CONTENT

If the soil typically has a significant rock or gravel content (i.e. when soil has more than 10 % gravel or the stones are >2 cm), then it is recommended that the coarse particle fraction is determined to allow for a correction in the estimation of carbon stocks using eq. 6 (section 3.3.1.2). In rocky soils[17], avoiding this step might lead to an increased error in the stocks calculations.

3.3. SOC Stocks Calculations

Once data for the SOC% and bulk density is retrieved from the lab for each sampling point, there are three different procedures that could be used to quantify the SOC stocks for the project area:

---

[17] Coughlan, K., Cresswell, H., & McKenzie, N. (2002). Soil Physical Measurement and Interpretation for Land Evaluation . CSIRO PUBLISHING

A. To calibrate remote sensing data based on correlations between SOC % and the corresponding spectral data from sampling points. In this case, a SOC% map is created based on the resultant model, and so a bulk density map needs to be created separately through interpolation or pedotransfer functions, to be able to calculate the carbon stocks through map algebra (Fig. 3.A.).
B. To calibrate remote sensing data based on correlations between SOC stocks at sampling points and the corresponding spectral data. In this case, SOC stocks are estimated in advance at each sampling point based on the corresponding SOC%, bulk density and sampling depth data (Eq. 6). A map of SOC stocks is created based on the resultant model, which is then used to quantify the total SOC stocks within the managed grasslands in the project area (Fig. 3.B).
C. To estimate SOC stocks at point locations and interpolate those values to calculate the total stocks for the project area (Fig. 4).

Section 3.3.1 outlines the two remote sensing-based approaches (A and B, Fig. 3).
Section 3.3.2 outlines the spatial interpolation alternative (C).
Section 3.3.3 provides for the steps to estimate the final total carbon stocks for the project at a given time.

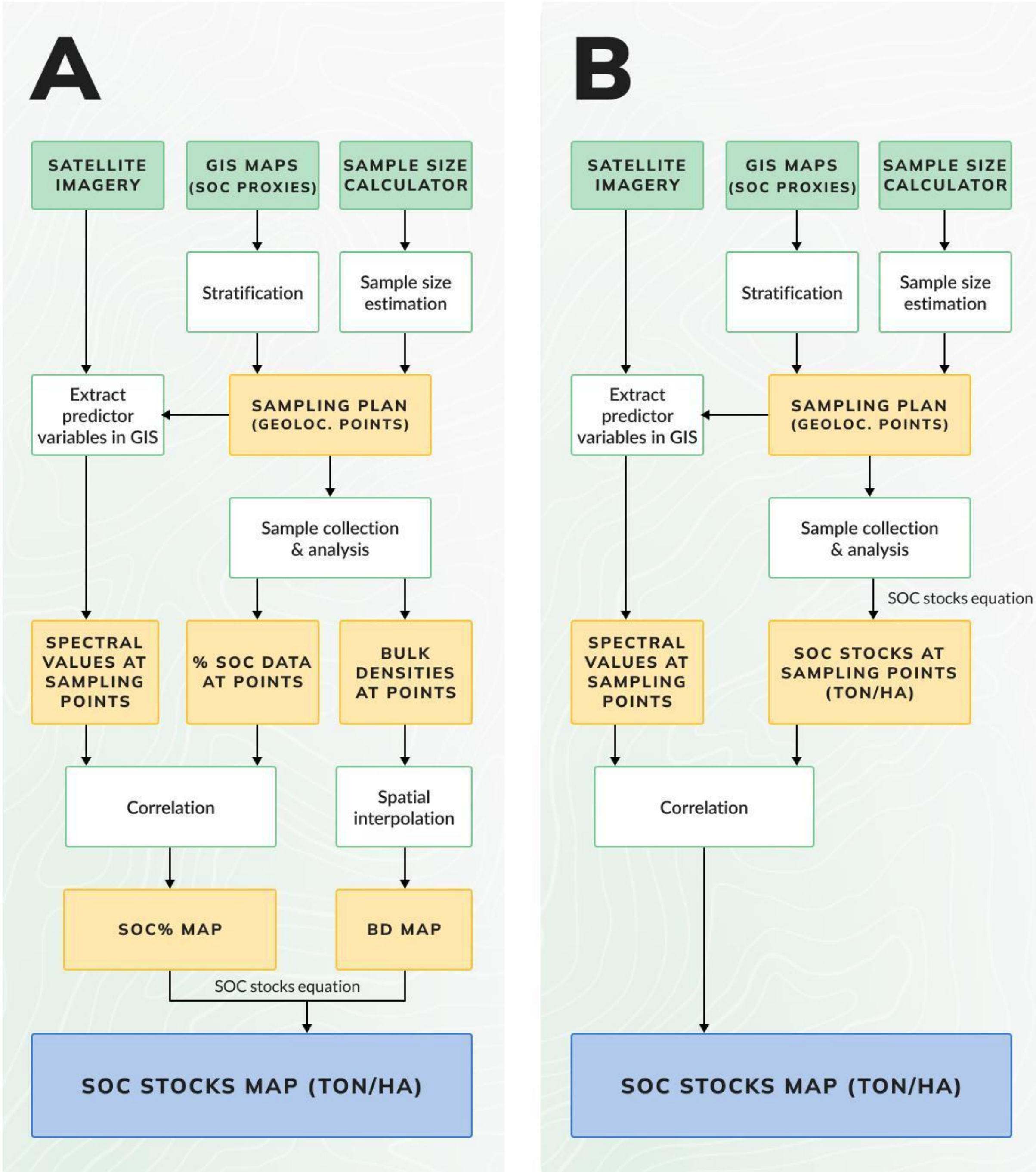


Figure 3. General Methodology for Soil Organic Carbon monitoring using Satellite Remote Sensing coupled with sampling. Soil organic carbon stocks can be quantified based on: (A) correlations between spectral values and SOC% values, or (B) correlations between spectral values and SOC Stock values.

3.3.1. CALCULATING SOIL ORGANIC CARBON STOCKS USING A SATELLITE CALIBRATION APPROACH

This methodology was originally developed inhouse by the Regen Network Science team based on correlations found between several sentinel-2 bands and SOC data from Australian rangelands under AMP grazing, and further testing at some Argentinean and US rangelands with natural grasslands vegetation cover. There are several scientific studies that further support our findings, some of them highlighted by a review done by Angelopoulou et al (2019)[18]. Gholizadeh *et al.* (2018)[19] proved the advantages of Sentinel-2 to derive high-quality information on variations in SOC compared to airborne sensors. Castaldi *et al.* (2019)[20] illustrated that the spatial resolution and spectral characteristics are adequate to describe SOC variability both within field and at a regional scale. Similar findings were provided by Vaudour *et al.* (2019)[21]. Although some of these studies were more focused on the analysis of bare soil areas, in a more recently published study from Ayala Izurieta *et al.* (2022)[22] SOC stocks at the herbaceous páramo ecosystem (central Ecuador) were highly correlated with the Sentinel-2 bands and indices that link to the aboveground biophysical characteristics and their dynamics.

Because of the innovative and nascent nature of this methodology, its applicability limitations remain unknown, so it cannot be ensured that such correlations will be found for all the ecoregions or rangeland management systems of the world or under all the climate conditions. In cases where this approach does not achieve the minimum accuracy requirements, the Monitor should implement the interpolation approach explained in section 3.3.2.

3.3.1.1. EXTRACTING SPECTRAL VALUES AT SAMPLING POINTS

Satellite imagery and other remote sensing data can be paired with percent SOC values or SOC stocks values from collected soil samples to train statistical models which can be used to estimate SOC stocks at unsampled locations. The GNSS coordinates recorded at soil sample locations tie the two datasets together. Imagery used for the remote sensing approach must have a spatial resolution of 20 meters or finer, and good spectral resolution. Ancillary data, such as digital elevation models (DEMs), pedologic maps, and derived indices may also be used for analysis. Tables 2 and 3 provide examples of data which could be used for analysis.

---

[18] Angelopoulou, T.; Tziolas, N.; Balafoutis, A.; Zalidis, G.; Bochtis, D. Remote Sensing Techniques for Soil Organic Carbon Estimation: A Review. *Remote Sens.* **2019**, *11*, 676. https://doi.org/10.3390/rs11060676

[19] Gholizadeh, A.; Žižala, D.; Saberioon, M.; Borůvka, L. Soil organic carbon and texture retrieving and mapping using proximal, airborne and Sentinel-2 spectral imaging. Remote Sens. Environ. **2018**, 218, 89–103.

[20] Castaldi, F.; Hueni, A.; Chabrillat, S.; Ward, K.; Buttafuoco, G.; Bomans, B.; Vreys, K.; Brell, M.; van Wesemael, B. Evaluating the capability of the Sentinel 2 data for soil organic carbon prediction in croplands. ISPRS J. Photogramm. Remote Sens. **2019**, 147, 267–282.

[21] Vaudour, E.; Gomez, C.; Fouad, Y.; Lagacherie, P. Sentinel-2 image capacities to predict common topsoil properties of temperate and Mediterranean agroecosystems. Remote Sens. Environ. **2019**, 223, 21–33

[22] Ayala Izurieta, J.E., Jara Santillán, C.A., Márquez, C.O. *et al.* Improving the remote estimation of soil organic carbon in complex ecosystems with Sentinel-2 and GIS using Gaussian processes regression. *Plant Soil* **479**, 159–183 (2022). https://doi.org/10.1007/s11104-022-05506-1

Table 2. Sentinel-2 bands and their corresponding wavelengths.

Band	Resolution	Central Wavelength	Description
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Red Edge 1
B6	20 m	740 nm	Red Edge 2
B7	20 m	783 nm	Red Edge 3
B8	10 m	842 nm	Near Infrared (NIR)
B8A	20 m	865 nm	Red Edge 4
B11	20 m	1375 nm	Short Wave Infrared 1 (SWIR 1)
B12	20 m	1610 nm	Short Wave Infrared 2 (SWIR 2)

Table 3. Ancillary data from remote sensing indices, topographic variables and soil data.

Name	Description	
Normalized Difference Vegetation Index (NDVI)	NDVI is a measure of vegetation health	Equation: $\frac{NIR-Red}{NIR+Red}$
Normalized Difference Moisture Index (NDMI)	NDMI is a measure of vegetation water content	Equation: $\frac{NIR-SWIR}{NIR+SWIR}$
Bare Soil Index (BSI)	BSI identifies bare ground cover within a landscape	Equation: $\frac{((Red+SWIR) - (NIR+Blue))}{((Red+SWIR) + (NIR+Blue))}$
Normalized burn ratio 2 (NBR2)	NBR2 is used to detect burn scars on the landscape	quation: $\frac{SWIR1 - SWIR2)}{SWIR1 + SWIR2)}$
Soil-adjusted Total Vegetation Index (SATVI)	SATVI is a vegetation index that reduces sensitivity to effects from soil	quation: (SWIR1-Red)/(SWIR1+Red+L)*(1+L) - (SWIR2/2) here L=1 (or 0.5)
Elevation	Elevation is a measure of the distance above sea level	Elevation
Slope	Slope represents the rate of elevation change from a digital elevation model	Elevation
Aspect	Aspect measures the slope direction	Elevation
Topographic Wetness Index (TWI)	TWI is a measure of topographic control on hydrological processes	TWI = ln(a/tan b) Where: a = upslope contributing area (m2) and b= slope in radians

Percent Silt	A measure of the composition of silt in the soil from 5-15cm and from 15-30cm	NA
Percent Clay	A measure of the composition of clay in the soil from 5-15cm and from 15-30cm	NA

The workflow below outlines the method to calculate SOC stocks using Sentinel-2 imagery and ancillary data, however other high resolution imagery, such as PlanetScope, WorldView, or GeoEye, can be used. All images and ancillary data included in the analysis should be specified, and any preprocessing steps must be well researched, checked, and documented by the *Monitor* to assure the highest quality results.

1. Sentinel-2 surface reflectance (BOA) imagery with a sensing date +/- 6 months around the sampling date should be used. It is highly recommended cloud free images be used as cloudy images often affect results even if clouds don't directly cover the study area. The *Monitor* must document any preprocessing tasks performed on Sentinel-2 tiles used for analysis.
2. Typically multiple Sentinel-2 images are available within a +/- 6 month period. So, it is recommended to analyze several images independently to find the best correlations from the whole time series.
3. Ancillary data such as the variables listed in Table 3 does not have to fall within the +/- 6 month sensing period as long as no significant change in the variable has occurred.
4. The QGIS[23] Point Sampling tool (or analogous tool) could be used to extract remote sensing data at each sampling location. This data should be exported and paired with soil organic carbon percentage and bulk density values, or directly to the SOC stocks per unit area (ton/ha), according to the approach followed (see section 3.3.1.2. options A and B below).

3.3.1.2. Option A. CORRELATION BETWEEN SOC PERCENTAGE AND REMOTE SENSING DATA

In this case, the remote sensing model is based on the relationship between spectral data and the SOC% values at sampling points, instead of using the stock values. The output is a SOC% map of the project grasslands area that must be combined with a bulk density map in order to estimate the SOC stocks (Fig. 3.A., in section 3.3.1.).

The following steps 1 to 3 outline how to calculate the total SOC stocks for a given sampling round:

Step 1: Creating the SOC% raster

[23] Point Sampling Tool Plugin for QGis

The first step is to find the most accurate model to predict SOC% values based on the sampled data and the remote sensing data from the project area, for the corresponding sampling round. Models should be applied to the dataset created in Section 3.3.1.1(4) to uncover correlations between estimated SOC percentages and remote sensing data from the sampling points. Various machine learning techniques, such as basic regression, boosting, random forests, and deep learning, could be used for forecasting SOC% values at unsampled locations within the project area. The Monitor retains the flexibility to choose any approach, accompanied by a comprehensive report detailing the chosen method, metrics employed for accuracy assessment, and the rationale behind selecting a particular model.

I) **Basic Regression**: Multiple linear regression and non-linear regression models can be fit to the Sentinel-2 image bands and other predictor variables included in analysis. Once models have been generated for all bands, model accuracy should be evaluated following section 3.6.4. The model with the highest predictive accuracy should be selected to predict SOC% throughout the project area, prioritizing smaller errors over higher R^2 values when there is divergence. Design considerations:

   - Outliers can be removed, but the methods used and a justification must be included in the report. Outlier removal should be performed only under exceptional circumstances by using standard statistical techniques such as external studentized residuals, z-scores, or box plots. Removing too many outliers may result in overfitting and can compromise the size and reliability of the dataset, so any outlier removal must be justified by the *Monitor* in the report.
   - The maximum possible value of SOC% from the output map should be clipped to the maximum SOC% value from the samples from the Project Area. This is a conservative measure that prevents overestimations beyond the range of input values that were used to generate the model.

> *Note: See Supplement 2 for information and resources on automation tools which can be used to help carry out a multiple regression analysis.*

II) **Other Machine Learning**: In contrast to basic regression models which rely on prior assumptions about the relationship between predictor and the response variables, many machine learning models don't require prior assumption knowledge. These types of models can be useful in more complex study areas by discovering patterns that more basic regression models might overlook. It is important to note, however, that many machine learning models tend to perform best with large training data sets and this constraint will limit the cases when use of machine learning models are justified. The model accuracy will be evaluated following section 3.6.4.

The selected model will be run based on the corresponding Sentinel-2 bands and/or ancillary data rasters from the whole project grasslands area to estimate SOC% at the unsampled pixels. The raster output from this step is a map for the entire project area, where each pixel has a value of SOC% .

Step 2: Creating the bulk density raster

Bulk density can be estimated using one of the following approaches:

I. **Spatial interpolation:** Spatial interpolation algorithms such as kriging, regression kriging, Inverse Distance Weighting (IDW), or splining can be used to estimate bulk density values at unsampled locations. We recommend trying several, and choose the best result. The resulting bulk density estimates should be scored and assessed following section 3.6.4. The spatial interpolation method used should be specified by the *Monitor.*

II. **Pedotransfer functions:** Pedotransfer functions (PTF) relating percent soil organic carbon to bulk density may be used as a method to generate a bulk density raster for the project area. The pedotransfer function used should be supported by peer reviewed literature and assessed by comparing PTF estimates with bulk density values collected during sampling.

Step 3: Creating the SOC Stocks raster

Soil organic carbon stocks are calculated through map algebra by applying Equation 6 to the percent soil organic carbon and bulk density rasters, using soil sampling depth as a constant:

$$\textbf{SOC stock(ton/ha)} = \textbf{SOC\%} \times \textbf{BD (g/cm3)} \times \textbf{Soil Depth (cm)} \qquad \text{(Eq. 6)}$$

The raster output from this step is a SOC stock map for the entire project area, where each pixel has a value of SOC stock in ton/ha.

For example, if sampling depth was 30cm, for a pixel with a SOC% value of 4% and a bulk density of 1.3 g/cm3 then the output SOC stock will be 156 ton/ha.

3.3.1.2. Option B. CORRELATION BETWEEN SOC STOCKS AND REMOTE SENSING DATA

In this case, the remote sensing model is based on the relationship between spectral data and the SOC Stock values at sampling points. The output is a SOC stock map that is used to estimate the total stocks of the project grasslands area (Fig. 3.A., in section 3.3.1.).

The first step is to estimate SOC stocks per sampling point. The general equation for calculating SOC stocks is:

$$\textbf{SOC stock (ton/ha)} = \textbf{SOC\%} \times \textbf{BD (g/cm3)} \times \textbf{Soil Depth (cm)} \qquad \text{(Eq. 6)}$$

For rocky soils (i.e. when soil has more than 10 % gravel or the stones are >2 cm), it is recommended that the equation includes a coarse particle (CP) correction factor as follows:

$$\textbf{SOC stock (ton/ha)} = \textbf{SOC\%} \times \textbf{BD (g/cm3)} \times \textbf{Soil Depth (cm) x (1- CP/100)} \qquad \text{(Eq. 6bis)}$$

Where CP is the coarse particle fraction, in percentage.

So, based on the sampling depth, the SOC% and the bulk density data provided by the laboratory , a SOC stock value can be calculated for each point.

For example, for a sampling point with a SOC% value of 4%, a bulk density of 1.3 g/cm3 and a sampling depth of 30cm, the estimated SOC stock would be = 4 1.3*30= 156 ton/ha.*

Models should be fit to the dataset created in Section 3.3.1.1(4), to detect correlations between the estimated SOC stocks at the sampling points and the corresponding remote sensing data. Various machine learning techniques, such as basic regression, boosting, random forests, and deep learning, could be implemented for forecasting SOC% values at unsampled locations within the project area.

I. **Basic Regression**: Multiple linear regression and non-linear regression models can be fit to the Sentinel-2 image bands and other predictor variables included in analysis. Once models have been generated for all bands, model accuracy should be evaluated following section 3.6.4. The model with the highest predictive accuracy should be selected to predict SOC stocks throughout the project area. Design considerations:
    - Outliers can be removed, but the methods used and a justification must be included in the report. Outlier removal should be performed using standard statistical techniques such as external studentized residuals, z-scores, or box plots. Removing too many outliers may result in overfitting and can compromise the size and reliability of the dataset, so any outlier removal must be justified by the Monitor in the report.
    - The maximum possible value of SOC stock (ton/ha) from the output map should be clipped to the maximum SOC stock value from the samples from the Project Area. This is a conservative measure that prevents overestimations beyond the range of input values that were used to generate the model.

Note: See Supplement 2 for information and resources on automation tools which can be used to help carry out regression analysis.

II. **Other Machine Learning:** In contrast to basic regression models which rely on prior assumptions about the relationship between predictor and the response variable, many machine learning don't require prior assumption knowledge. These types of models can be useful in more complex study areas by discovering patterns that more basic regression models might overlook. It is important to note, however, that many machine learning models tend to perform best with large training data sets and this constraint will limit the cases when use of machine learning models are justified. The model accuracy will be evaluated following section 3.6.4.

The model will be run based on the corresponding Sentinel-2 bands and/or ancillary data rasters from the whole project grasslands area to estimate SOC stocks at the unsampled pixels. The raster output from this step is a SOC stock map for the entire project area, where each pixel has a value of stock, in ton/ha .

3.3.2. Option C. CALCULATING SOIL ORGANIC CARBON STOCKS USING A SPATIAL INTERPOLATION APPROACH

Spatial interpolation methods such as kriging, Regression Kriging, Inverse Distance Weighting (IDW), or splining can be used to estimate carbon stocks at unsampled locations. The spatial interpolation method used should be specified by the *Monitor*.

Fig. 4 below outlines the general workflow.

The maximum possible value of SOC stock (ton/ha) from the output map must be clipped to the maximum SOC stock value from the samples from the Project Area. This is a conservative step that prevents overestimations beyond the range of input values that were used to generate the model.

Accuracy from the resultant SOC stock raster must be assessed following section 3.6.4.

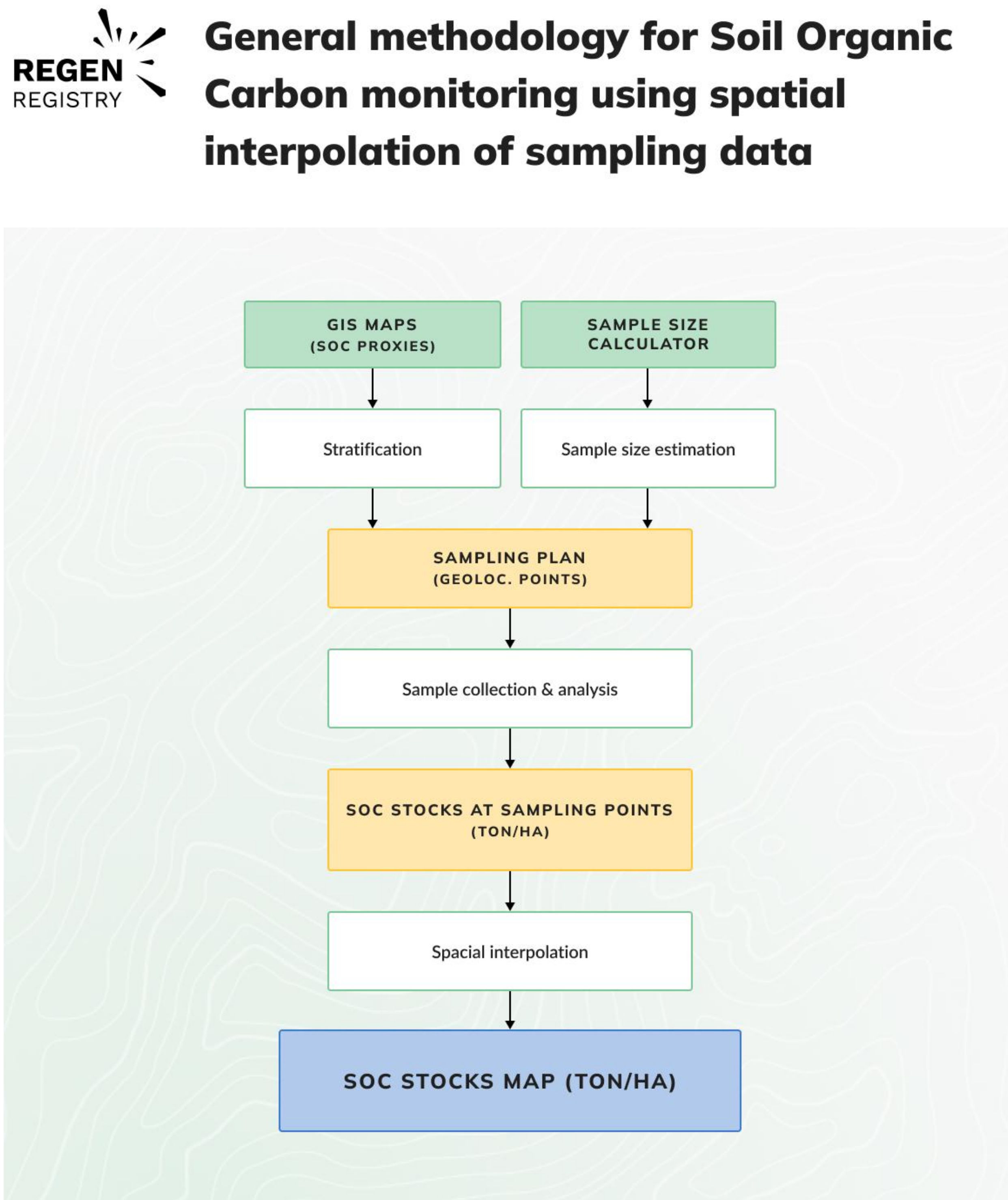


Figure 4. General Methodology for Soil Organic Carbon monitoring using spatial interpolation of sampling data.

3.3.3. CALCULATING FINAL SOC STOCKS

To ensure only grasslands are included in the final soil organic carbon stock estimate, the grasslands mask created in Section 2.1.1 should be used to estimate final stocks. The QGIS zonal statistics tool (or equivalent tool) can be used to estimate the average SOC stock (ton/ha) across all the pixels within the Net Grasslands mask, which then must be multiplied by the total number of hectares of net grasslands area calculated in Section 2.1.1. The resulting number is the **final soil organic carbon stock estimate** for the sampling round, in tonnes.

> *Note: A special attention must be paid to the units here. Please make sure that all the previous calculations provided the correct units at the pixel level (hectares, ton/ha where appropriate).*

3.4. Converting SOC Stocks to CO_2 Equivalents

To convert soil organic carbon stocks to CO_2 equivalent stocks, simply multiply the SOC stocks (in metric tons) by a conversion factor of 3.67:

$$\mathbf{CO_2eq.\ (metric\ ton) = SOC\ (metric\ ton) * 3.67} \qquad \text{(Eq. 7)}$$

3.5. Calculating the Greenhouse Gas Emissions

This methodology requires accounting of cattle GHG emissions, and any other emission sources that result in significant (>5%) GHG due to the project activity. For electricity and fuel usage, only the additional emissions from the baseline will be accounted for, whereas cattle and agrochemicals emissions will be considered as totals. GHG emissions must be accounted for on an annual basis and included in the net CO_2e reduction calculation (see section 3.6.3.) of every monitoring report for its corresponding period.

3.5.1. EMISSIONS FROM LIVESTOCK

Livestock emissions must be calculated for each year of the project lifetime in accordance with the IPCC Tier 2 approach[24], or the Tier 3 approach when more refined factors are locally available (see for example Argentinean factors reported under the UNFCCC)[25]. Equation 8[26] shows how livestock emissions should be calculated using the number of animals present, the number of days the animals were located in the project area, and a tier 2 (or higher) emission factor for the corresponding group of livestock. The livestock type, region, and the source of the emission factors must be cited in the report.

$$\mathbf{E_{liv} = Q \times D \times EF_{liv}/1{,}000} \qquad \text{(Eq. 8)}$$

Where:

E_{liv} is the total emissions from livestock for a particular year for the project area, in metric tons of CO_2e.

Q is the number of animals within the project area in that year, in livestock head.

---

[24] 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use.

[25] MAyDS. 2022. Informe Nacional de Inventario del Cuarto Informe Bienal de Actualización de la República Argentina a la Convención Marco de las Naciones Unidas para el Cambio Climático (CMNUCC).

[26] Carbon Credits (Carbon Farming Initiative—Measurement of Soil Carbon Sequestration in Agricultural Systems) Methodology Determination 2018

D is the number of days in the reporting period that the livestock was within the project area.

EF_{liv} is the emission factor for the corresponding livestock category, estimated based on the gross energy intake and methane conversion factor following the IPCC Tier 2 approach[27] or a Tier 3 when more refined local information is available.

There are many ways livestock heads can be reported as per the *Project Proponent*. For example:

1. If total livestock head is reported for a monitoring year, use total livestock head for **Q** and the number of days in the project area for ***D.***
2. If livestock head is provided in terms of opening and closing head for a given monitoring year, take the average between the two for **Q** and set the number of days in project area **D** to 365.

3. If livestock head is recorded for each quarter of a monitoring year, take the average of the four quarters for **Q**, and set the number of days in project area **D**, to 365.

3.5.2. EMISSIONS FROM FERTILIZER

If fertilizers are used within the Project Area, the total Greenhouse Gas (GHG) emissions from fertilizers for the calculation year must be quantified for each year of the project lifetime, and used to calculate the creditable carbon change. Calculations of fertilizer emissions must be performed in accordance with the IPCC Tier 2 approach[28] and available country-specific emission factors, or Tier 3 methods when possible. The following basic equation could be used for the overall calculation:

$$FE_{t-0} = \sum_{x=1}^{t} (EF_{FE} \; * \; FE_{x}) \qquad \text{(Eq. 9)}$$

Where:

FE_{t-0} = emissions *(tCO_2e)* from fertilizer use during the whole calculation period

t = number of years in the calculation period (yr)

FE_x = N fertilizer input in year *x* (kgN)

EF_{FE} = Conversion factor for emissions from N fertilizer [tCO_2e kg N^{-1}].

The *Project Proponent* should provide fertilizer specific information as it relates to the project area including a) the type/s of fertilizer used and b) the mean annual fertilizer input during the monitoring period (often reported in kg). Conversion factors (often with units of tCO_2e/kg fertilizer), aligned with specific fertilizer types, are used to convert kg of fertilizer to annual emissions in tCO_2e. The fertilizer

[27] 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use.

[28] 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Chapter 11: N2O Emissions from Managed Soils, and CO2 Emissions from Lime and Urea Application

type, mean annual fertilizer input, conversion factor, and final emission quantification should be cited in the report. FE_x will be documented by the project owner.

3.5.3. FUEL & ELECTRICITY USE EMISSIONS

Direct and indirect emissions from increased fuel and electricity usage from the baseline to the calculation year must be accounted for each year of the project lifetime by using equation 10. This includes all fuel sources from stationary combustion, mobile combustion, and electricity.

$$\Delta FU_{t-0} = \sum_{x=1}^{t} (FU_{PR,x} - FU_{BL}) + (EU_{PR,x} - EU_{BL}) \qquad \text{(Eq. 10)}$$

Where:
ΔFU_{t-0} = *emissions from increased fuel and electricity use in the calculation period [tCO_2e]*
$FU_{PR,x}$ = *emissions from use of fuels under the project scenario in year a of the calculation period [tCO_2e]*
FU_{BL} = *mean annual emissions from use of fuels under the baseline scenario [tCO_2e]*
$EU_{PR,x}$ = *emissions from use of electricity under the project scenario in year x of the calculation period [tCO_2e]*
EU_{BL} = *mean annual emissions from use of electricity under the baseline scenario [tCO_2e]*
t= *number of years in the calculation period [yr]*

The *Project Proponent* should provide fuel specific information as it relates to the project area including a) stationary, mobile combustion, or electricity, b) fuel type, c) amount of fuel used, or d) emission factors used. Appropriate sources for emission factors must be used, such as the EPA Emission Factors for Greenhouse Gas Inventories[29].

3.5.3.1. Fuel Emissions

Emissions from the use of fossil fuels for a given year x (FU_x) shall be documented by the project owner and generally calculated with the equation below, based on fuel consumption by machine type and fuel emission factor:

$$FU_x = \sum_{MT} (FUL_{MT,x} * FEF_{MT}) \qquad \text{(Eq. 11)}$$

Where:
FU_x= *emissions from use of fossil fuels in year x (tCO_2e ha-1)*

[29]https://www.epa.gov/sites/production/files/2020-04/documents/ghg-emission-factors-hub.pdf

$FUL_{MT,x}$ = fuel consumption by the machinery type (MT) used in year x (litres)
FEF_{MT} = emissions factor for the fuel used in machinery MT (tCO_2e litres-1)
MT = machinery type (gasoline two-stroke, gasoline four-stroke, diesel)

3.5.3.2. Electricity Use Emissions

Emissions from electricity use shall be calculated from the equation below (Eq. 12), both for the baseline and for each year of the project lifetime, based on electricity consumption by equipment type using the respective emission factor. If electricity is generated using fuel, emissions should be calculated from fuel combustion using the equation above, rather than electricity consumption.

$$EU_x = \sum_{SE=1}^{n} (EUW_{SE,x} * EEF_{SE}) \qquad \text{(Eq. 12)}$$

Where:
EU_x = emissions from use of electricity in year *x* [$tCO_2e\ ha^{-1}$]
$EUW_{SE,x}$ = electricity consumption from source SE in year *x* [kWh]
EEF_{SE} = emissions factor for the electricity used in source SE [$tCO_2e\ kWh^{-1}$]
SE = electricity source type (grid, fossil fuel generator, etc)

For EU_{BL}, input is calculated based on the mean of data for the prior 5 years to project start.

3.5.4. ADDITIONAL AGROCHEMICAL EMISSIONS

Agrochemical emissions in the project activity in the calculation period will be documented by the project owner and for each emitter type (specific pesticide, fertilizer, or other agrochemical) and calculated using the equation below:

$$AE_{t-0} = \sum_{x=1}^{t} ((AQ_{ET} * AEF_{ET})_x \qquad \text{(Eq. 13)}$$

Where:

AE_{t-0} = Agrochemical emissions in the project activity in the calculation period (tCO_2e)
$AQ_{ET,x}$ =quantity of agrochemicals for emitter type ET applied (kg)
AEF_{ET} = emissions factor of the agrochemical used (for emitter type ET) ($tCO_2e\ kg^{-1}$)
ET = emitter type
x = year of the calculation period (tCO_2e)
t = number of years in the calculation period (yr)

The *Project Proponent* should provide agrochemical specific information as it relates to the project area including a) quantity of agrochemical use, b) emitter type, or c) emission factors used.

3.5.5. Other Emissions

Any other emission sources (OE_{t-0}, $equation\ X$) that result in significant GHG due to the project activity that constitutes greater than 5% of the total CO_2 benefits generated by the project should be accounted for each year of the project lifetime.

3.6. Calculating the Creditable Carbon Change

3.6.1. BASELINE DEFINITION

This methodology adopts a measurement project-based, static baseline[30] which is calculated as the total SOC stocks, in metric tons, from the *Initial Monitoring Date*, (i.e. the date of the first sampling round). All sampling rounds after the *Initial Monitoring Date* will be compared to the baseline to calculate creditable carbon change, minus any net changes already accounted for during the crediting period, to avoid double counting.

3.6.2. CHANGES IN CO_2e BETWEEN REPORTING PERIODS

The change in SOC stocks between reporting periods is estimated as the difference between the total SOC stocks from the current monitoring period, minus total SOC stocks from the previous monitoring period* (Equation 14).

$$\textbf{SOC stock change} = \textbf{tSOC}_{(t+1)} - \textbf{tSOC}_{t} \qquad \text{(Eq. 14)}$$

The same applies for estimating the change in the total SOC converted into CO_2 equivalents between two sampling periods (Equation 15).

$$\textbf{CO}_2\textbf{e change} = \textbf{CO}_2\textbf{e}_{(t+1)} - \textbf{CO2e}_{t} \qquad \text{(Eq. 15)}$$

Note: If the previous monitoring period is not the baseline and it has shown a decrease in carbon stocks, then the comparison should be made between the current monitoring round and the previous one with the highest stocks.* ***New credit issuances can only issue credits for the additional net positive difference in stocks that has not already been accounted for in the previous monitoring rounds.*

3.6.3. NET CO_2e REMOVAL

The net CO_2e removal in the project area for a given reporting period is calculated as the difference between the changes in SOC stocks, expressed as metric tons of CO_2e, minus the total GHG emissions, also in CO_2e units:

$$\textbf{NET CO}_2\textbf{e REMOVAL} = \textbf{CO}_2\textbf{e change} - \textbf{E}_{liv} - \textbf{FE}_{t\text{-}0} - \Delta FU_{t-0} - AE_{t-0} \qquad \text{(Eq. 16)}$$

3.6.4. UNCERTAINTY/ERROR DEDUCTIONS

Under this methodology framework, some metric that represents the reliability of the quantification of changes in the carbon stocks must be provided at each monitoring round. This

[30] '*Coverage, Additionality and Baselines*—Lessons from the Carbon Farming Initiative and Other. Schemes'-Chapter 5: Baseline settings- (*CCA. Study,. April. 2014*).

metric will be used to check whether a minimum quality of results has been achieved, and to estimate the uncertainty or error deduction, if applicable.

Although oftentimes the largest contributing factor to spatial data uncertainty is the error, uncertainty and error are two distinct concepts, and as such cannot be used interchangeably.

Error is the difference between the true value and the measured value. In the context of this Methodology, the error will represent the difference between the measured carbon in the sampled points and the estimated carbon at the sampled points when implementing the regression model, or the ML approach, or the spatial interpolation.

Uncertainty in this context would represent the uncertainty of the SOC stock estimates from the predicted stock map considering modeled error at all the pixels (not just at the sampled ones).

Under this methodology framework, either the Error (section 3.6.4.1) or the Uncertainty (section 3.6.4.2) associated with the quantified changes in stocks must be reported in each Monitoring report. The decision on which metric will be used for deductions must be made at the beginning of the project (Baseline report) and remain throughout the project lifetime. If feasible, Uncertainty metrics are always preferred, although they will imply more expertise. The Project Developer and the Monitor will have to balance between complexity of implementation and market acceptance when choosing one or the other. A special attention to use the right terminology in the Monitoring reports must be paid to avoid lack of credibility.

3.6.4. Option 1. Calculating the Error Deductions

The total error from a crediting period (E) will be estimated following these 2 main steps:

1. Estimate the total error from the current monitoring round
2. Sum the total errors from both monitoring rounds involved in the calculation of the changes in stocks (section 3.6.2.) to get the total error "E".

Step 1: Estimate the total error from the current monitoring round

The errors from each of the main sources will be calculated through the root mean square error (RMSE) using leave-one-out cross validations (LOOCV).

- In case of correlating SOC % (section 3.3.1.2. Option A), the sources or errors that must be considered are two: the SOC% and the BD values from the sampling points. Once both RMSE are calculated using the LOOCV, they must be summed to obtain the total RMSE from the monitoring round.
- In case of directly correlating SOC stocks calculated at the sampling points (section 3.3.1.2. Option B) or interpolating the SOC stocks (section 3.3.2.), calculate the RMSE from the SOC stocks sampled values.

Step 2: Estimate "E"

To estimate the final error from the change in carbon stocks between two periods, or "E", the RMSE (not normalized) from both periods will be summed and then normalized by the average (observed) stocks at the sampling points, from both periods. Finally multiply the nRMSE by 100 to obtain E (%).

An alternative approach, only possible when using permanent plots, is to estimate E directly from a map created using change in SOC stock measured at the sample plot level. Then, leave-one-out cross-validation can be used to estimate the RMSE between sampled change in SOC stock and predicted change. The resultant RMSE will be normalized using the average sampled change in stocks, and multiplied by 100 to obtain E (%).

If E is less than or equal to 20%, the *Monitor* may use the net CO_2 reduction value generated in Section 3.6.3 without making any deductions to account for error (i.e. Error Deduction (ED) = 0). If E is greater than 20%, the *Project Proponent* must use the Error Deduction (ED) equation (Eq. 17) to calculate the amount of error to deduct from the creditable carbon stocks:

ED = E * (2*(E/50)) (Eq. 17)

Examples for error deduction are shown below in table 4.

Table 4. Examples of error and the corresponding discounts.

ERROR (E)	% of E to be deducted	Error Deduction (ED)
E≤20%	0%	-No Deduction-
E= 20%	16% of E	ED= 3.2% from net CO_2e removal
E=25%	25% of E	ED= 6% from net CO_2e removal
E=35%	49% of E	ED= 17% from net CO_2e removal
E=45%	81% of E	ED= 36% from net CO_2e removal
E= 50%*	100% of E	ED= 50% from net CO_2e removal

*The maximum E allowed from any reporting period is 50%.

The *Creditable Carbon Change* after Error Deduction is then estimated as:

CREDITABLE CARBON CHANGE =(NET CO_2e REMOVAL)×(1−$ED/100$) (Eq. 18)

3.6.4. Option 2. Calculating the Uncertainty Deductions

The total uncertainty from a crediting period (U) will be estimated following 2 main steps:

Step 1: Estimate the uncertainties from the current monitoring round

When correlating SOC% (section 3.3.1.2. *Option A*), there are mainly two sources of uncertainty from the stocks quantification to consider: the SOC% map, and the BD map. Both partial uncertainties will be independently estimated and then summed.

In case of directly correlating or interpolating the SOC stocks (section 3.3.1.2. *Option B)*, the only source of uncertainty to consider will be the SOC stocks map.

Project-level uncertainty can be determined through various geostatistical methods. One approach involves calculating the relative standard error using residual errors derived from LOOCV analysis input into multiple Conditional Simulations (CS) iterations. Below, we provide concise guidelines for obtaining uncertainty values from multiple linear regressions, machine learning (ML) models, or interpolation maps using CS.

I. Train the machine learning model or multiple linear regression model using the geolocated samples data.
II. Generate a prediction map for the entire study area using the trained model.
III. Calculate the residuals (predicted - observed values) using LOOCV for each geolocated sample.
IV. Fit a variogram model to the residuals: A variogram model will describe the spatial correlation structure of the residuals. You can fit the variogram using a variety of software tools such as R, Python, or specialized geostatistical software.
V. Perform conditional simulations: Use the fitted variogram model to simulate new random residual values for unsampled locations. These residual values can be added to the predictions generated by your model to generate multiple realizations of the predictions at unsampled locations.
VI. At the end of the simulations, calculate the standard error for each grid cell (pixel)
VII. Calculate the relative standard error for each cell by dividing the standard error by the predicted value for the corresponding cell.
VIII. The uncertainty for the area is finally calculated by taking the mean of all cells of the relative standard error layer:

    U(%)= (mean(standard error layer / predicted layer)) * 100

This approach, known as "conditional simulation," conditions the simulated residuals on observed values, generating multiple realizations of predictions. It proves valuable for estimating prediction uncertainty, especially when dealing with a limited number of samples.

An alternative geostatistical approach addressing spatial autocorrelation is well elucidated in Wadoux and Heuvelink's 2023 paper.

The Monitor retains the flexibility to choose other suitable approaches for uncertainty estimations, accompanied by a comprehensive justification detailing the chosen method.

To run uncertainty analysis will require someone with a high level of expertise in geostatistics. Please contact the Science team for recommendations.

Step 2: Estimating the total uncertainty "U" from the crediting period

In order to estimate U, the total uncertainty from the two monitoring rounds involved in the quantification of the creditable carbon change (section 3.6.2.) will be summed.

If the uncertainty (U) of the change in stocks for the reporting period is less than or equal to 20%, the *Monitor* may use the net CO_2 reduction value generated in Section 3.6.3 without making any deductions to account for uncertainty (ex. Uncertainty Deduction (UD) = 0). If uncertainty is greater than 20%, the *Project Proponent* must use the Uncertainty Deduction (UD) equation to calculate the amount to deduct from the creditable carbon stocks:

$$UD = U * (2*(U/50)) \qquad \text{(Eq. 19)}$$

Examples for UD are shown in table 5 below.

Table 5. Examples of uncertainties and the corresponding discounts.

UNCERTAINTY (U)	% of U to be deducted	Uncertainty Deduction (UD)
U≤20%	0%	-No Deduction-
U= 20%	16% of U	UD= 3.2% from net CO_2e removal
U=25%	25% of U	UD= 6% from net CO_2e removal
U=35%	49% of U	UD= 17% from net CO_2e removal
U=45%	81% of U	UD= 36% from net CO_2e removal
U= 50%	100% of U	UD= 50% from net CO_2e removal

The maximum U allowed from any reporting period is 50%. The *Creditable Carbon Change* after Uncertainty Deduction is then estimated as:

$$\text{CREDITABLE CARBON CHANGE} = (\text{NET } CO_2\text{e REMOVAL}) \times (1 - UD/100) \qquad \text{(Eq. 20)}$$

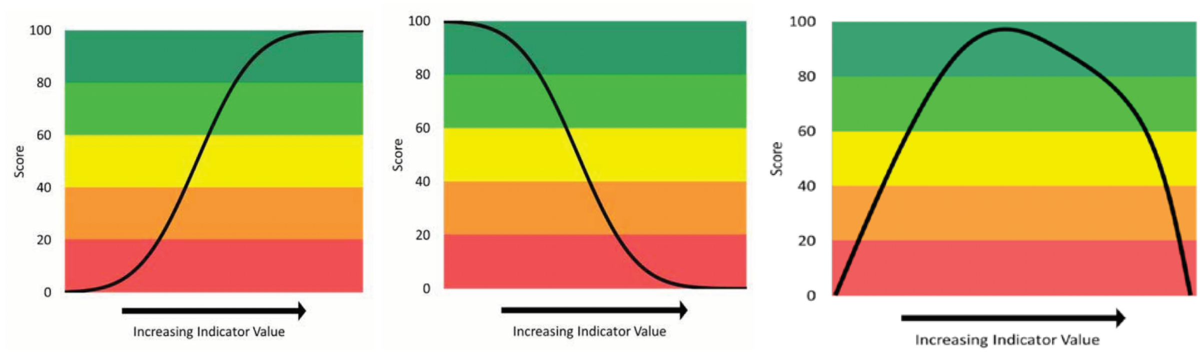
4. Calculating the Soil Fertility Indicators

The main soil fertility indicators for Grasslands projects are pH, macronutrients (Nitrogen, Phosphorus, and Potassium), and other soil cations such as Calcium and Magnesium.

In order to assess the soil fertility of a pasture, the desired levels (i.e. benchmarks) of the most relevant soil fertility indicators for the Project Area must be established during the baseline period.
These levels will vary depending on soil types and ecoregion.
The soil indicators to be assessed in at least 30% of the samples will be chosen according to their relevance for assessing soil fertility in the Project Area, and must include at least the following:

- Soil pH
- Main Macronutrients: Phosphorous, and at least one Nitrogen parameter (i.e. Ammonia, Nitrate or Total Nitrogen).
- Soil Cations: at least three Soil Cations from the following list:
    - Calcium
    - Magnesium
    - Potassium
    - Sodium
    - Aluminum

The *Monitor* could use the scoring approach proposed by the Cornell University Framework[31] to evaluate each of the soil-fertility variables. Under this approach, and depending on the indicator, there are different cumulative normal distribution scoring curves that can apply. For example, the chemical indicator potassium is scored using a sigmoid function that relates better scores to higher levels of potassium. Phosphorus and pH, on the other hand, are both scored using an optimum, Gaussian-type curve.



Sigmoid curve Reverse Sigmoid curve Gaussian-type curve

Scoring functions should be regionally adapted by the Monitor according to thresholds based on literature or local standards (e.g. scientific papers, local reports, or consultation to soil experts from local universities), which must be cited or attached to the monitoring report. For each monitoring period, each indicator will be ranked per sample according to the local benchmarks. There are two options for assessment on a per sample basis. The first being the establishment of a distinction between samples falling into optimal vs non-optimal ranges (aligned with the binary scoring section below). Samples categorized as "optimal" are those which fall within the desired levels based on the project's ecoregion and soil type. The second option is a non-binary assessment, where samples can fall into a "poor", "moderate", or "optimal" range (see non-binary scoring section below).

To incorporate the distribution of rankings across the samples for each indicator, the following decision tree is used to determine the final ranking.

Binary Scoring

If the local benchmarks for the assessed indicator only provide for optimal and non-optimal values, the classification score for the final ranking should be calculated using Equation 21.

$$Classification\ Score = \frac{\Sigma\ Soil\ Fertility\ Ranking}{Total\ Number\ of\ Samples} * 100 \qquad \text{(Eq. 21)}$$

Where *soil fertility ranking* is:

[31] Manual -Comprehensive Assessment of Soil Health - Cornell Framework

- Non-optimal = 0.25
- Optimal = 1

Please use the *Classification Score* to determine the final ranking according to Table 6.

Table 6. Soil Fertility Ranking for a Binary Classification:

Classification score	Final Ranking
0-25%	NEEDS IMPROVEMENT
>25-50%	FAIR
>50-75%	GOOD
>75-100%	EXCELLENT

Non-Binary Scoring

If the local benchmarks for the assessed indicator provide clear indications of poor, moderate and optimal ranges, the final rankings should be calculated using Equation 21, where *Soil Fertility Ranking is:*

- Poor: 0.33
- Moderate: 0.67
- Optimal: 1

Please use the *Classification Score* to determine the final ranking according to Table 5.
See Supplement Section 1.1 for a soil fertility assessment example.

4.1. pH

The optimal range of values for pH must be determined by the *Project Monitor* using local metrics for the region and specific soil type(s) found within the project area. Healthy pH levels for soil fertility follow an optimum, Gaussian-type curve. To estimate the optimum range for pH, build the normal distribution curve according to the average pH values of soil samples collected in the ecoregion. The optimal pH levels and standard deviations must be backed by a trustworthy scientific source and included in the report.

4.2. Macronutrients (NPK)

4.2.1. NITROGEN

Nitrogen metrics measure the productivity of nutrient cycling functions in the soil. The most common indicators used to quantify soil Nitrogen are *Nitrate-Nitrogen*, *Ammonia- Nitrogen* and *Total Nitrogen*. An increase in the indicators of Nitrate-Nitrogen and Total Nitrogen lead to increased soil fertility, therefore both of these indicators follow a cumulative distribution function. Nitrate-Nitrogen and Total Nitrogen follow a cumulative distribution function, meaning an increase in either variable indicates better soil fertility. Ammonia-Nitrogen is different and follows an optimum curve.

In order to estimate curves for each parameter, the average values and standard deviations from pastures in the region must be reported. Alternatively, local scientific studies showing threshold values for optimum, moderate and poor categorization can be used as a reference to build the scoring ranges.

4.2.2. PHOSPHORUS

The availability of soil phosphorus varies with the acidity of the soil. The more acidic the soil, the more phosphate 'fixed' by the soil and made unavailable to plants. As a result, critical values for soil phosphorus change with the soil type. A cumulative distribution function best fits the relationship between soil fertility and phosphorus and should be used as the scoring curve for this indicator.

4.2.3. POTASSIUM

Plants amass potassium from two soil sources: exchangeable potassium that is immediately available, and non-exchangeable potassium which becomes available at much slower rate. Clay soils have a higher nutrient holding capacity than sandy soils and thus can have higher levels of immediately available potassium. In light of this fact, soil test interpretation and benchmark categorization must be based on soil texture, as the critical value increases with increasing clay content.[32]
A cumulative distribution function best fits the relationship between soil fertility and potassium and should be used as the scoring curve for this indicator.

4.3. Soil Cations

The following nutrients can be quantified and reported individually according to the scoring system.

- Calcium
- Magnesium
- Potassium
- Sodium
- Aluminum

Thresholds for these categories will be defined and justified according to the best knowledge for the project area (scientific papers, local reports, consultation to soil experts from local universities, etc).

[32] Brown Book. What are the optimum nutrient targets for pastures?

5. Calculating the Ecosystem Health Indicators

The general framework used to evaluate ecosystems health[33] was originally proposed by Costanza (1992)[31] and later refined in 1999 by Costanza and Mageau[34]. According to Costanza, a healthy ecosystem has the ability to maintain its structure (organization) and function (vigor) over time in the face of external stress (resilience)[35]. This framework provides the foundational basis for methodologies which can assess ecosystem health dynamics and changes in grassland ecosystems.

5.1. Ecosystem Vigor

Ecosystem vigor is widely used as a primary factor for quantifying ecosystem health[36]. The vigor of a living system is a measure of its activity, metabolism and/or primary productivity[35].

5.1.1. VEGETATION INDEX

The Normalized Difference Vegetation Index (NDVI) is a good indicator of plant vigor, and has been used in previous research for the assessment of grassland ecosystem health using remote sensing[37]. NDVI is calculated using red and near-infrared light reflected by vegetation (Eq. 22). Healthy vegetation absorbs most of the visible light while reflecting a large portion of the near-infrared light resulting in a high NDVI value. In contrast, with unhealthy vegetation the, reflected red light increases and the reflected near-infrared light decreases,[38] resulting in lower NDVI values.

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{(Eq. 22)}$$

Alternatively, the Enhanced Vegetation Index (EVI) might be preferred to avoid the saturation of the NDVI (Eq. 23).

$$EVI = 2.5 \;*\; \frac{NIR - RED}{NIR + C1 * RED - C2 * BLUE + L)} \qquad \text{(Eq. 23)}$$

---

[33] Xu and Guo. 2015. Some Insights on Grassland Health Assessment Based on Remote Sensing [31] Costanza R. 1992. Towards an operational definition of health. In: Ecosystem health: new goals for environmental management
[34] Costanza R. 1999. What is a Healthy Ecosystem?
[35] Costanza R. 2012. Ecosystem health and ecological engineering
[36] Xu and Guo. 2015. Some Insights on Grassland Health Assessment Based on Remote Sensing
[35] Costanza R. 1999. What is a Healthy Ecosystem?
[37] Xu and Guo. 2015. Some Insights on Grassland Health Assessment Based on Remote Sensing
[38] Normalized Difference Vegetation Index (NDVI). NASA Earth Observatory

where:

C 1 = atmospheric resistance red correction coefficient

C 2 = atmospheric resistance blue correction coefficient

L = canopy background brightness correction factor [1. 0]

To measure ecosystem vigor for grasslands in the project area, NDVI/EVI values for a project must be compared to the values in a *control area*. The *control area* could be one of the following options, which will need to remain constant through the lifetime of the project:

A) **Business as usual belt:** All the grassland areas within a surrounding area or belt of 10km width. This requires good ability to classify the grasslands or pastures and leave out other herbaceous land covers (i.e cropland).

B) **Business as usual target properties:** A representative property or group of properties within the same ecoregion, soil types and general conditions, where business as usual management of grasslands is taking place and is likely to persist during the lifetime of the project (min. 1,000 ha).

C) **Best case scenario:** An identified area of significant size (min. 1,000ha) within the same ecoregion, soils, etc, where best case scenario of grasslands health happens due to historical proper management or due to conservation practices.

The following steps are followed for scoring the vigor of the grasslands within a project area:

1. Map out the control area boundaries using one of the the options described above:
   A) For the Business-as-usual belt, create a 10km buffer around the property boundary using the extent of the spatial boundaries defined in Section 2.1.
   B) For the Business-as-usual target properties, map the boundary polygons of the selected properties.
   C) For the Best case scenario grassland, map the identified property/reserve boundaries.
2. Calculate the 75th percentile NDVI/EVI value per pixel for a time series from the previous calendar year.
3. Create a grasslands mask using methods from Section 2.1.1. to remove any man-made objects, trees, bodies of water or other such land types from the NDVI/EVI image. Visually inspect the mask to ensure its accuracy.
4. Calculate the average NDVI/EVI value within the whole project area grasslands mask from section 2.1.1.1, by using the QGIS zonal statistics (or equivalent) tool. Next, calculate the average NDVI/EVI values within the control zone/s masked in (4).
5. Compare the NDVI/EVI averages between the project area and the buffer zone and generate a score based on the scoring charts below.

Scoring for options A and B (business as usual control):

EXCELLENT: Project average NDVI/EVI is >25% higher than the NDVI/EVI of the *control area*.

GOOD: Project average NDVI/EVI is 10-25% higher than the NDVI/EVI of the *control area*.

FAIR: Project average NDVI/EVI is within an interval of +/- 10% the average NDVI/EVI of the *control area*.

NEEDS IMPROVEMENT: Project average NDVI/EVI is below 10% lower than the average NDVI/EVI of the *control area*.

Scoring for option C (best case scenario control):

EXCELLENT: Project average NDVI/EVI is equal or higher than the average NDVI/EVI of the *control area*.

GOOD: Project average NDVI/EVI is 0-10% lower than the average NDVI/EVI of the *control area*.

FAIR: Project average NDVI/EVI is 10-25% lower than the NDVI/EVI of the *control area*.

NEEDS IMPROVEMENT: Project average NDVI/EVI is more than 25% lower than the average NDVI/EVI of the *control area*.

The report must include the NDVI/EVI results from control and project areas, and a link to the buffer vector file and the NDVI/EVI raster used.

5.2. Ecosystem Organization

Ecosystem organization represents the structure of an ecosystem and describes the interactions among various components of the ecosystem[39]. This depends on the landscape heterogeneity (LH) and landscape connectivity (LC).[40] The LH can be represented by landscape diversity, which can be determined using the Shannon's diversity index[41]. The LC depends on the overall connectivity of the landscape and that of important ecological patches[42], which can be assessed using landscape metrics.

5.2.1 VEGETATION STRUCTURE LANDSCAPE METRICS

The LH and LC can be assessed at the ecosystem vegetation structural level (grasses, forbes, tussocks, shrubs, trees) using remote sensing and GIS. The metrics and grain size that should be chosen for a particular project will heavily depend on the ecoregion of the project area and the minimum needs for key species or endangered species that inhabit that ecosystem.
For instance, woody vegetation is a key component of most natural grassland ecosystems. Some landscape metrics like the proportion of woody vegetation cover, patch sizes, distances between patches, and/or the shape of patches of woody vegetation can be used as indicators of

[39] Costanza R. 2012. Ecosystem health and ecological engineering.
[40] Ge et al. 2022. Assessment of Ecosystem Health and Its Key Determinants in the Middle Reaches of the Yangtze River Urban Agglomeration, China.
[41] Turner, M.G. Landscape Ecology: The effect of pattern on process. Annu. Rev. Ecol. Syst. 1989, 20, 171–197.
[42] Peng, J.; Liu, Y.; Li, T.;Wu, J. Regional ecosystem health response to rural land use change: A case study in Lijiang City, China. Ecol. Indic. 2017, 72, 399–410.

organization in grasslands, and compared to reference benchmarks from the natural local ecosystems.

The chosen landscape metrics must be estimated at the same time interval, or season, for each year from a land cover classification. For the land cover classification, imagery with a spatial resolution of 20 meters or finer, such as Sentinel-2 (ESA), must be used. The satellite source, GIS software and classification procedure (e.g. supervised nearest neighbor, random forest machine learning algorithm) used for the estimation of woody vegetation cover must be specified in the report, and images must be pre-processed following the workflow described in Section 3.3.1.1. Alternatively, classifications might be pulled from a dataset like Dynamic World[43].

There are several tools that can be used in GIS to estimate landscape metrics. We recommend the use of the LecoS (Landscape Ecology Statistics) plugin in QGIS, which is based on Fragstats.

For each reporting period, a single measurement of each landscape metric is required. The benchmarks for the excellent-good-fair-needs improvement ranking of the vegetation structural landscape metrics must be set locally according to the natural ecosystems characteristics and the habitat needs from key or endangered species in the ecoregion. The choice of landscape metrics and thresholds for scoring must be based on pertinent information from scientific literature. The corresponding cites to the scientific literature must be provided in the report.

5.2.2. PROTECTION OF WETLANDS AND WATERCOURSES

In case there are waterbodies of any kind (ephemeral, permanent or intermittent) within the project area, the percent of the total waterbody perimeter protected from animal entry will be quantified. The potential presence of ephemeral waterbodies must be considered by looking onto historical imagery.

Scoring:

EXCELLENT: 100% of the perimeter of waterbodies are protected from animal entry.

GOOD: The percentage of the perimeter of waterbodies in the project area that is protected from animal entry is higher than 70%.

FAIR: The percentage of the perimeter of waterbodies in the project area that is protected from animals varies between 50-70%.

NEEDS IMPROVEMENT: Less than 50% of the perimeter of waterbodies in the project area is protected from animal entry.

5.3. Ecosystem Resilience

Resilience represents the ability for an ecosystem to maintain its structure and function in the presence of stress, and can be measured by the system's capacity to return its original state following perturbation[17].

---

[43] Brown CF et al. 2022. Dynamic World, Near real-time global 10 m land use land cover mapping. Scientific Data 9:251. Nature Publishing Group.

5.3.1. BARE SOIL ESTIMATION

Bare soil (i.e. [1 - vegetation cover]) has been identified as a good indicator of ecosystems resilience[44] and grasslands health[45]. The Bare Soil Index (BSI) is a numerical indicator estimated from satellite imagery that combines blue, red, near infrared and short wave infrared spectral bands to capture soil variations. These spectral bands are used in a normalized manner. The short wave infrared and the red spectral bands are used to quantify the soil mineral composition, while the blue and the near infrared spectral bands are used to enhance the presence of vegetation. The formula to calculate the BSI using Sentinel-2 imagery is specified in Equation 24[46]:

$$BSI_{S2} = \frac{(Band11 + Band4) - (Band8 + Band2)}{(Band11 + Band4) + (Band8 + Band2)} \qquad \text{(Eq. 24)}$$

In order to have a relative estimation of the bare soil within the project area versus the *control area*, the following steps are carried out for scoring the ecosystem resilience:

1. Using the project area and the control areas mapped in Section 5.1.1., download and preprocess satellite imagery that falls within +/- 1 month from the reported sampling period. Sentinel-2 (10 square meters) or higher resolution is required and must meet the requirements and pre-processing steps specified in Section 3.3.1.1. Averaging several dates without clouds around the sampling period increases the accuracy of the results.
2. Calculate the BSI for the project area and the control in (2). The resulting BSI raster must be validated through visual inspection of imagery performed by the *Monitor* or ground truth data provided by the *Project Proponent*, to find the range of BSI values that accurately reflect only bare soil areas on the ground.
3. Calculate the area covered by bare soil within the Project Area only, using zonal statistics and the grasslands mask created in section 2.1.1.
4. Calculate the area covered by bare soil within the control area only, using zonal statistics and the grasslands mask created in Section 5.1.1..
5. Estimate the areas covered by bare soil in both the project area and the buffer area.
6. Compare the percent bare soil cover between the project area and the buffer area and use the scoring chart below to generate a score for ecosystem resilience.

Scoring for options A and B (business as usual control):

EXCELLENT: Project Area has a percentage cover of bare soil that is notably lower than the percent bare soil cover in the *control area*. The difference is higher than 50%.

GOOD: Project Area has a percentage cover of bare soil that is lower to the percent cover in the *control area*. The difference is smaller than 50% and higher than 20%.

FAIR: Project Area has a percentage cover of bare soil that is +/- 20% of the percent bare soil cover in the *control area*.

---

[44] Li et al. 2013. Three-Dimensional Framework of Vigor, Organization, and Resilience (VOR) for Assessing Rangeland Health

[45] Ludwig et al. 2000. Monitoring Australian Rangeland Sites Using Landscape Function Indicators and Ground- and Remote-Based Techniques

[46] Spectral Indices with Multispectral Satellite Data

NEEDS IMPROVEMENT: Project Area has a percentage cover of bare soil that is higher than 20% with respect to the *control area*.

Scoring for option C (best case scenario control):

EXCELLENT: Project Area has a percentage cover of bare soil that is similar (+/-10%) the percent bare soil cover in the *control area*.

GOOD: Project Area has a percentage cover of bare soil that is between 10 and 20% higher than the percent cover in the *control area*.

FAIR: Project Area has a percentage cover of bare soil that is between 20 and 50% higher than the percent bare soil cover in the *control area*.

NEEDS IMPROVEMENT: Project Area has a percentage cover of bare soil that is higher than 50% with respect to the *control area*.

The BSI results from the control and project areas must be included in the report.

6. Calculating the Animal Welfare Ranking

The Animal Welfare ranks within 4 possible categories (Needs Improvement- Fair-GoodExcellent) depending on the percentage of accomplished items from local recommendations. Refer to Supplement Section 1.2. for an example of Australian requirements. The report should include statements regarding compliance with the requirements chosen for the project.

Scoring:

NEEDS IMPROVEMENT: <40% requirements are met.

FAIR: Between 40% and 70% requirements are met.

GOOD: >70% requirements are met.

EXCELLENT: 100% requirements met

7. Overall Scoring

1. SOC: Total $tCO2_e$ Net Removal from section 3.6.3.
2. CO-BENEFITS:

The following scoring system shall be followed, using Table 6 below as a template for the calculation of the final scores for the main Co-Benefits.

7.1. Partial and Final Scores

Each indicator within the Ecosystem Health and Soil Fertility co-benefits, as well as the Animal Welfare ranking, will be assigned with points in Table 7, as follows:

- Needs Improvement point = 0.25
- Fair point = 0.50
- Good point = 0.75
- Excellent Point = 1

FINAL SCORE = Sum of the indicators points / Total number of indicators

Calculation Example of the final score for Ecosystem Health

If the partial resulting scores for each indicator of Ecosystem health were:

- Organization = GOOD = 0.75
- Vigor = FAIR = 0.50
- Resilience = EXCELLENT = 1.00

Then the final average score for Ecosystem Health is estimated as :

Ecosystem Health = (0.75+0.5+1)/ 3 = *0.75 (GOOD)*

7.2. Ranking of Final Scores

According to the final Score, the Soil Fertility metrics and the Ecosystem Health metrics are ranked as follows:

- Final Score $\leq$ 0.40 = *NEEDS IMPROVEMENT*
- 0.40 < Final Score $\leq$ 0.60 = *FAIR*
- 0.60 < Final Score $\leq$ 0.80 = *GOOD*
- Final Score > 0.80 = *EXCELLENT*

Table 7. Template for the calculation of the partial and total scores of the Co-Benefits.

MAIN INDICATOR	PARTIAL INDICATOR	Rating (cross-check the corresponding rating)				**FINAL SCORE**
		Improvement				
Soil Fertility Indicator	pH					**Qualitative NI-F-G-E according to sum of weighted points**
	N					
	P					
	K					
Sum of points from the Soil Fertility Indicators						*Write here Final Score and Qualitative Result*
MAIN INDICATOR	PARTIAL INDICATOR	Improvement				
Ecosystem Health Indicator	Vigor					**Qualitative NI-F-G-E according to sum of weighted points**
	Organization					
	Resilience					
points from the Ecosystem Indicators						*Write here Final Score and Qualitative Result*
Score for Animal Welfare						*Write here the Qualitative Result*

* NI=Needs Improvement; F=Fair; G=Good; E=Excellent

8. Data Reporting

8.1. Report

After each sampling round, a report must be submitted to the Regen Registry including a description of the methods used for soil sampling, analysis of samples, as well as the equations and references used. The reported results for each section of this Methodology must be accompanied by all the information that supports them. In the case of GIS or remote sensing data, it is required that the maps are included as images within the report for illustrative purposes. The original vector and raster files must be kept by the *Monitor*. Any documentation containing calculations and statistical analysis should also be saved.

A full checklist of the data is provided in Supplement 3.

8.2. Data Storage

All data used during the analysis should be held during the whole *permanence* period by the *Monitor* and/or *Project Proponent* for monitoring verification. This data includes:

- All raster and vector data used in geospatial analysis to generate results for any section of the methodology.
- A copy of all laboratory reports.
- All the relevant field data from the soil sample collection process (dates, tools, procedures, sample locations).
- Documentation outlining calculations and results of statistical analysis.

A full checklist of the data is provided in supplement 3.

9. Data Verification

The *Verifier* should verify the following items within the following subsections 9.1-5:

9.1. Soil Organic Carbon Data

- The geolocation of samples is within the boundaries of the project area, as declared in the project plan, and within the net grasslands area of the project according to the grasslands mask.

- Data reported in the soil lab reports must match the data used for the soil carbon stocks quantification. These data include:
  - Percent soil organic carbon
  - Bulk density

- Spectral values extracted from the satellite imagery and ancillary data must match the data used during analysis.
    1. The *Verifier* should download the original imagery and ancillary data used and follow the pre-processing steps used by the *Monitor*
    2. Following the steps outlined in Section 3.3.1.1, spectral values should be extracted and compared to the data used to generate statistical models.
- Models used to estimate percent soil organic carbon or stocks should be re-created and compared to reported values.
- Final soil organic carbon stock estimates should be recreated and compared to reported values.

9.2. GHG Emissions

- Using the data provided by the *Project Proponent* animal emissions should be recreated and compared to the reported values
- Using the data provided by the *Project Proponent* fertilizer Emissions should be recreated and compared to the reported values

9.3. Soil Fertility Indicators

Data from the original soil lab reports must match the data used to assess soil fertility. These data include:

- pH
- Macronutrients
    - Phosphorus
    - Potassium
    - Nitrogen (at least one of the following)
        - Total Nitrogen
        - Nitrate Nitrogen
        - Ammonium Nitrogen
- Soil Cations: at least three of the following:
    - Calcium
    - Magnesium
    - Potassium
    - Sodium
    - Aluminum
- Reported soil fertility ranking should be assessed to ensure that they match reported rankings

9.4. Animal Welfare

- Review animal welfare rankings to ensure the proper number of requirements were met.

9.5. Ecosystem Health

- NDVI:
    - Assessment of the NDVI analysis used over the project area

○ Visual inspections on the ground or by remote sensing for the project area and surrounding area

- Vegetation Structure Landscape Metrics:
  - ○ Assessment of the remote sensing protocols used to analyze vegetation landscape metrics within the project area
  - ○ Visual inspections on the ground or by remote sensing
- Bare Soil:
  - ○ Assessment of the remote sensing protocols used to analyze bare soil within the project area
  - ○ Visual inspections on the ground or by remote sensing in both the project area and surrounding fields

> In order to check that all the required information was included in the monitoring report, we recommend that the *Verifier* uses the checklist provided in Supplement 3.

Supplements

S.1. Co-Benefit Examples

S.1.1. SOIL FERTILITY EXAMPLE ASSESSMENT

pH Example:

Methodology Description:

The standard method of measuring soil pH in [project area] is to use a 1:5 (soil:water) suspension method.

Benchmarks:

- According to [source], within [project area] “plant growth, and most soil processes, are favored by a pH range between 5.5 and 8” . Within this range, an optimal range of pH is 6-7 .

Given these ranges, the soil pH ranking for pastures in X is:

-POOR: < 5.5 or > 8.0

-MODERATE: > 5.5 and <6.0 or >7.0 and 8.0<

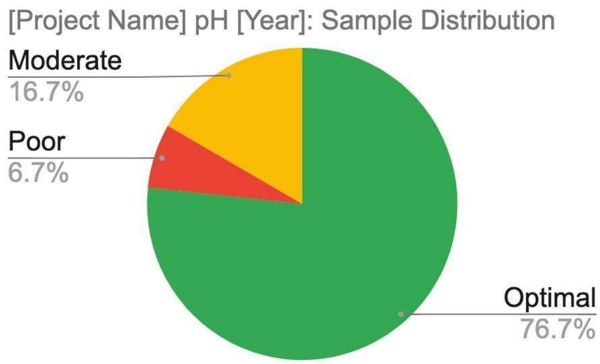
-OPTIMAL: 6.0 - 7.0

Results:

- Average pH values from [monitoring year] [project name] soil samples: [average of all samples]

- According to the ranking system the classification for [monitoring year] samples falls into the [Poor/Moderate/Optimal] range

The distribution of the pH rankings for the [project name] [monitoring year] data falls within the ranges illustrated below:



S.1.2. ANIMAL WELFARE EXAMPLE

An example of animal welfare metrics are outlined below according to Cattle Standards and Guidelines for Australia. The Animal Welfare metric ranks within 4 possible categories depending on the percent of accomplished items from the following list (more detailed information Australian Animal Welfare Standards). The calculation is only considered in relation to the total number of items that are applicable to the project.

1. Responsibilities: Are responsibilities fully addressed, clear responsibilities outlined in individual role descriptions and supported by appropriate company policies and training?
2. Access to feed and water: Do the animals on this land have reasonable access to adequate and appropriate feed and water?
3. Risk management: Are records of risk management kept via company policies and monthly manager reports? Are animals managed to minimize the impact of threats to their welfare including, extremes of weather, natural disasters, disease, injury and predation? Are there inspections of the animals at intervals, and at a level appropriate to the production system? Are there systems in place to ensure appropriate treatment for sick, injured or diseased animals at the first reasonable opportunity?
4. Facilities: Are facilities constructed and maintained to allow humane treatment of animals to ensure their welfare?
5. Animal handling: Are staff trained in handling and management practices that are appropriate (such as low stress stock handling) to minimize the risk to the welfare of the animals? See details in Section 5 of Australian Standards linked above.

6. Castration / dehorning: Are the practices of castration, dehorning and spaying only done when necessary and in a manner that minimizes the risk to the welfare of the animal, particularly pain and distress? See details in Section 6 of Australian Standards linked above.
7. Breeding: Are breeding and management practices appropriate to minimize the risk to the welfare of the animals? See details in Section 7 of Australian Standards linked above.
8. Calf raising systems: Are calf-rearing systems appropriate to minimize the risk to their welfare? See details in Section 8 of Australian Standards linked above.
9. Dairy: Are dairy animals managed to minimize the risk to their welfare? Is a daily inspection taking place of lactating dairy cows? Are there systems in place to minimize the heat stress of animals? Is tail docking only carried out under veterinary advice to treat injury or disease? Do the animals kept on feed pads for extended periods have access to a well drained area for resting?
10. Feedlots: Are animals in feedlots managed in a way that minimizes the risk to animal welfare? See details in Section 10 of Australian Standards linked above.
11. Slaughtering: Where it is necessary to kill animals, is it done promptly, safely and humanely? See details in Section 11 of Australian Standards linked above.

S.2. Option for Automation

Regen Network Development Inc. has built a series of work packages automating many of the workflows found within the methodology, greatly reducing the amount of time and work needed to complete a monitoring round. The two main workflows automated within this project are image processing (described in Section 3.3.1.1), and the calculation of CO_2 equivalent stocks and livestock emissions using the satellite-based calibration workflow (Section 3.3).

S.2.1 CARBON STOCK ESTIMATION

An automated workflow that uses Google Earth Engine to predict SOC percent and SOC stock for a study area using soil sample data and Sentinel-2 imagery can be found here: https://github.com/regen-network/open-science/tree/master/socMapping. In that GitHub repository you will find a user guide and two Jupyter Notebook scripts.

The workflow consists of two steps. The first step extracts pixel data from time series Sentinel-2 imagery and other layers that correspond with soil sample point locations. The second step uses the extracted data from the first step to find the variables that provide the best fitting linear regression model. Variables from the model with the best fit are then used to calculate metrics using leave-one-out cross-validation (R square, Adjusted R square, RMSE, and normalized RMSE) to calculate accuracy of the predictions. This is done for each date of the time-series Sentinel-2 imagery. Output is a CSV file that can be viewed to find the image date and specific variables that produce the best SOC predictions.

S.3. Data reporting checklist

S.3.1. FIELD DATA

- Sampling dates corresponding to each sampling round, indicating the baseline.
- Sample size:
    - Data entry parameters for the sample size calculator*:
        - Landscape variability class
        - grasslands area of the project (ha)
    - Outputs:
        - Minimum sample size
        - Optimal sample size
        - Indicate the final sample size after sample collection

**If a different method is used to estimate the sample size, please add a scientific citation or reference and inform the main inputs and outputs from its implementation.*

- Sampling depth through all the project lifetime, both for SOC%+ BD and for soil fertility.
- Tool used to extract soil cores and key metrics (e.g.: If core sampler used, include tool diameter in mm).
- If you followed any recommendations or standards for data collection and handling, please add the citation, mention the source or reference the professional providing guidance.

S.3.2. GIS DATA- CARBON ACCOUNTING

- Project boundary (polygon)
- Sampling points (points)- GNSS coordinate for each sample location and sub-samples (if applicable)
- The GNSS receiver model used for geolocating the sampling points must be reported in the monitoring report.
- GNSS device used to record sample location
- If subsamples are taken, please document the number of subsamples at each point, and ideally also the geometry of the sub-samples. Distance and direction from a reference point are recommended.
- Grasslands mask (polygon)
- If stratification is performed:
    - The monitoring report must specify the methods and variables used to define strata.
    - A geospatial file defining stratified zones used for each sampling round must be provided with each report.
    - Also, any additions or any changes in the sampling points between sampling rounds must be clearly reported.
- The remote sensing images and any ancillary data used for the regression/ machine learning or interpolation models (full reference to sensors or satellite, bands, dates).
- The Monitor must provide a detailed report of the method used for calculating the SOC stocks, and any metrics used to evaluate Uncertainty or Error, as well as the justification for selecting a specific model.

- Outliers can be removed, but the methods used and a justification must be included in the report.
- The Monitor must report the spatial interpolation method or PTF used for the calculation of Bulk density if choosing option A in section 3.3.1.2.
- Any deviations from the methodology must be reported.

Acceptable polygon data formats include ESRI shapefile OGC GeoPackage, KML/KMZ and GeoJSON.

S.3.3. LAB DATA- SOIL ORGANIC CARBON STOCKS (100% SAMPLES)

- The original lab reports should be provided, containing the raw data for:
    - SOC concentration (%) per sample.
    - Bulk density, or the input data for calculations and the final estimates, per sample.
- Some reference to the lab (name, link) must be provided.

S.3.4. FARM DATA- GHG EMISSIONS ACCOUNTING

- The number of animals present, the number of days the animals were located in the project area, and the default emission factor (and its citation) for the corresponding group of livestock, must be cited in the report.
- Any other relevant data for the estimation of GHG from other sources, if it applies.

S.3.5. LAB DATA- SOIL FERTILITY (MIN. 30% OF TOTAL SAMPLES)

The original lab reports should be provided, containing the raw data for:

- pH
- Macronutrients
    - Phosphorus
    - Potassium
    - Nitrogen (at least one of the following)
        - Total Nitrogen
        - Nitrate Nitrogen
        - Ammonium Nitrogen
- Soil cations: at least three (3) of the following:
    - Calcium
    - Magnesium
    - Potassium
    - Sodium
    - Aluminum

Local benchmarks for each of the included indicators should be also provided, and the depth of the samples from which these benchmarks were generated must be reported.

S.3.6. GIS DATA- ECOSYSTEM HEALTH

Ecosystem Vigor and Resilience:

- Project boundary (polygon)
- Control area (polygon)
- Grasslands mask (polygon)
- Images used for analysis
- The report must include the NDVI or EVI results from control and project areas
- The report must include the bare soil results from control and project areas.

Ecosystem Organization:

- Vegetation Structure Landscape Metrics: The choice of landscape metrics and thresholds for scoring and the corresponding cites to the scientific literature must be provided in the report.
- Information on the water bodies or watercourses within the property, when corresponding (area, perimeter, geolocation)

S.3.7. FINAL RESULTS AND SCORES

- The table with partial and final scores
- The creditable carbon change (tCO_2e) and its corresponding partial components: UD or ED, and Net CO_2e REDUCTION values for the reporting period.