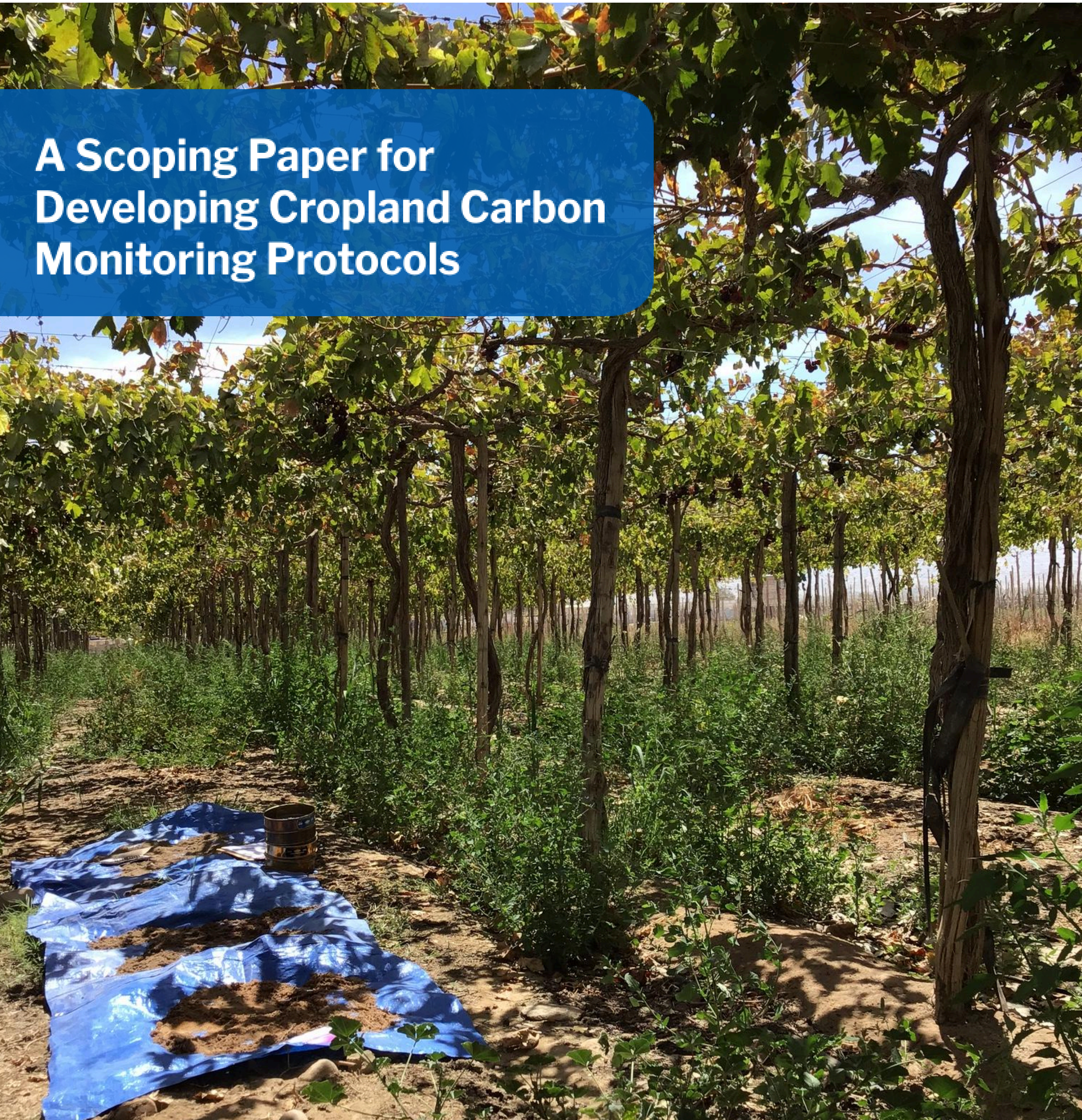
Point Blue
Conservation
Science



A Scoping Paper for Developing Cropland Carbon Monitoring Protocols

A Scoping Paper for Developing Cropland Carbon Monitoring Protocols

February 2024

Prepared by

Point Blue Conservation Science

Greg Richardson | Erika Foster, PhD
Avalon Cook | Chelsea Carey, PhD

Suggested citation: Richardson, G., Foster, E.J., Cook, A., Carey, C.J. 2021. A scoping paper for developing cropland carbon monitoring protocols. Point Blue Conservation Science Contribution No. 2500, Petaluma, CA

Photo credits: Erika Foster. Cover photo: Soil sampling in vineyard. Inside cover: A view of cover crop growth above- and belowground.

Point Blue Conservation Science – Point Blue's 160 scientists work to reduce the impacts of climate change, habitat loss, and other environmental threats while developing nature-based solutions to benefit both wildlife and people.

Conservation science
for a healthy planet
3820 Cypress Drive, #11
Petaluma, CA 94954
pointblue.org

Summary

Programs incentivizing soil health and regenerative agriculture have been rapidly expanding at local, state and national levels across the public, nonprofit and private sectors. In parallel, expectations are growing for the farming community to track changes in ecosystem properties like carbon levels that result from corresponding changes in management (USDA, 2022; Ogieriakhi and Woodward, 2022; Lenhardt and Egoh, 2023). A need exists to support standardized monitoring efforts with flexible protocols that match available resources and can map onto commonly incentivized practices for cropland[1] conservation.

In collaboration with partner organizations and individual experts, Point Blue Conservation Science aims to meet this need through development of The Crop-C Monitoring Program. Outputs include a scientifically robust and user-friendly monitoring guide (the Crop-C Monitoring Handbook) and development of a secure database to scale the impacts of resulting data.

In its final form the Crop-C Handbook will allow users to create fit-for-purpose sampling designs and easily pair these with measurement protocols that match monitoring objectives. In addition to providing rigorous standards as a baseline, Crop-C will create transparency related to data quality. Specifically it will offer guidance regarding which choices improve confidence in the monitoring data and assign points to decisions that increase confidence in data accuracy. Examples include taking more samples from a field, using more sophisticated lab methodologies, and monitoring more carbon pools/indicators. By design, Crop-C users can share their results in a secure aggregated database, with various options for anonymization. This will enable analysis of the data to expand scientific understanding of how carbon changes in response to adoption of key conservation agriculture practices across regions.

This document includes a broad overview of the high-level goals for Crop-C, sampling design considerations, a suite of carbon indicators (i.e. pools), and monitoring methods. This report does not include a systematic review of all existing carbon accounting protocols, nor prioritization of which practices or sites sequester more carbon. Instead, the focus is on supporting farming producers and their community of consultants and technical service providers with the development of practical and scientifically rigorous monitoring.

[1] Cropland is defined here as agricultural land on which plants are grown for harvest and sale. This includes cultivated and uncultivated, irrigated and rainfed, conventional and organic lands; from rice to agroforestry to planted and baled hay fields. It does not include rangelands, hydroponic nor container plantings. For grazed pasture and rangelands, see Range-C.

Table of Contents

Table 1. Crop-C Monitoring Program Scope

Main objective	-Detect impact of practice on above and belowground carbon on-farm -Aggregate data to conduct science at scale to inform management
Ecosystem	-Cropland
Sampling scale (study area)	-Field, block, or plot where management practice is implemented (and a control if possible)
Temporal scale	-Project dependent
End-users (who collects data)	-Land managers (e.g., farmers, land stewards) -Technical assistance providers -Sustainable agriculture programs
Data use	-Compliance/performance monitoring for incentive programs -Adaptive cropland management -Direct-to-consumer storytelling -Applied scientific research

1. Introduction

Croplands are a source of food, feed, fiber and fuel as well as culture, livelihood and connection to natural systems. Covering approximately 12% of global land area (~3 billion acres), the global influence of farming is the product of innumerable local actions (Potapov et al, 2022). As it relates to the health of terrestrial and aquatic ecosystems, cropping decisions can improve and/or degrade regional air and water quality, biodiversity and associated habitat (Sanaulla et al. 2020; DeClerck et al. 2023).


Oats drying in windrows before being baled for hay. (credit: E. Foster)

The past decade has seen a rapid expansion of regenerative agriculture and soil health programs aimed at incentivizing practices that simultaneously improve the vitality and resilience of both farming and natural systems. A key indicator of success is the amount of additional carbon sequestered within living and organic materials above and belowground. This is because carbon is paramount to agroecological function. Soils with higher levels of organic carbon tend to have increased fertility, water holding capacity, and disease suppression (Bradford et al. 2019; Lal 2020). As such, soils richer in organic matter provide crops with improved resilience to extreme weather like flood events, heatwaves and periods of drought. In addition, carbon in agricultural soils and biomass is directly drawn down from the atmosphere via photosynthesis and is widely considered an important climate mitigation strategy. The agronomic benefits of soil carbon and carbon's importance as an ecosystem property is now widely recognized as a win-win solution and has created opportunities for collaboration across farming communities, conservationists and policy makers alike.

As momentum builds in support of increasing on-farm carbon levels, numerous programs have "cropped up" to advance the adoption of conservation practices by providing technical service and financial support. Yet, while many of these programs offer recommendations for *what* to measure when it comes to carbon, there is often insufficient guidance and/or flexibility regarding *how* to take these measurements. This is what the Crop-C Monitoring Handbook aims to provide.

Narrowing the Scope: Managing and Monitoring Cropland Carbon

Point Blue Conservation Science is developing Crop-C to support scientifically sound and fit-for-purpose monitoring of carbon changes in croplands. This scoping paper is the blueprint for Crop-C development, outlining the motivations for monitoring, potential carbon indicators and methods, and conservation-practice considerations. When complete, established networks of farmers, scientists, and agency staff can utilize Crop-C to ensure that monitoring efforts are both efficient and effective, using robust standardization. Our intention is for cropland data to be collected in a rigorous, yet accessible way, such that the effects of management practices can be analyzed on a site, regional, state, or national scale. The Crop-C framework will be easy to use, flexible between sites and management contexts, and consistent enough to be analytically comparable. The resulting Crop-C data will be harmonized in a central database and leveraged to refine recommendations for best management practices and potentially inform cropland policies to benefit producers. Importantly, Crop-C does not provide guidance on making management decisions and aids a land steward *after* they *have decided* to implement a practice which they expect to impact carbon storage at their site.

Setting the Context

As part of a larger project funded through the USDA Climate-Smart Commodities program, development of the Crop-C Monitoring Program is modeled after the existing Range-C Monitoring Program. The proposed objectives of this Crop-C scoping paper are to:

1. Establish a framework for the Crop-C Handbook, including identifying key decisions for effectively monitoring carbon levels in croplands after the adoption of conservation farming practices; and
2. Support the development of a large-scale verifiable dataset documenting changes in carbon that can inform future prioritization for cropland stewardship.

As highlighted in Figure 1 below, the final users of Crop-C such as farmers, landowners, policy-makers, and scientists may be motivated by different or overlapping interests (e.g., economic gains, ecosystem services, scientific understanding), which are supported by a growing number of funding streams and programs. These include certifications, regenerative labels, direct-to-consumer storytelling, carbon farm plans, stewardship initiatives, incentive programs, existing monitoring networks, and government contracts or grant programs.

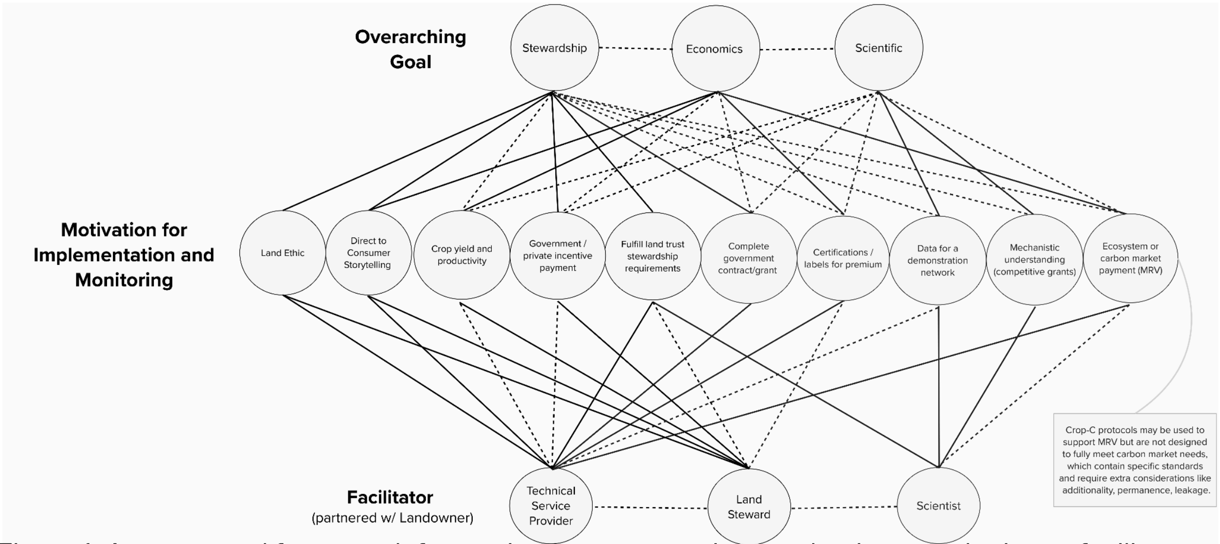


Figure 1. A conceptual framework for motivations, supporting mechanisms, and primary facilitators involved in soil carbon monitoring. Solid lines represent direct connections between entities and dotted lines represent indirect connections. The Crop-C Program aims to directly or indirectly support all monitoring motivations except carbon offset markets, which require special attention and consideration for Measurement, Reporting, and Verification.

We intend to align Crop-C's recommendations with existing frameworks for monitoring changes in agricultural carbon and database development. These include NRCS' CEMA 221 and Conservation Reserve Program, the Soil Inventory Project (TSIP), and state initiatives like the CDFA Healthy Soils Program. We intend to highlight how Crop-C aligns and differs from these key programs. There may be ways that Crop-C can offer insights to users interested in carbon markets (e.g. Verra, Nori, Indigo Ag, Gold Standard, BCarbon, RegenNetwork) but Crop-C is not intended for this purpose. Each carbon market has its own requirements for monitoring, reporting and verification (MRV) and requires considerations outside the scope of Crop-C like permanence, additionality, and leakage (Oldfield et al. 2021). As such, it is our primary goal to support the broader ecosystem of carbon monitoring efforts by enabling interoperability where possible and by filling existing gaps. We are unaware of another guide, for example, that offers fit for purpose sampling designs based on users' site conditions, management practices and desired data accuracy.

It is our intention to use a tiered approach with multiple protocols that can articulate with a range of monitoring objectives (Billings et al. 2021). Not only would users have the flexibility to choose methods that fit their goals and resource constraints, but points can be rewarded through the tiered system for choosing methods that are known to be more precise, accurate and reliable, as described in the "Data Quality Indexing" section below. This should help to build a more robust dataset for assessing practice impact across U.S. croplands.

Two advisory committees, a Technical Working Group and Practitioner Working Group, will be asked to provide feedback on the scope and objectives of this project and to help develop key design guidelines.

Featured Management Practices

The set of management practices included in this scoping paper are common conservation agriculture techniques and are regularly featured in existing soil health, carbon farming[2], and regenerative agriculture programs. This list cannot be exhaustive, and endeavors to include practices applied widely in the US and across multiple cropping systems. Each practice is presented below along with its National Resource Conservation Service (NRCS) [Conservation Practice Standard] in parenthesis, where applicable.

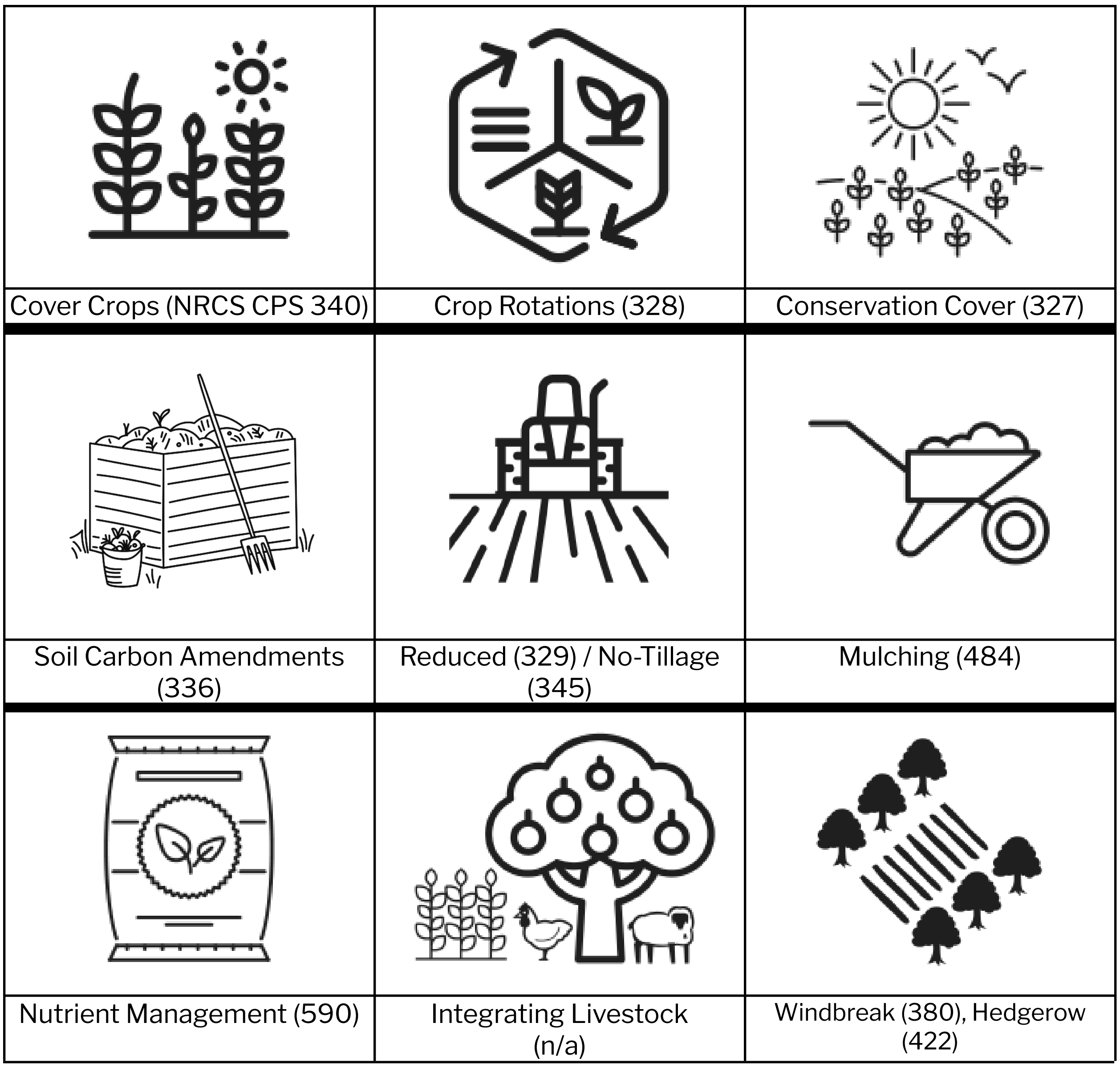


Figure 2. Proposed management practices featured in Crop-C Handbook, which predominantly map onto existing NRCS Conservation Practice Standards (CPS).

[2] Carbon farming is a term describing agricultural operations in which the accumulation of carbon in soils and plant biomass is a primary objective.

Navigating Complexity

In a given farm field, adopting a new management practice can lead to a wide range of changes to carbon levels. Results can be highly variable due to a myriad of factors including soil properties, current and previous management, and climatic conditions. Furthermore, the implementation of a given practice can be performed in various ways. For example, if a farmer is planting cover crops the results will be influenced by what species are planted, during what time of the year, how much biomass the plants produce, how they are terminated / returned to the soil, and if the fields are subsequently tilled (McClelland et al, 2020). Each of the nine conservation management practices featured by Crop-C include a similar spectrum of decisions that can impact ecosystem carbon.

Capturing true field conditions via a series of samples is also obfuscated by field spatial variability and (un)expected levels of error in lab and field testing (Bradford et al., 2023; Stanley et al. 2023). Nevertheless, it is possible to turn to decades of scientific research to find trends that result from adopting carbon farming practices and to account for their range of potential outcomes (Lal 2004; Paustian et al. 2016; Gelardi et al. 2023). The Crop-C Handbook factors the aforementioned variability into the planning process for effective carbon monitoring.

2. Carbon Monitoring Design

This section outlines a range of considerations when creating an agricultural carbon monitoring plan. It is built upon the existing framework laid out by Range-C. The resulting monitoring plans will be specific to each user, per the wide range of motivations for agricultural carbon sequestration (see Figure 1).

While we intend to include a brief "Pre-Assessment" to help users validate whether monitoring for carbon is an effective use of their time and resources, our focus will be on developing flexible and robust sampling plans. A tiered system (á la Billings et al., 2021) that offers a menu of design options, indicators, and recommended methods can help to support this kind of approach. We recommend the target audience be technical assistance providers and engaged land stewards who generally contain more capacity to follow a sampling plan than the average farmer.

The Crop-C Handbook offers an easy-to-use monitoring design process that includes spatial and temporal sampling strategies to precisely detect change in carbon with treatment over time. The protocols can be applied to fields of size less than 1 acre to 100s of acres and use sampling schemes that match the 'footprints' of each relevant practice (e.g. linear for hedgerows, dispersed for compost application). We intend for the Crop-C Handbook to allow users to calculate costs/limitations (e.g., requirement of expert knowledge or cost of more in-depth lab analysis) to weigh against the potential benefits. These protocols will consider inclusion of aspects of the existing Range-C Handbook, including:

Monitoring Elements (detailed below)
Pre-Assessment
Inference Scores
Study Area
Sampling Density
Sampling Locations
Sampling Timing and Frequency
Sample Compositing
Featured Management Practices
Monitoring: Indicators and Methods

Pre-Assessment

Proposal: Because carbon monitoring can be a resource intensive process, we feel it is prudent to ask Handbook users upfront to reflect on whether it is the right decision for their situation. This brief section will reference the motivations diagram (Figure 1) and offer considerations to take into account before proceeding. This could include checking if users have a defined reason to monitor, as well as a plan for how they intend to use the data (including contributing to broader efforts through Point Blue's centralized database and interpretation tools).

In addition, we may suggest a cursory evaluation of whether it is reasonable to detect change in C levels based on the circumstance. For example, there are scenarios where the likelihood of carbon accumulation - and our ability to detect this change - is limited by external factors (e.g. sandy soils, dry climates). Where one expects extremely high spatial variability, low-impact management practices and short project timelines, detecting change over time may be impractical.

Considerations: This is a section that was not included in the first edition of Range-C, which deliberately met users after they had developed goals and decided to pursue carbon monitoring. The addition of this check-point is aimed toward supporting users in defining the utility of their C monitoring efforts - so that the benefits of doing this work are more widely felt and sustained.

This section may include a simple flow chart to help land stewards decide if carbon monitoring is appropriate. We intend for it to be simple and clear to avoid potential confusion or paralysis in users regarding how to proceed. It is not necessary for users to know all the answers; these are merely considerations to take into account.

Data Quality Index

Proposal: As with Range-C, when a sampling decision is expected to increase the accuracy, precision, or statistical inference of the data, it would be considered a "Tier 1" option, versus "Tier 2" or "Tier 3". Each tier would have a number of points assigned to it that reflects its relative impact on the data's statistical inference. The sum of each tiered decision's points would feed into a final "inference score". This score creates transparency around data quality for future meta-analysis, with the co-benefit of gamifying the experience and encouraging users to make choices that improve the reliability of their results.

Considerations: This approach has already been established and laid out in Range-C (detailed in Appendix A) and is just starting to be field tested. While we may not know the full scope of how well it works before initiating the development of Crop-C, we hope to be able to draw on feedback. Ultimately, our decision is whether the pros outweigh the cons to establish a tiered system with inference scores for Crop-C and then how best to do this.

If inference scores are incorporated into Crop-C, the task at hand will be determining how to adjust the scores from what was decided for Range-C, in a fashion that is defensible.

While we are unfamiliar with other frameworks that assign scores to monitoring data based on the rigor of the methods used, confidence levels are common to scientific reporting. The Monitoring Manual for the Bureau of Land Management's (BLM) Assessment, Inventory and Management (AIM) program provides detailed instructions about meeting desired statistical power and selecting sampling densities in Appendix C. The International Panel on Climate Change (IPCC) also offers guidance on how they define and use confidence levels that may be useful here. Nevertheless, this appears to be a novel approach and adds meaningful value to the broader effort of validating the impacts of conservation practices on carbon levels in croplands.

Study Area

Proposal: The eligible study area will be the entire area where a specific management practice is implemented on a farm. Typically, this will be at a field, irrigation block, or plot scale. When possible, we highly recommend including a paired control (i.e., an untreated) area of the same size and landscape characteristics. Addition of a control site will improve one's inference score, as described on the previous page.

Considerations: By including the entire area where a management practice is implemented, there are no upper bounds to the acreage and types of topography included. This invites spatial variability that, in turn, could make it difficult to identify true changes in carbon resulting from management. Guidance could include isolating the dominant landscape expression (soil type, degree and orientation of a slope, etc.) in a given field or area where the management is being implemented. However, a full *field-scale* sampling plan is not only reasonable but arguably necessary to accurately track changes across an entire field - rather than extrapolating from plots or subdivisions of the field (Bradford et al. 2023).

Soil sampling in a field with center-pivot irrigation (credit: G Richardson)

As it relates to control sites, we recognize there are conditions that may prohibit incorporating them into a monitoring plan. These include difficulty in finding a comparable site with matching characteristics and management history, farmer resistance to set aside land for a control, and higher associated lab and labor costs. Nevertheless, having a control offers the maximum amount of inference to disentangle management impacts from other drivers of temporal change (such as climate shifts)- both at the network scale and for individual projects (Kimiti et al. 2020). Having a paired treated and control area also helps to minimize issues with dynamic baselines (Bradford et al. 2023), observer bias, and laboratory measurement uncertainties. Research has been conducted to determine the minimum number of samples to capture variability at different scales, even up to country-wide (Conant and Paustian 2002).

Sampling Density

Proposal: Adequate sampling density (i.e. the number of samples collected in a given area) is often lacking in many carbon monitoring frameworks, as a baseline carbon stock or change in carbon is often required to calculate the number of samples exactly (Stanley et al. 2023, Kravchenko and Robertson, 2011, VandenBygaart et al. 2011). We plan to help Crop-C users determine sampling densities for their projects based on three main factors:

1. *Expected spatial variability:* We aim to guide users through the process of categorically assigning their fields as having "high", "medium", or "low" expected spatial variability. This can be done using the table below and selecting the category in which the most items accurately describe their field. The below table is an example from Range-C.

Expected Variation in Carbon	System Characteristics
High	- Contains full hill slope (top to bottom of hill) - Slopes face ≥ 3 cardinal directions (N, W, S, E) - Greater than 3 soil types - Large area (> 25 acres) - Uneven drainage with partial saturation for 1+ months - Growing perennial crops in rows (orchard, vineyard, etc.) - Mixed land use history in same field - Major interventions (e.g. tile drainage, laser levelled)
Medium	- Sloped (but doesn't include full top to bottom of hill) - Slopes face ≥ 2 cardinal directions (N, W, S, E) - 2-3 soil types - Medium sized area (5-25 acres) - Uneven drainage with partial saturation for weeks - Perennial crops grown in rows within past 10 years - Consistent land use history across field - Moderate spatial interventions (e.g. strip tillage)
Low	- Relatively flat (≤ 2% slopes) - Slopes face only one cardinal directions (N, W, S, E) - 1 soil type - Small area (< 5 acres) - Even drainage across field - ≥ 10 years since perennial crops grown in rows - Consistent land use history across field - No major interventions (e.g. tile drainage, laser levelled)

Figure 3. Draft of a table for selecting expected spatial variability in a given field. Users would choose the category that most applies to their situation.

2. *Expected "effect size": the impact resulting from a given management practice*: We can use COMET-Farm and the underlying DayCent model (Swan et al., 2015) to project changes in carbon from management practices. Through an independent literature review, we also identified expected breadths of change in carbon stocks resulting from these farming management practices.
3. *Desired level of certainty (i.e. statistical power and confidence)*: Expected spatial variability and expected rates of change can be used to inform a power analysis - or statistical determination of how many samples need to be collected to accurately capture change. If a person wants greater certainty in their data, they can modify the statistical significance - alpha(α) - and power (1-beta [β]) that they are striving to

achieve. We propose offering three tiers to Crop-C users, with the following statistical targets:

- High: $p=0.05$ (95% chance of capturing a true change); $\beta = 0.1$ (10% chance of missing change);
- Medium: $p=0.10$ (90% chance of capturing a true change); $\beta = 0.2$ (20% chance of missing change);
- Low: $p=0.20$ (80% chance of capturing a true change) ; $\beta = 0.3$ (30% chance of missing change).

In general, more samples are necessary when expected spatial variability is high, impacts from management practices are relatively low, and high levels of certainty are desired.

For every management practice, we suggest creating "look-up tables" to help users determine how many samples to take based on the above factors. These look-up tables create clear sampling size recommendations, thus helping users acquire data that fits their intended purpose and carries transparency around data quality when it is eventually aggregated and analyzed. The below figure is an example of a lookup table from Range-C.

Number of Samples for COMPOST AMENDMENT							
Soil Carbon				**Herbaceous Biomass & Roots**			
	Study Area Variability				**Study Area Variability**		
Certainty	**Low**	**Med**	**High**	**Certainty**	**Low**	**Med**	**High**
Low	3	3	6	**Low**	3	3	5
Med	3	5	10	**Med**	4	6	10
High	4	7	17	**High**	5	9	16

Figure 4. Example of a "Look-Up Table" with recommended number of samples to take per field. Each 3x3 table will be specific to the management practice and the indicator (i.e. carbon pool) being studied.

Considerations:

1. Expected spatial variability - The true spatial variability of a field is typically unknown ahead of time and, as a result, it is often necessary to estimate using known influential factors. Some conditions that lead to higher variability can easily be observed, like changes in slope and orientation. Other factors include how many soil types / series are present in a field, or if parts of the field have had different management histories. Baseline samples can illuminate *actual* spatial variability and allow for an evaluation whether the chosen sampling density is adequate to detect a change over a period of time.

2. Expected effect size - Expected rates of carbon sequestration (e.g. tons Mg C / ha / yr) from farm management practices are based on external meta-analyses and modeling efforts. These values are the best estimates we have, yet they are built on imperfect data and often contain significant variability in effect sizes. This is to be expected based on the vast range of options for how a management practice is applied and under what conditions. To increase data reliability, the protocols will provide general guidance around sampling density and frequency, integrating the best available data and our mechanistic understanding of terrestrial carbon sequestration dynamics. As Crop-C protocols are implemented and data is shared and aggregated across multiple farms, these sample density estimates will continue to improve.

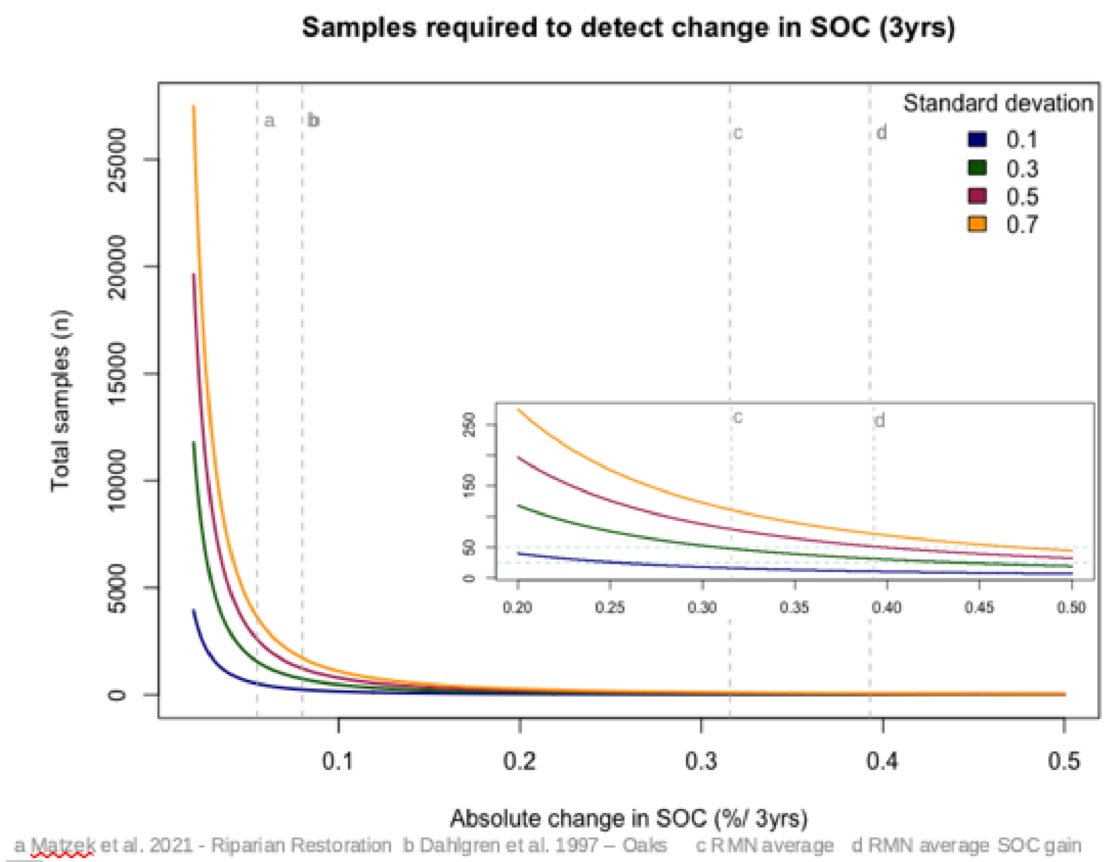


Figure 5. A simple power calculation estimating the number of soil samples needed based on the expected absolute change in soil organic carbon (SOC) over a three year period. Values were drawn from Point Blue Conservation Science's Rangeland Monitoring Network (RMN) sites, in California. A range of standard deviations is used, although the observed standard deviation of the RMN samples for SOC was 0.55 (denoted by the blue line). The analysis was conducted similarly to Oldfield et al. (2021), using the R software pwr () package two tailed t-test with an α set at 0.05 for a Type I false-change error rate and β of 0.20 for a Type II missed-change error rate (i.e., a power of 0.80). The first two dotted lines represent estimated absolute changes in SOC (%) over a 3 year period from peer-reviewed literature in

California rangelands: (a) 0.046 from Matzek et al. 2020 and (b) 0.08 from Dahlgren et al. 1997. The inset is meant to help show the number of samples needed to detect SOC change in RMN data, with dotted gray lines at (c) representing the mean change of (0.20) SOC from 0-10 cm (and converted to absolute change) and (d) the mean RMN SOC from only sites that gained carbon, equal to 0.38 % from 0-10 cm. The inset also includes two horizontal dotted lines as a reference at a sample size of 25 and 50.

3. Desired level of certainty - More rigorous sampling designs help to ensure that results are reliable. In statistics, this reliability is commonly validated using a significance level – alpha (α) – of 0.05 and a statistical power – (1-beta [β]) – of 0.8 or higher (McDonald, 2014). When users want to be more certain that their data is an accurate reflection of what's occurring in the field, they will use lower α and β values to reduce the likelihood that their finding was a fluke.

   Certainty levels (α and β) can be modified to reflect real or perceived costs (economic or ecological) associated with a Type I or Type II error[3] (Field 2007). The certainty levels selected for Crop-C are widely adopted in scientific literature for determining statistical significance of the measured change.


Researchers collecting samples in an alfalfa field. *(credit: E. Foster)*

[3] *Here, significance is the probability of rejecting the null hypothesis while it is true (Type I error or "false positive") and power is the probability of rejecting the null hypothesis while it is false (a "true positive"). Using the goal of this monitoring framework as an example, a Type I error would mean mistakenly concluding there is a response of carbon to a given management practice when there is not, and could result in incentivizing or relying on practices to manage carbon that are not actually effective. In contrast, a Type II error would mean failing to detect an effect that actually exists and may result in land managers not receiving credit for building carbon and, at a systems level, eventual removal of effective practices from the carbon management "toolbox".*

Sampling Locations

Proposal:

After determining the number of samples to take per field, the location of sampling points can be established. As a foundation, we recommend following a simple random sampling design whereby points are randomly selected prior to Crop-C users arriving in the field. This is a relatively straightforward process for those with a range of technical expertise while still reducing sampling bias. We suggest using one of two methods to obtain random points and locate them in the field:

1. Using the free mapping software QGIS to select points (as briefly described in Range-C Appendix D), paired with a GPS unit to find them in the field, or
2. Use a random number generator to determine the length along and distance from a line from which to take samples in the field (as described in Range-C Appendix E).

For users seeking greater sampling efficiencies (via more technical sampling designs), we propose offering guidance on how to set up stratified and/or spatially balanced sampling plans (Potash et al., 2023). This would be provided with the caveat that it requires greater technical skill to effectively set up and later analyze, such that its use will be up to the end-users' discretion.

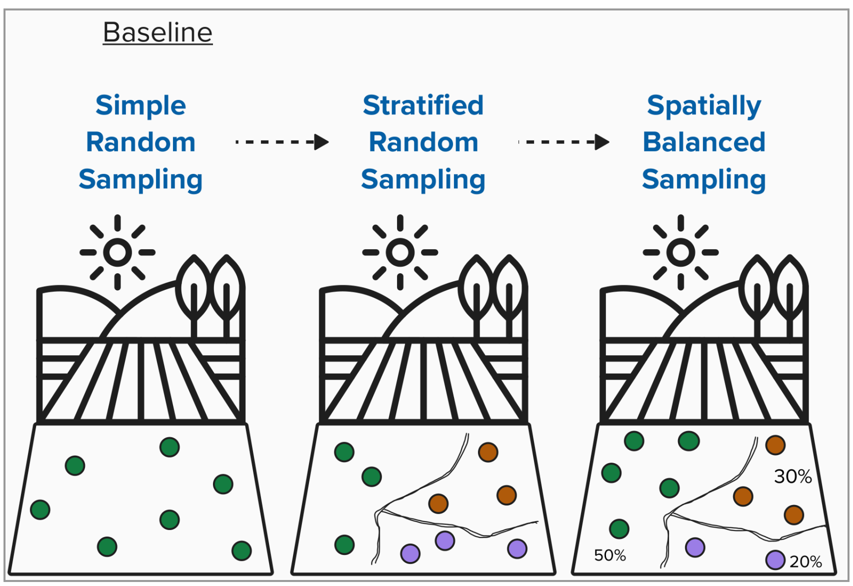


Figure 6. Simple random sampling (left) is planned as the recommended baseline sampling design for Crop-C users. We intend to offer instructions for stratified random sampling (center) and spatially balanced sampling (right) to implement at users' discretion.

Distinct instructions and design recommendations may be necessary per cropping system category. We suggest delineating these, as follows:

1. Field crops (including rice and planted/baled hay)
2. Perennial orchards, vineyards, & berries
3. Annual row crops
4. Small-scale diversified

Field crops are the simplest and can most easily follow the baseline proposal above. One exception are rice fields, which likely have unique sampling considerations.

For categories #2 and #3 above, the sampling points will be defined by field designated zones: in-row, in alleys / furrow, or on the shoulders between the two. We propose that users take one of two approaches:

1. Randomly sample the whole field whereby the number of samples taken from each zone are proportionate to the relative area of that zone - for example, if 60% of the field is in-row then 60% of samples are collected from that space, and so on.
2. Sample only from the zone where the effects of a management practice are expected. Adjust the data on a per acre basis according to how much of the field that zone represents. For example, if cover crops are grown only on the beds of annual row crops and not on the shoulders or in the furrows, then sample soil from just the beds. Adjust the final change in C accumulation by the proportion of the area the beds make up in the field.

If the boundaries between the field zones are difficult to distinguish, or the relative area of each zone cannot be accurately measured, then the first method should be used.

For small-scale, diversified operations, the variability imposed on the landscape by cropping features is highly varied. One row may be used to grow carrots, the next few for grains, neighbored by a row of trees that borders a small area for grazing. Our current expectation is that these farms will be encouraged to engage in stratified sampling plans whereby each zone is distinguished by the four cropping system types above.

We recommend sampling from permanent locations (i.e. returning to the same sites every time) and using the same sampling methodology and protocols each time.

Considerations:

At the broadest level, we must choose between sampling designs that are probability (i.e., random) versus non-probability (i.e., non-random) based. Non-probability sampling uses subjective judgment to determine sampling locations and therefore not all locations within the study area have an equal chance of being sampled. This creates issues around representativeness, making it difficult to generalize findings and evaluate precision of estimates (EPA, 2002). We therefore suggest making it a requirement that users choose a probability sampling approach for this monitoring framework.

Probability-based sampling strategies include simple random sampling, spatially balanced random sampling, systematic sampling, and stratified sampling. Our baseline recommendation is to use simple random sampling for simplicity's sake. It may be a barrier to adoption to require more technically demanding sampling designs to an audience with a wide range of technical skills.

That said, stratified sampling can be combined with simple random sampling to address areas with distinct conditions in the same field. Stratified sampling involves subdividing the whole study area into smaller, similar units via geography, landscape features, soil type, vegetation, management, or any other characteristic that moderates indicator variability (EPA 2002; Donovan, 2013). Sampling locations are then identified within each strata to create a stratified sample. For field-scale assessments, this approach has been described as not only superior, but necessary (Brus et al. 2013). However, stratification requires technical knowledge and preparation to execute effectively, which if done wrong can actually make sampling less efficient. Stratification also requires use of more complex analyses to produce mean and variance estimates, yet more resources have become available on the web to lower barriers to use (Stratifi, Journada Toolbox, SoilStack). As existing protocols vary in their use or recommendation for stratification, Crop-C will need to offer careful guidance on *when* to stratify. The usefulness of stratification for enhancing efficiency may also decrease as the size of the study area decreases, even at a field scale (Potash et al., 2023, section 4.4.2), and often no more than three strata are recommended within a single project.

Other approaches have been shown to further improve sampling efficiencies (Potash et al, 2023). As such, we see a benefit to offering guidance regarding when and how to implement other sampling designs to improve sampling efficiency and make the best use of limited monitoring resources. Spatially balanced random sampling can overcome some of the limitations of simple random sampling by identifying random locations that are evenly dispersed over the study area. This enhances representativeness and efficiency - particularly when strong spatial trends are present (Kermorvant et al, 2019). One of the most widely used spatially balanced designs in natural resource monitoring is Generalized Random Tesselation Stratified (GRTS) sampling (Stevens and Olsen 2004), which underpins the sampling design for Point Blue's RMN (Porzig et al. 2018) and the Bureau of Land Management's AIM program (Herrick et al. 2009). It has been shown to be more helpful for increasing precision than stratification in some cases (Lackey and Stein 2013), and may be a good sampling strategy to consider for this monitoring framework (especially for practices that cover relatively large areas).

Systematic sampling via use of a predetermined regularized pattern (with random starting point) is another way to address some of the limitations of a simple random sampling approach (Bijleveld et al, 2012). Grid sampling and transects are common examples of systematic approaches, but patterns may take other shapes (e.g. triangular) (Willis et al, 2018). In general, this approach should outperform simple random sampling, garnering a more representative sample due to its uniform spatial coverage (Tan, 2005). Indeed, systematic sampling is commonly deployed in precision agriculture and soil monitoring networks, with approximately 44% of monitoring schemes in Europe using some form of systematic approach (van Leeuwen et al, 2017). One limitation of this approach, however, is that an unbiased estimate of design variance does not exist, making it challenging to calculate reliable confidence intervals for estimated population parameters (Opsomer et al, 2012; Magnussen et al, 2020). Still, because of its relative simplicity and ability to provide more precise estimates compared to simple random sampling (Mostafa and Ahmad, 2018), systematic sampling may be another sampling strategy to consider, especially for practices that cover relatively small areas).

For annual and perennial crops grown in rows, it is logistically simpler to collect samples across the entirety of the field. However, if management practices are limited to specific zones then it will be a much more efficient use of resources to sample from only these zones and adjust calculations accordingly. It can be hard to imagine a farmer wanting to spend time and money taking soil samples from the furrowed wheel tracks of a tomato field when cover crops were only planted on top of shaped beds. Yet, if samples are only collected from specific zones of a field, there are risks. One is having to determine in the field where the edge of a management practice's influence will be, even when the intervention is no longer visible (e.g. a year after compost application). By extension, calculating the portion of the field that's represented can invite biases and error, as a shift from 50% to 60% of a field can impact the final outcomes by as much as 20%!

Practices for repeated sampling:

Using permanent sampling locations offers improved precision over selecting new points each time (Herrick et al. 2009), decreases the minimum detectable difference, and helps to ensure spatial and temporal differences are not confounded. It is also arguably simpler, since sampling locations only have to be identified once. It is worth noting that a hybrid approach also exists, where some proportion of new and existing locations are resampled in a rotating panel (Nieuwenbroek 1991). This approach helps to maximize spatial representation while also capturing temporal variability and is used by the National Park Service and the Bureau of Land Management for inventory and monitoring. Given the difficulty of overcoming spatial variability at field scales, for the Crop-C protocols we aim to prioritize precision.

Sampling Timing and Frequency

Proposal: Ideally, baseline sampling should occur before any management interventions occur and consistency is maintained in the seasonal timing of sampling across project years. Thereafter, sampling intervals will depend on the management practice being utilized and can range from 1 year (e.g. compost application) to 10 years (e.g. livestock integration) based on expected rates of carbon accumulation (COMET-Planner, Swan et al. 2015).

Follow-up samples should be obtained during the same time of year that the original baseline samples were collected. Generally, we recommend sampling when the effects of management practices will be easiest to detect. The below are guidelines per carbon pool:

- Aboveground woody biomass: Late-fall to early-spring when trees and shrubs are not actively growing. This will capture the previous year's growth.
- Above- and belowground herbaceous biomass: collect during peak biomass before the plants are harvested, grazed or terminated.
- Soil organic carbon: All samples should match the original sampling dates/season. Additional recommendations per management practice:

Management Practice	When to measure
Crop Rotations	*End of one or more cycles*
Hedgerows and Windbreaks	*In parallel with woody biomass sampling*
Reduced- / no-tillage	*Prior to typical tillage events (especially when there's a control)*
Carbon Amendments	*Just prior to application (baseline); same time of year, thereafter*

- Other: pH, bulk density and soil texture: Measure in parallel with the above samples.

Considerations:

Many agricultural carbon accounting protocols recommend taking soil carbon measurements no more than every 5 years (Oldfield et al. 2021). This is largely because spatial variability makes it difficult to accurately identify small changes in carbon. Waiting longer periods allows more time for the impact of a practice to accumulate and, therefore, creates a better likelihood of detecting change. However, it is reasonable for stakeholders to want to receive carbon accumulation data as soon as it can be obtained. This will depend partially on the management practice's expected carbon sequestration rates. When management practices accumulate carbon faster, changes will become detectable sooner.

On a practical level, farmers and researchers tend to engage in trials that have their own timelines, such as with research that runs one to five years. Detecting changes on management relevant time scales can be prioritized, and reflected in the look-up tables for sampling density. At the very least, it may be worth cautioning Crop-C users on the challenges of reliably detecting change over short durations and particularly when applying practices known to show slower rates of change, or in conditions that limit carbon accumulation (e.g. arid climates and sandy soils), although this level of detail may not be suitable for a broadly applicable, flexible protocol.

Sample Compositing (Field-Scale)

Proposal: After the number and location of sampling points have been established, we recommend that users only composite *subsamples* at each point. For example, taking a few samples within a foot of the sampling point and mixing these together to represent that point. We do not recommend compositing samples from different points in the field for the purpose of preserving variance data. However, keeping the soils separate is not required. Compositing does not impact the inference score because associated estimates of information loss are difficult to make without prior data from the field (Stanley et al. 2023).

Considerations:
Sample compositing is a commonly used approach to efficiently capture field conditions and it is a key decision point for monitoring. The primary benefit is reduced analysis cost, but it can obscure spatial variability information within the study area (Willis et al 2018), and can require additional technical/lab replicates due to adding a new layer of variability within the composite (Stanley et al. 2023; Spertus 2021). These limitations should not be a concern if the end user composites across areas where they want to capture but not necessarily understand variation (e.g. at the point scale). This highlights an important decision point to ensure the farmer or land steward understands management impacts at the field level, and the aggregated data proves useful at a broader systems level.

Sample Aggregation (Regional)

Proposal: Aggregating samples across project sites in a region can offer meaningful statistical advantages that lower the number of samples needed per field, and associated costs (Bradford et al. 2023). While offering farmers data about what's happening in their fields is a primary objective of Crop-C, there are use-cases where regional aggregation may be desirable for an organizing body like a company with many suppliers or field sites, or for place-based initiatives. Because this approach is newer and there are limited resources on carbon monitoring that explain how to do this, we are interested in exploring if Crop-C can fill this gap and support those seeking to aggregate data across project sites, particularly where quantification of change is not necessary on a per-farm basis.

Considerations:
Aggregation can occur as part of the upfront sampling design (leading to fewer samples and lower inference scores per field), or can be applied to data *after* individual field sampling plans have been administered. In the latter scenario, a higher number of samples would be taken from a field so that it stands alone in achieving a desired statistical power. However, in the spirit of Crop-C being a fit-for-purpose guide, the choice to aggregate data from the onset could be a meaningful feature for those that have this option. In these cases, we may encourage users to follow the sampling density recommendations associated with less spatial variability and lower certainty needs in order to remain aligned with existing standards.

Management Practices

Proposal: We recommend featuring management practices that are the most regularly studied, promoted and impactful interventions. We suggest distinguishing these practices from one another because they have different expected levels of impact on carbon levels, and they often warrant their own monitoring approaches.

As introduced in Figure 2 above, the proposed practices are:

1. Cover Crops (NRCS Std. 340)
2. Residue and Tillage Management via Reduced Till (329) and No-Till (345)
3. Crop Rotations (328)
4. Soil Carbon Amendments (336)
5. Mulching (484)
6. Conservation Cover (327)
7. Nutrient Management - Nitrogen Fertilizer Reductions (590)
8. Integrating Livestock
9. Establishment of Hedgerows (422) / Windbreaks (380)

When farmers are using Crop-C for practices not listed above, it may be possible to choose a comparable practice to use as a guide. For example, in some cases alley cropping will be similar in function to growing a cover crop.

Each project should record metadata about management practices, including fertilization, irrigation, planting dates, etc. These are detailed below on pages 31 and 32.

Considerations:

These practices cover commonly applied management interventions, and are derived from a list developed for the “Alliance to Catalyze Transition Incentives through Open Networks for Climate-Smart Agriculture” (ACTION for CSA) grant. Point Blue Conservation Science is a partner on this grant, which was awarded by the USDA as part of their Partnerships for Climate Smart Commodities program.

An underlying assumption behind Crop-C is that a farmer is implementing a practice with the intent to increase carbon and monitor changes. As mentioned above, not all practices have the same impacts and this can influence sampling density and frequency decisions. Number 7 above - the reduction of synthetic nitrogen applications via Nutrient Management (590) - is expected to have N_2O reduction benefits but limited to negative effects on soil carbon. As such, this may not be a good fit for the final Crop-C handbook.

For standardization purposes, each management practice is associated with a corresponding NRCS Conservation Practice Standard number, where applicable.

3. Monitoring: Indicators and Methods

Carbon in cropland is found above and belowground, in living tissues and dead, in organic and inorganic forms. We provide considerations below regarding which carbon pool indicators to measure and associated methods. Tier 1 choices are associated with higher Crop-C inference scores.

In this scoping paper we focus on empirical carbon field measurements. As such, we are not focusing on remote sensing tools, which typically require additional technical expertise.

Carbon Pool	Methods of Measurement	
	Tier 1	Tier 2
Soil Organic Carbon	Fractionation with dry combustion. Acid pretreatment when carbonates are present. Bulk density required.	Dry combustion with optional acid pre-treatment. Bulk density required.
Soil Inorganic Carbon	Pressure calcimeter	Dry combustion with acid pre-treatment
Aboveground Woody Biomass	Volumetric measurements calibrated to estimate biomass carbon	n/a
Aboveground Herbaceous Biomass	Cut, dry and weigh biomass from areas of specific size	Visual estimation, calibrated to biomass weights
Fine Root Production	Extract soil, clean roots, dry and weigh	n/a

Table 2. List of carbon indicators and methods planned for Crop-C. These recommendations are built upon the foundational work associated with developing Range-C. Methods associated with each indicator are listed in the subsections below.

The above methods will be coupled with standardized protocols in the Crop-C Handbook, which will provide added consistency around the collection, handling and processing of soil samples. This includes delineating appropriate sampling tools (soil probes, shovels), sample storage, and how the soils are dried, crushed, sieved and shipped prior to analysis. We intend to follow the recommendations provided in Range-C, except where special circumstances for croplands require modifications.

Indicators and Methods

Soil Organic Carbon

Sample soil to a minimum of 12 inches (30 cm), with a probe or bucket auger. Dividing a core into distinct depth increments is optional but offers improved chances of detecting change (Kravchenko et al 2011).

- <u>Tier 1 methodology</u>: Size fractionation and automated dry combustion. If an HCl test deems carbonates are present, pre-treat with acid to remove inorganic carbon.
- <u>Tier 2 methodology</u>: Automated dry combustion, with optional acid pre-treatment.

To estimate carbon stocks (e.g., tons of carbon per acre), soil bulk density must be measured. See the bulk density section below (page 31) for more details.

Considerations:

Most agricultural research on soil organic carbon (SOC) focuses on the top 20 to 30 cm, where carbon concentrations are usually greatest. Often, however, more soil carbon (by weight) is located deeper in the profile (Potash et al. 2023, Knebl et al, Syswerda 2011, Raffeld et al. 2024). Sampling below 30cm depth can be difficult without the right tools or under unfavorable conditions like in rocky soils. And greater sampling depth requires more sampling time and analysis costs when divided into depth increments. Yet deeper soil sampling may be critical to accurately capturing changes to SOC on agricultural land, particularly for establishing perennial vegetation or adopting no- or reduced-tillage (Olson and Al-Kaisi, 2015). The DayCent model for carbon cycling was recently modified in September 2022 to convert calculations from the top 20cm to the top 30cm. We selected 30 cm as the recommended minimum depth, for consistency with DayCent and most cropping systems research.

While a 30cm sampling depth may be adequate in most situations, it may not in others. In particular perennial cropping systems or conversion to no till can lead to topsoil gains in soil carbon, but this is regularly offset when evaluating soil profiles to a meter or deeper (Sierra et al. 2023; Ogle et al. 2012; Blanco-Canqui et al. 2021). As such, there may be circumstances where deeper sampling methodologies will be advantageous.

Soil organic carbon can be estimated in situ, yet is predominantly measured by collecting samples and sending them to a laboratory for analysis via wet or dry combustion (Chatterjee et al. 2009). Dry combustion methods are more widely used than wet combustion and include weight loss on ignition (LOI) and automated dry combustion. The LOI method oxidizes soil organic matter (SOM) in a sample by heating it to a very high temperature and then measures the mass difference to produce a value for SOM. This value can be converted to SOC using the approximate factor of 0.50 (Pribyl, 2010). However, the LOI method can decompose inorganic carbon constituents and remove water that may be remaining in the sample, effectively overestimating SOM content (Sollins et al, 1999). Despite this limitation, LOI-derived measurements of SOM content have been shown to correlate strongly with SOC content via automated dry combustion (Chatterjee et al. 2009) which is considered the superior method for routine analysis (Sollins et al. 1999, Paustian et al. 2019). Due to its low cost, LOI is used frequently among the farming community.

Soil fractionation is used to quantify the portion of soil carbon that is bound as particulate organic matter (POM) vs. mineral-associated organic matter (MAOM). Each pool is associated with distinct rates of carbon cycling. This is meaningful in the context of Crop-C as it illuminates the expected longevity that stored carbon will remain in a soil system. POM is more susceptible to decomposition and has been characterized as having soil residence times of approximately 1 to 50 years. The chemical bonds of MAOM are less vulnerable to decomposition and have been described as containing residence times of approx. 10 to 1000 years (Levallee et al. 2020). Fractionation is typically cost-prohibitive outside of academic contexts but becoming more readily available; we intend to include it as a tiered option within Crop-C due to the added definition of landscape carbon that it provides.

Soil Inorganic Carbon

Particularly in dryland environments, soil inorganic carbon (SIC) as $CaCO_3$ can represent a large portion of the soil carbon stocks, which can be affected by management (Lorenz and Lal, 2018; Naorem et al. 2022; Rasa et al. 2021). For the purposes of these protocols we focus on management and measurements of SOC as an indicator but also plan to support SIC measurements in the framework.

Considerations:

While it is difficult to intentionally increase soil inorganic carbon levels through agricultural management practices, inorganic carbon can still be a meaningful pool of terrestrial carbon. Especially when tracking changes in total soil carbon levels, distinguishing between organic and inorganic sources can provide meaningful insights about carbon distribution and cycling dynamics. This is especially important in alkaline soils that contain more SIC.

Aboveground Woody Biomass

In the context of Crop-C, aboveground woody biomass will apply primarily to hedgerow and windbreak plantings. New plantings of woody perennial crops (e.g. shrubs, vines and trees) do not squarely qualify as a conservation practice; however, such practices influence tree and shrub crops' growth and can thereby contribute meaningfully to aboveground carbon sequestration. In order to calculate how management practices influence orchard growth rates, a satisfactory control is required and pruning regimens must be considered.

For hedgerow and windrow plantings we recommend using a volume-based approach to estimating aboveground carbon stocks at the hedgerow scale. This is effective both for mature plantings that have grown into a thicket, as well as new plantings with gaps between plants. Measure total length, width, and height of the hedgerow and record the values in Appendix K of the Range-C Handbook ("Hedgerow Biomass" tab). If the hedge has variation in width and height, then take multiple measurements at fixed intervals and report the average. Then, estimate the density of the hedgerow by calculating percent cover by laying a tape measure or rope with regularly marked intervals (we suggest every 5 feet, but distance can vary depending on how long the hedgerow is) along the length of the hedgerow (Range-C Handbook Fig. 21, page 55). Record whether the hedgerow canopy covers each marked interval, and record the number of points covered (i.e., the number of "hits") in Appendix K ("Hedgerow Biomass" tab). This information will be used to estimate total aboveground and belowground biomass.

Considerations:
From a carbon sequestration perspective, aboveground woody biomass is highly relevant for some practices (e.g. hedgerow establishment) and not relevant for others (e.g., cover crop). In the most direct and intensive manner, the measurement of aboveground woody biomass involves destructive sampling of biomass and subsequent analysis of plant carbon content. This approach to sampling and analysis can be time and cost intensive, not to mention counter to the goals of management. As a result, many protocols implement a set of allometric equations or models to calculate biomass and subsequently estimate carbon from reported values and relationships in the literature (Chojnacky et al. 2014). Relatively straightforward metrics, including height and diameter at breast height (DBH), can be used to facilitate estimation (Dybala et al., 2019). The California Air Resource Board has a method for estimating the carbon stock from biomass measurements depending on dominant tree cover (Battles et al., 2014). Percent cover estimates are often paired with tree age and existing tables for common species biomass, such as the EPA Method for Calculating Carbon Sequestration by Trees in Urban and Suburban Settings (US DOE, 1998).

Aboveground Herbaceous Biomass
To be measured when plants approach peak biomass, whether at their full maturity or just prior to harvest, termination (e.g. tillage, herbicide application, etc.) or grazing. Maintaining a consistent time of year and phenological stage for this measurement is critical as it can be highly variable year to year.

Tier 1: Aboveground biomass can be determined by clipping vegetation to the soil surface from a hoop or quadrat of known dimension (e.g. 100 cm^2), making sure all plants with a primary stem inside of the area are pulled inside for clipping. Cut the plant flush with the ground, and place the clipped biomass into a pre-labelled paper bag. Optional to combine two replicates in the same bag. Do this in multiple locations across the field, per the sampling plan and lookup tables. Biomass samples are then dried at 65 °C / 150 °F for approximately 48 hours (until there's no additional moisture loss) and weighed.

Tier 2: Estimate biomass visually. These methods require careful initial calibration with actual plant weights (i.e. destructive harvesting). As such, the first sampling time will usually follow the Tier 1 method. Visual approximations are made by tossing a hoop or quadrat of known dimensions (e.g. 100 cm^2) in a random direction from the main soil organic carbon point location and estimate biomass from within the area where it lands. Do this at least three times around a single point by either 1) using a Robel Pole to determine plant density and estimate biomass; or by 2) counting the number of plant species occuring with the hoop and using pre-established weight estimates for each species to determine total forage biomass (by adding all estimated plant weights together).

Considerations:
Herbaceous biomass cycles quickly relative to most carbon pools. This should be reflected in lower inference scores (i.e. number of points) assigned to these measurements.

Aligning sampling dates with peak biomass can be challenging in practice, particularly on operating farms where weather-dependent harvest windows can be determined day-of. Accessing grain fields can also be difficult at this stage without damaging crop yields (e.g. causing lodging). Special consideration may be needed in these cases.

Fine Roots

Tier 1 (only): Use a hole saw to collect a root core to at least 6-in depth from within 3 feet of where soil organic carbon was collected.

Separate the roots from the soil by rinsing with water in a No. 40 sieve. Spend a fixed amount of time (at least 3 minutes) removing non-root debris from the samples, such as plant leaves and sticks. Place the sample and tin in an oven at 150 ℉ for at least 48 hours, or until constant weight. Remove the tin and spend another three minutes per sample discarding any pieces that are conspicuously not roots (e.g., buried bark) (Byrne 2021). Weigh to the nearest 0.01 gram. Use an Appendix to calculate root biomass as grams/$meter^2$.

Considerations:
Roots play a critical role in sequestering carbon out of the atmosphere and enhancing soil properties such as aggregation and structure (Angers and Caron 1998; Rasse et al. 2005). The production of fine roots is therefore a relevant indicator that relates to carbon sequestration and soil health. Changes in this indicator may be expected to occur to some degree across all practices in this framework.

Additional Indicators

We recommend collecting data on the following metrics as important contextual variables for understanding carbon response to management:

Soil pH: Lab analysis using a 1:2 soil sample to solution of $CaCl_2$ (Tier 1), or in-field using a hand-held pH meter (Tier 2) calibrated with buffer solutions. Mix 1 part soil with 2 parts distilled water (by volume) to make a paste, let it sti for 10 minutes and measure with the pH meter. A 15g subsample of soil from a well-mixed soil sample can be used.

Texture: Soil texture using the hydrometer method (Tier 1) will generally be performed by a service laboratory and is more consistently precise. Soil texture by feel (Tier 2) can be determined in the field or on air-dried samples in the lab. Collect 40-100g of soil from within 1 foot of the main sampling point and to the same depth.

Bulk Density: This is required for soil carbon quantification. We recommend using the "millet method" for upper soil horizons, "slide-hammer method" to greater depths (when digging a pit is not an option), or the "ruler method" within a probe-hole after extracting a core, as a last resort. These are described on pages 60 and 61 of the Range-C Handbook. Ideally, calculate bulk density values on an equivalent soil mass basis as described in the "Fixed Mass Example" tab of Appendix M in the Range-C Handbook.

Meta-data and Management Information

Metadata is information about the primary data that is important for tracking documentation and analysis purposes. It can include information like geographic, location, soil depth, sampling date, and protocol used.

Collecting meaningful metadata will be critical to facilitate aggregation and study of data across the network, especially if and when fit for purpose approaches to data collection are recommended as part of the framework. Collecting meaningful management data beyond the level of presence absence will also be key to help answer questions around practice impact.

All practices must collect information on farm inputs (fertilizer, irrigation) and mechanical treatment (tillage, bed preparation). For Range-C, this type of information can be collected using Appendix P "Practice and Protocol Questionnaire". We provide potentially relevant practice-specific management on the next pages (Section 4).

4. Practice-Specific Considerations

Table 3. Practice-specific details as proposed for Crop-C

Management Practice	Definition*	Expected Impact* (Mg C ha^{-1} y^{-1})	Management Metadata	Sampling Considerations
Cover Crops	Grasses, legumes and forbs planted for seasonal vegetative cover, typically between cash crops	0.18	Species planted each year; planting method; planting density (e.g. seed/acre per plant species); termination method; irrigated vs. rainfed; inputs (fertilizer, biocides); years of practice implementation.	Time of year and stage of plant maturity; Spatial variability across a field, especially for multi-species cover crops; root structures (e.g. fibrous vs. taproot); expected depth of root growth (per plant type and soil conditions)
Reduced- and No-Till	Limiting soil disturbance to manage crop and plant residue on the soil surface year round	0.08 (reduced tillage) 0.22 (no-till)	Equipment details (seed-drill, tillage implement types and specs); tillage depth; number of tillage / cultivation passes per crop; residue cover after final tillage pass; years of practice implementation	Time of year to sample; variability in residue cover; tillage depth
Crop Rotations	A planned sequence of crops grown on the same ground over a period of time	0.16	Crop types in rotation (incl. ley / pasture); years in this rotation, planting density (amount of seed per acre), irrigated vs. rainfed, inputs (fertilizer, biocides, etc.),	Current phase of rotation; diversity of rotation (species- & functional); what makes a reasonable control to compare against; time of year and stage of plant maturity to sample; plant spatial variability across a field; expected root depth
Soil Carbon Amendments	Application of carbon-based amendments derived from plant materials or treated animal byproducts	0.89	Application rates (ton/ac; lbs./ft^2); type of material (e.g. compost vs. biochar); feedstocks; application method / equipment; C:N ratios of amendments; treatment / processing method prior to application; practice frequency (e.g. yearly or every 3 years), years since initial practice implementation	How to sample soil only, not amendments; spatial variability of application rate
Mulching	Application of plant residues or other suitable materials to the land surface	0.18	Application rates (ton/ac; lbs./ft^2); type of material (e.g. rice straw); composition of material (e.g. C:N ratio); practice frequency (e.g. yearly or every 3 years), years since initial practice implementation	Spatial variability of application rate; Removing mulch from soil sample

Management Practice	Definition*	Expected Impact* (Mg C ha^{-1} y^{-1})	Management Metadata	Sampling Considerations
Conservation Cover	Establishing and maintaining permanent vegetative cover	0.68	Species planted; original planting date; replanting details; previous land use; land preparations (e.g. tillage) prior to planting; inputs (fertilizer, biocides, etc.); rainfed or irrigated	Time of year; spatial heterogeneity in plant community composition and biomass
Windbreaks / Hedgerows	Single or multiple rows of dense vegetation to reduce winds and/or for conservation purposes	0.76 (per linear ft. per row)	Species planted; planting spacing; years since original planting; re-planting info for subsequent years; irrigated vs. rainfed; inputs (fertilizers, biocides, etc.)	Spatial variability (due to species heterogeneity); accessibility (due to branches / vegetation barriers)
Integrating Livestock	Managing the harvest of vegetation with livestock to achieve ecological, economic, and/or agronomic objectives	TBD	Species of livestock; stocking density (e.g. animal units per acre); height of remaining biomass; groundcover percentage after grazing.	Sampling before and/or after grazing; changes in surface soil compaction; physiological maturity of forage / crops;
Nutrient Management	Approx. 15% reduction in synthetic nitrogen fertilizer rates by off-setting with organic matter amendments such as manure	-0.03	Nitrogen fertilizer type, application method, timing and rates; portion of nitrogen inputs replaced (0-100%); lab reports on soil nitrogen status (ie. chemistry and biological cycling)	Timing of application; spatial variability of application rate.

*Derived from Swan et al. 2015 and USDA-NRCS Conservation Practice Standard (CPS) guides

REFERENCES:

Angelopoulou, T., Balafoutis, A. T., Zalidis, G. C., & Bochtis, D. (2020). From Laboratory to Proximal Sensing Spectroscopy for Soil Organic Carbon Estimation—A Review. Sustainability, 12(2), 443. https://doi.org/10.3390/su12020443

Angers, D. A., & Caron, J. (1998). Plant-induced Changes in Soil Structure: Processes and silvFeedbacks. Biogeochem., 42(1/2), 55–72. https://doi.org/10.1023/a:1005944025343

Battles, J.J., Collins, B.M., Saah, D.S., (2014). California Forest and Rangeland Greenhouse Gas Inventory Development FINAL REPORT 1–147.

Billings, S.A., Lajtha, K., Malhotra, A., Berhe, A.A., de Graaff, M. -A., Earl, S., Fraterrigo, J., Georgiou, K., Grandy, S., Hobbie, S.E., Moore, J.A.M., Nadelhoffer, K., Pierson, D., Rasmussen, C., Silver, W.L., Sulman, B.N., Weintraub, S., Wieder, W., (2021). Soil organic carbon is not just for soil scientists: measurement recommendations for diverse practitioners. Ecol. Appl. 0, 1–19. https://doi.org/10.1002/eap.2290

Bijleveld, A. I., Van Gils, J. A., Van Der Meer, J., Dekinga, A., Kraan, C., Van Der Veer, H. W., & Piersma, T. (2012). Designing a benthic monitoring programme with multiple conflicting objectives. Methods in Ecology and Evolution, 3(3), 526–536. https://doi.org/10.1111/j.2041-210x.2012.00192.x

Blanco-Canqui, H., Shapiro, C. A., Jasa, P. J., & Iqbal, J. (2021). No-till and carbon stocks: Is deep soil sampling necessary? Insights from long-term experiments. Soil and Tillage Research, 206, 104840. https://doi.org/10.1016/j.still.2020.104840

Bradford MA, Eash L, Polussa A, Jevon FV, Kuebbing SE, Hammac WA, Rosenzweig S, Oldfield EE. (2023). Testing the feasibility of quantifying change in agricultural soil carbon stocks through empirical sampling. agriRxiv. doi:10.31220/agrirxiv.2023.00200. https://doi.org/10.31220/agrirxiv.2023.00200.

Bradford MA, Carey CJ, Atwood LW, Bossio DA, Fenichel EP, Gennet S, Fargione J, Fisher JRB, Fuller E, Kane DA, et al. (2019). Soil carbon science for policy and practice. Nature Sustainability. 2(12):1070–1072. doi:10.1038/s41893-019-0431-y. https://doi.org/10.1038/s41893-019-0431-y.

Brus, D.J., de Gruijter, J.J., (2013). Effects of spatial pattern persistence on the performance of sampling designs for regional trend monitoring analyzed by simulation of space-time fields. Comput. Geosci. 61, 175–183. https://doi.org/10.1016/j.cageo.2013.09.001

Byrne, K. M. (2021). Technical note: A rapid method to estimate root production in grasslands, shrublands, and forests. Rangeland Ecology & Management, 76, 74–77. https://doi.org/10.1016/j.rama.2021.02.004

Chatterjee, A., Lal, R., Wielopolski, L., Martin, M. Z., & Ebinger, M. H. (2009). Evaluation of different soil carbon determination methods. Critical Reviews in Plant Sciences, 28(3), 164–178. https://doi.org/10.1080/07352680902776556

Chojnacky, D. C., Heath, L. S., & Jenkins, J. C. (2013). Updated generalized biomass equations for North American tree species. Forestry: An International Journal of Forest Research, 87(1), 129–151. https://doi.org/10.1093/forestry/cpt053

Conant, R. T., & Paustian, K. (2002). Spatial variability of soil organic carbon in grasslands: implications for detecting change at different scales. Environmental Pollution, 116, S127–S135. https://doi.org/10.1016/s0269-7491(01)00265-2

Dahlgren, R.A., Singer, M.J., Huang, X., (1997). Oak tree and grazing impacts on soil properties and nutrients in a california oak woodland. Biogeochemistry 39, 45–64. https://doi.org/10.1023/A:1005812621312

DeClerck, F., Koziell, I., Benton, T. G., Garibaldi, L. A., Kremen, C., Maron, M., Del Rio, C. R., Sidhu, A., Wirths, J., Clark, M., Dickens, C., Carmona, N. E., Fremier, A. K., Jones, S. K., Khoury, C. K., Lal, R., Obersteiner, M., Remans, R., Rusch, A., Winowiecki, L. A. (2023). A Whole Earth approach to Nature-Positive Food: Biodiversity and agriculture. In Springer eBooks (pp. 469–496). https://doi.org/10.1007/978-3-031-15703-5_25

Donovan, P., (2013). Measuring soil carbon change: A flexible, practical, local method. Soil Carbon Coalit. 4, 1–61.

EPA QA/G-5S, (2002). Guidance on choosing a sampling design for environmental data collection. Washington, DC.

Field, S., O'Connor, P. J., Tyre, A. J., & Possingham, H. P. (2007). Making monitoring meaningful. Austral Ecology, 32(5), 485–491. https://doi.org/10.1111/j.1442-9993.2007.01715.x

Foster, E.J., Paustian, K., Taylor, P., Fitzgibbon, M., Porzig, E.L., and Carey, C.J. (2023). The Range-C Monitoring Program: Handbook of Field Methods. V1.0. Point Blue Conservation Science, Petaluma, California.

Gelardi, D. L., Rath, D., & Kruger, C. E. (2023). Grounding United States policies and programs in soil carbon science: strengths, limitations, and opportunities. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1188133

Herrick, J.E.,, Van Zee, J.W., McCord, S.E., Courtright, E.M., Karl, J.W., and Burkett, L.M. (2009) Monitoring Manual for Grassland, Shrubland, and Savanna Ecosystems. USDA - ARS Jornada Experimental Range. SECOND EDITION Volume I: Core Methods. ISBN 0-9755552-0-0

Kermorvant, C., D'Amico, F., Bru, N., Caill-Milly, N., & Robertson, B. L. (2019). Spatially balanced sampling designs for environmental surveys. Environmental Monitoring and Assessment, 191(8). https://doi.org/10.1007/s10661-019-7666-y

Kimiti, D. W., Ganguli, A. C., Herrick, J. E., Karl, J. W., & Bailey, D. W. (2020). A decision support system for incorporating land potential information in the evaluation of restoration outcomes. Ecological Restoration, 38(2), 94–104. https://doi.org/10.3368/er.38.2.94

Kravchenko, A., & Robertson, G. P. (2011). Whole‐Profile Soil Carbon Stocks: The Danger of Assuming Too Much from Analyses of Too Little. Soil Science Society of America Journal, 75(1), 235–240. https://doi.org/10.2136/sssaj2010.0076

Knebl, L., Leithold, G., Schulz, F., & Brock, C. (2017). The role of soil depth in the evaluation of management‐induced effects on soil organic matter. European Journal of Soil Science, 68(6), 979–987. https://doi.org/10.1111/ejss.12492

Lackey, L. G., & Stein, E. D. (2013). Evaluation of Design-Based sampling options for monitoring stream and wetland extent and distribution in California. Wetlands, 33(4), 717–725. https://doi.org/10.1007/s13157-013-0429-6

Lal, R. (2004). Soil carbon sequestration to mitigate climate change. Geoderma, 123(1–2), 1–22. https://doi.org/10.1016/j.geoderma.2004.01.032

Lal, R. (2020). Soil organic matter content and crop yield. Journal of Soil and Water Conservation, 75(2), 27A-32A. https://doi.org/10.2489/jswc.75.2.27a

Lenhardt J, Egoh BN. (2023) Opportunities and gaps in conservation incentive programs on California agricultural land. Frontiers in Sustainable Food Systems. 7. doi:10.3389/fsufs.2023.1239015. https://doi.org/10.3389/fsufs.2023.1239015.

Matzek, V., Lewis, D., O'Geen, A., Lennox, M., Hogan, S.D., Feirer, S.T., Eviner, V., Tate, K.W., . (2020) Increases in soil and woody biomass carbon stocks as a result of Rangeland riparian restoration. Carbon Balance Manag. 15, 1–15. https://doi.org/10.1186/s13021-020-00150-7

McClelland, S. C., Paustian, K., & Schipanski, M. (2021). Management of cover crops in temperate climates influences soil organic carbon stocks: a meta‐analysis. Ecological Applications, 31(3). https://doi.org/10.1002/eap.2278

Lavallee, J.M., Soong, J.L., Cotrufo, M.F., . (2020). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Glob. Chang. Biol. 26, 261–273. https://doi.org/10.1111/gcb.14859

Lorenz, K., & Lal, R. (2018). Carbon sequestration in cropland soils. In Springer eBooks (pp. 137–173). https://doi.org/10.1007/978-3-319-92318-5_3

Magnussen, S., McRoberts, R. E., Breidenbach, J., Nord‐Larsen, T., Ståhl, G., Fehrmann, L., & Schnell, S. (2020). Comparison of estimators of variance for forest inventories with systematic sampling - results from artificial populations. Forest Ecosystems, 7(1). https://doi.org/10.1186/s40663-020-00223-6

McDonald, J.H. (2014). Handbook of Biological Statistics (3rd ed.). P. 40-44. Sparky House

Publishing, Baltimore, MD.

Mostafa, S., & Ahmad, I. A. (2017). Recent developments in systematic sampling: A review. Journal of Statistical Theory and Practice, 12(2), 290–310. https://doi.org/10.1080/15598608.2017.1353456

Naorem, A., Somasundaram, J., Dalal, R. C., Patra, A. K., Rao, C. S., & Lal, R. (2022). Soil Inorganic carbon as a potential sink in carbon storage in Dryland Soils—A review. Agriculture, 12(8), 1256. https://doi.org/10.3390/agriculture12081256

Nieuwenbroek, N. J. (1991). Precision of Net Change in a Rotating Panel Survey. Journal of the Royal Statistical Society. Special Issue: Survey Design, Methodology and Analysis. Vol 40. No 2; pp. 195-201 https://doi.org/10.2307/2348491

Ogieriakhi MO, Woodward RT. (2022) Understanding why farmers adopt soil conservation tillage: A systematic review. Soil Security. 9:100077. doi:10.1016/j.soisec.2022.100077. https://doi.org/10.1016/j.soisec.2022.100077.

Ogle, S. M., Swan, A., & Paustian, K. (2012). No-till management impacts on crop productivity, carbon input and soil carbon sequestration. Agriculture, Ecosystems & Environment, 149, 37–49. https://doi.org/10.1016/j.agee.2011.12.010

Oldfield, E.E., A.J. Eagle, R.L Rubin, J. Rudek, J. Sanderman, D.R. Gordon. (2021) Agricultural soil carbon credits: Making sense of protocols for carbon sequestration and net greenhouse gas removals. Appendix B. Environmental Defense Fund, NY, NY. edf.org/sites/default/files/content/agricultural-soil-carbon-credits-protocol-synthesis.pdf

Olson, K. R., & Al‐Kaisi, M. (2015). The importance of soil sampling depth for accurate account of soil organic carbon sequestration, storage, retention and loss. CATENA, 125, 33–37. https://doi.org/10.1016/j.catena.2014.10.004

Opsomer, J. D., Francisco‐Fernández, M., & Li, X. (2012). Model‐Based non‐parametric variance estimation for systematic sampling. Scandinavian Journal of Statistics, 39(3), 528–542. https://doi.org/10.1111/j.1467-9469.2011.00773.x

Paustian, K., Collier, S. M., Baldock, J., Burgess, R. L., Creque, J., DeLonge, M. S., Dungait, J. a. J., Ellert, B. H., Frank, S., Goddard, T. W., Govaerts, B., Grundy, M. J., Henning, M. B., Izaurralde, R. C., Madaras, M., McConkey, B., Porzig, E. L., Rice, C. W., Searle, R., . . . Jahn, M. M. (2019). Quantifying carbon for agricultural soil management: from the current status toward a global soil information system. Carbon Management, 10(6), 567–587. https://doi.org/10.1080/17583004.2019.1633231

Paustian, K., Lehmann, J., Ogle, S. M., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. Nature, 532(7597), 49–57. https://doi.org/10.1038/nature17174

Porzig, E., Seavy, N.E., DiGaudio, R.T., Henneman, C., Gardali, T., . (2018). The Rangeland Monitoring Network: Handbook of Field Methods.

Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., Song, X., Pickens, A., Shen, Q., & Cortez, J. (2021). Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. Nature Food, 3(1), 19–28. https://doi.org/10.1038/s43016-021-00429-z

Potash, E., Guan, K., Margenot, A. J., Lee, D., Boe, A., Douglass, M., Heaton, E. A., Jang, C., Jin, V. L., Li, N., Mitchell, R., Namoi, N., Schmer, M. R., Wang, S., & Zumpf, C. (2023). Multi-site evaluation of stratified and balanced sampling of soil organic carbon stocks in agricultural fields. Geoderma, 438, 116587. https://doi.org/10.1016/j.geoderma.2023.116587

Pribyl, D. W. (2010). A critical review of the conventional SOC to SOM conversion factor. Geoderma, 156(3–4), 75–83. https://doi.org/10.1016/j.geoderma.2010.02.003

Raffeld, A. M., Bradford, M. A., Jackson, R. D., Rath, D., Sanford, G. R., Tautges, N. E., & Oldfield, E. E. (2024). The importance of accounting method and sampling depth to estimate changes in soil carbon stocks. Carbon Balance and Management, 19(1). https://doi.org/10.1186/s13021-024-00249-1

Raza S, Zamanian K, Ullah S, Kuzyakov Y, Virto I, Zhou J. (2021) Inorganic carbon losses by soil acidification jeopardize global efforts on carbon sequestration and climate change mitigation. Journal of Cleaner Production. 315:128036. doi:10.1016/j.jclepro.2021.128036. https://doi.org/10.1016/j.jclepro.2021.128036.

Rasse, D. P., Rumpel, C., & Dignac, M. (2005). Is soil carbon mostly root carbon? Mechanisms for a specific stabilisation. Plant and Soil, 269(1–2), 341–356. https://doi.org/10.1007/s11104-004-0907-y

Sanaullah M, Usman M, Wakeel A, Cheema SA, Ashraf I, Farooq M. (2020) Terrestrial Ecosystem Functioning Affected by Agricultural Management Systems: A Review. Soil & Tillage Research. 196:104464. doi:10.1016/j.still.2019.104464. https://doi.org/10.1016/j.still.2019.104464.

Sierra, C. A., Ahrens, B., Bolinder, M. A., Braakhekke, M. C., Von Fromm, S. F., Kätterer, T., Luo, Z., Parvin, N., & Wang, G. (2024). Carbon sequestration in the subsoil and the time required to stabilize carbon for climate change mitigation. Global Change Biology, 30(1). https://doi.org/10.1111/gcb.17153

Sollins, Phillip; Glassman, Carol; Paul, Eldor A.; Swanston, Christopher; Lajtha, Kate; Heil, Justin W.; Elliott, Edward T. (1999). Soil carbon and nitrogen: pools and fractions. In: Robertson, G. Philip; Coleman, David C.; Bledsoe, Caroline S.; Sollins, Phillip, eds. Standard soil methods for long-term ecological research. New York, NY: Oxford University Press: 89-105.

Spertus, J. (2021). Optimal sampling and assay for estimating soil organic carbon. Open Journal of Soil Science, 11(02), 93–121. https://doi.org/10.4236/ojss.2021.112006

Stanley, P., Spertus, J., Chiartas, J., Stark, P. B., & Bowles, T. M. (2023). Valid inferences about soil carbon in heterogeneous landscapes. Geoderma, 430, 116323. https://doi.org/10.1016/j.geoderma.2022.116323

Stevens, D. L., & Olsen, A. R. (2004). Spatially balanced sampling of natural resources. Journal of the American Statistical Association, 99(465), 262–278. https://doi.org/10.1198/016214504000000250

Swan, A., Williams, S.A, Brown, K., Chambers, A., Creque, J., Wick, J., Paustian, K. (2015) COMET-Planner: Carbon and Greenhouse Gas Evaluation for NRCS Conservation Practice Planning. Colorado State University and US Department of Agriculture.

Syswerda, S., Corbin, A., Mokma, D. L., Kravchenko, A., & Robertson, G. P. (2011). Agricultural Management and Soil Carbon Storage in Surface vs. Deep Layers. Soil Science Society of America Journal, 75(1), 92–101. https://doi.org/10.2136/sssaj2009.0414

Tan, K. H. (2005). Soil sampling, preparation, and analysis. In Tan K.H. Ed. Soil Sampling, Preparation, and Analysis. CRC Press, p. 1

Toevs, B.G.R., Karl, J.W., Taylor, J.J., Spurrier, C.S., Karl, M.S., Bobo, M.R., Herrick, J.E., (2011). Society for Range Management Consistent Indicators and Methods and a Scalable Sample Design to Meet Assessment , Inventory , and Monitoring Information Needs Across Scales. Soc. Range Manag. 14–20.

USDA press release. (2022) *USDA offers expanded conservation program opportunities to support climate smart agriculture in 2022*. https://www.usda.gov/media/press-releases/2022/01/10/usda-offers-expanded-conservation-program-opportunities-support

U.S. DOE (Department of Energy, Energy Information Administration). Method for Calculating Carbon Sequestration by Trees in Urban and Suburban Settings. Voluntary Reporting of Greenhouse Gases, U.S. (1998). Available online: https://www3.epa.gov/climatechange/Downloads/method-calculating-carbon-sequestration-trees-urban-and-suburban-settings.pdf.

Van Leeuwen, J. P., Saby, N., Jones, A., Louwagie, G., Michéli, E., Rutgers, M., Schulte, R. P., Spiegel, H., Tóth, G., & Creamer, R. (2017). Gap assessment in current soil monitoring networks across Europe for measuring soil functions. Environmental Research Letters, 12(12), 124007. https://doi.org/10.1088/1748-9326/aa9c5c

VandenBygaart, A., Bremer, E., McConkey, B., Ellert, B. H., Janzen, H. H., Angers, D. A., Carter, M. R., Drury, C. F., Lafond, G. P., & McKenzie, R. H. (2011). Impact of sampling depth on differences in soil carbon stocks in Long‐Term Agroecosystem Experiments. Soil Science Society of America Journal, 75(1), 226–234. https://doi.org/10.2136/sssaj2010.0099

Wendt, J.W., Hauser, S., (2013). An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. Eur. J. Soil Sci. 64, 58–65. https://doi.org/10.1111/ejss.12002

Willis, S., Roecker, S., Williams, C., Murphy, B. (2018) Soil sampling for soil health. Reicosky, D. (Ed.). Managing soil health for sustainable agriculture. Volume 2: Monitoring and management (1st ed.). Burleigh Dodds Science Publishing. https://doi.org/10.1201/9781351114585

Young, M.A., Macreadie, P.I., Duncan, C., Carnell, P.E., Nicholson, E., Serrano, O., Duarte, C.M., Shiell, G., Baldock, J., Ierodiaconou, D., . (2018). Optimal soil carbon sampling designs to achieve cost-effectiveness: A case study in blue carbon ecosystems. Biol. Lett. 14, 1–5. https://doi.org/10.1098/rsbl.2018.041