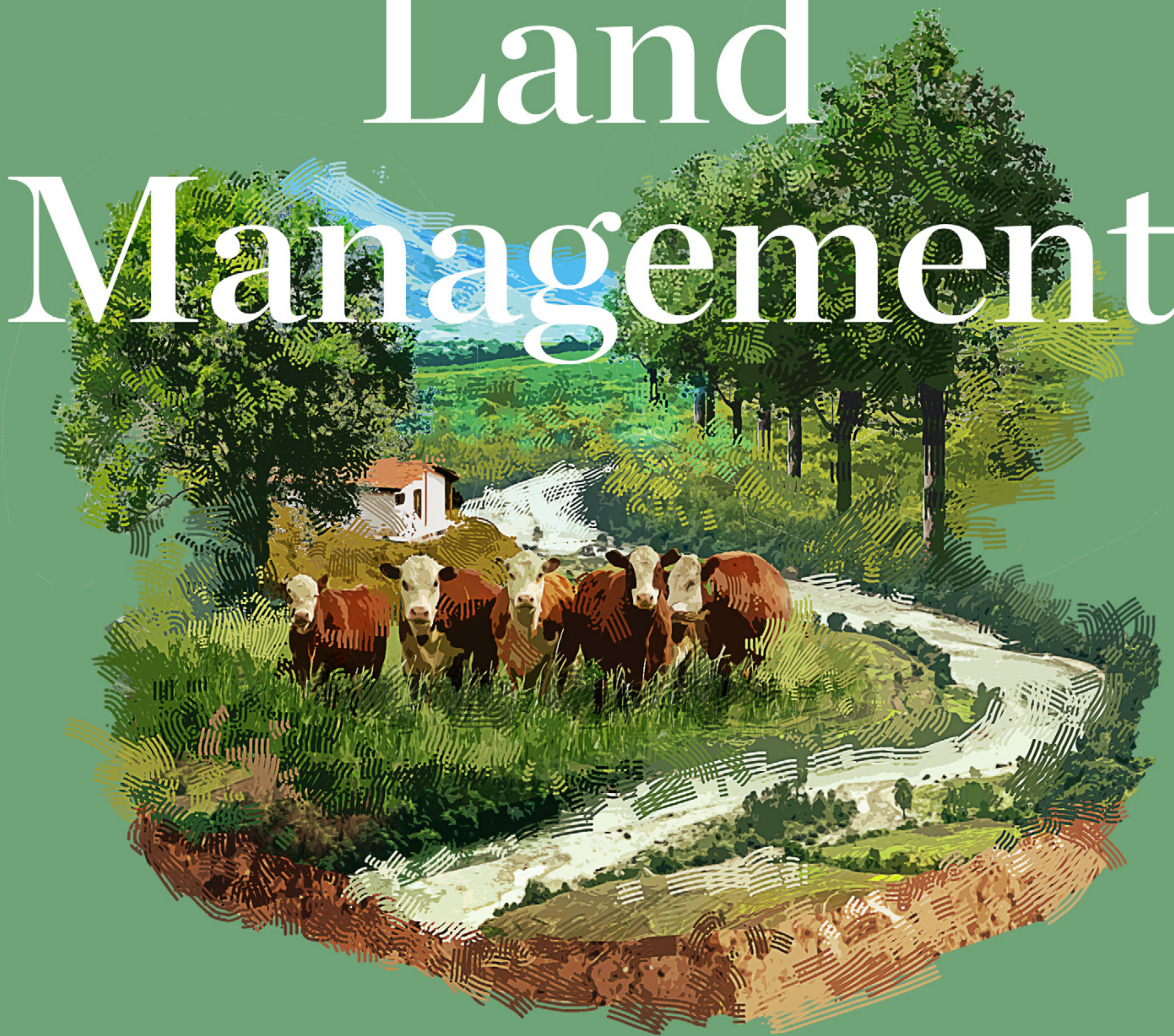
THE NATURE-BASED CREDIT SCIENCE DECODER SERIES

Agricultural Land Management



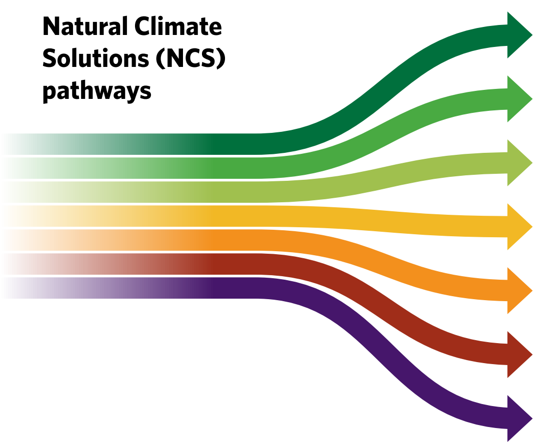
The Nature Conservancy

Accounting methods that center scientific best practices are the backbone of high-quality carbon projects.However, while scientific advancements have markedly improved carbon accounting to date, the continuous evolution of practices can make it difficult for buyers to understand which practices are high-quality when purchasing credits.

The Science Decoders are a series of explainers on current scientific best practices and gaps for carbon projects developed in seven common Natural Climate Solutions (NCS)pathways:

This first Decoder provides an overview of the scientific approaches that **Agricultural Land Management (ALM)** projects apply and highlights the best practices among them. We cover the ways in which projects define their baselines, measure and quantify emission reductions and removals, estimate uncertainty, and monitor project activities and permanence. These best practices are then compared to ALM methodologies in the market today. With this summary, buyers of high-quality carbon credits can better evaluate whether projects are effectively deploying rigorous scientific tools and approaches. They can also identify priority areas for research investment.

Natural Climate Solutions (NCS) pathways



1. Avoided Conversion of Grasslands and Shrublands (ACoGS)
2. Afforestation, Reforestation and Revegetation (ARR)
3. **Agricultural Land Management (ALM)**
4. Blue Carbon
5. Improved Forest Management (IFM)
6. Reduced Emissions from Deforestation and Degradation (REDD)
7. Wetlands Restoration and Conservation (WRC)

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What are ALM Carbon Projects?

Agricultural Land Management (ALM) projects generate carbon credits by implementing improved management practices on agricultural lands, including croplands and grazing lands. These improved practices depend on the context of the specific project but may include activities such as:

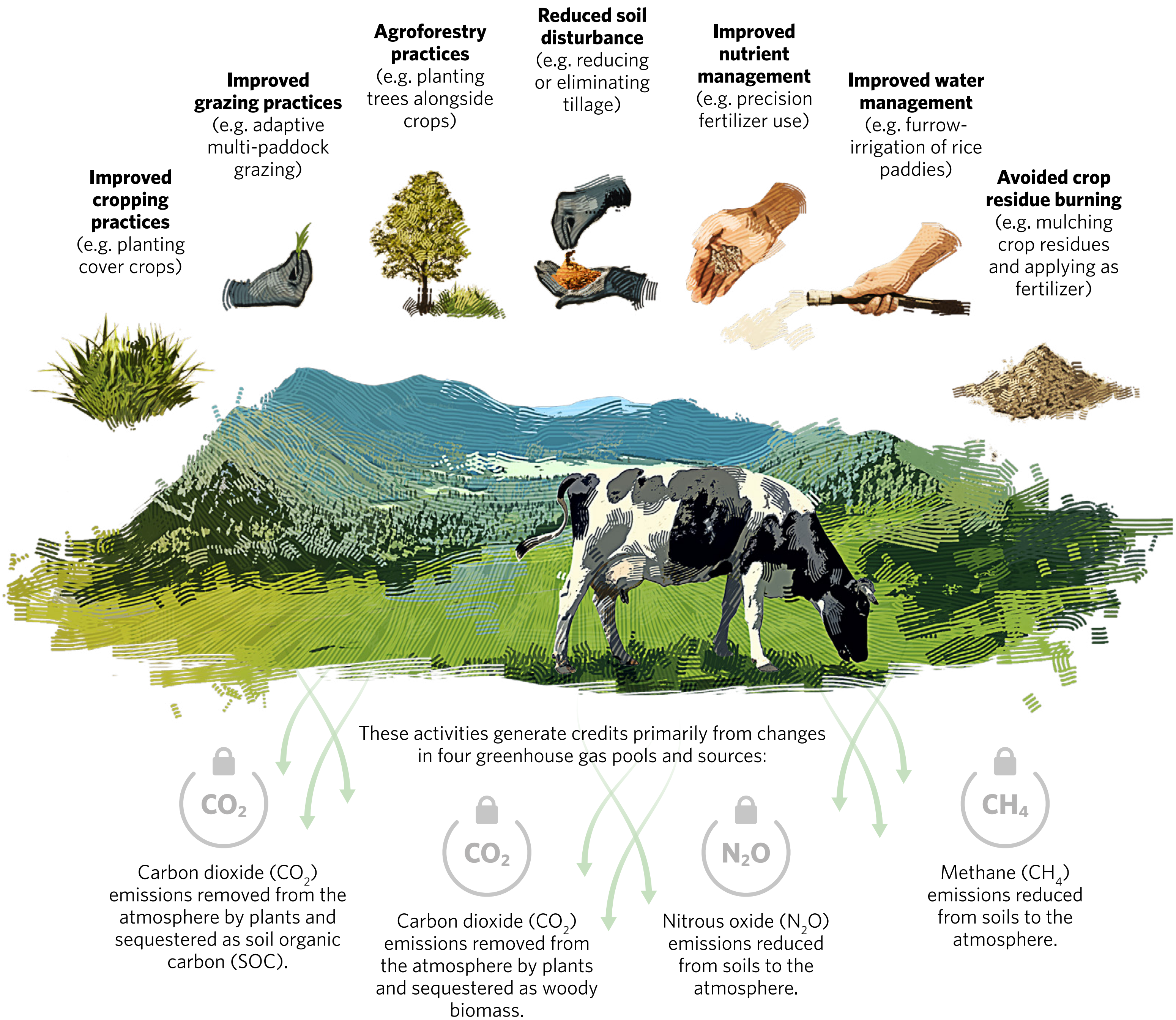
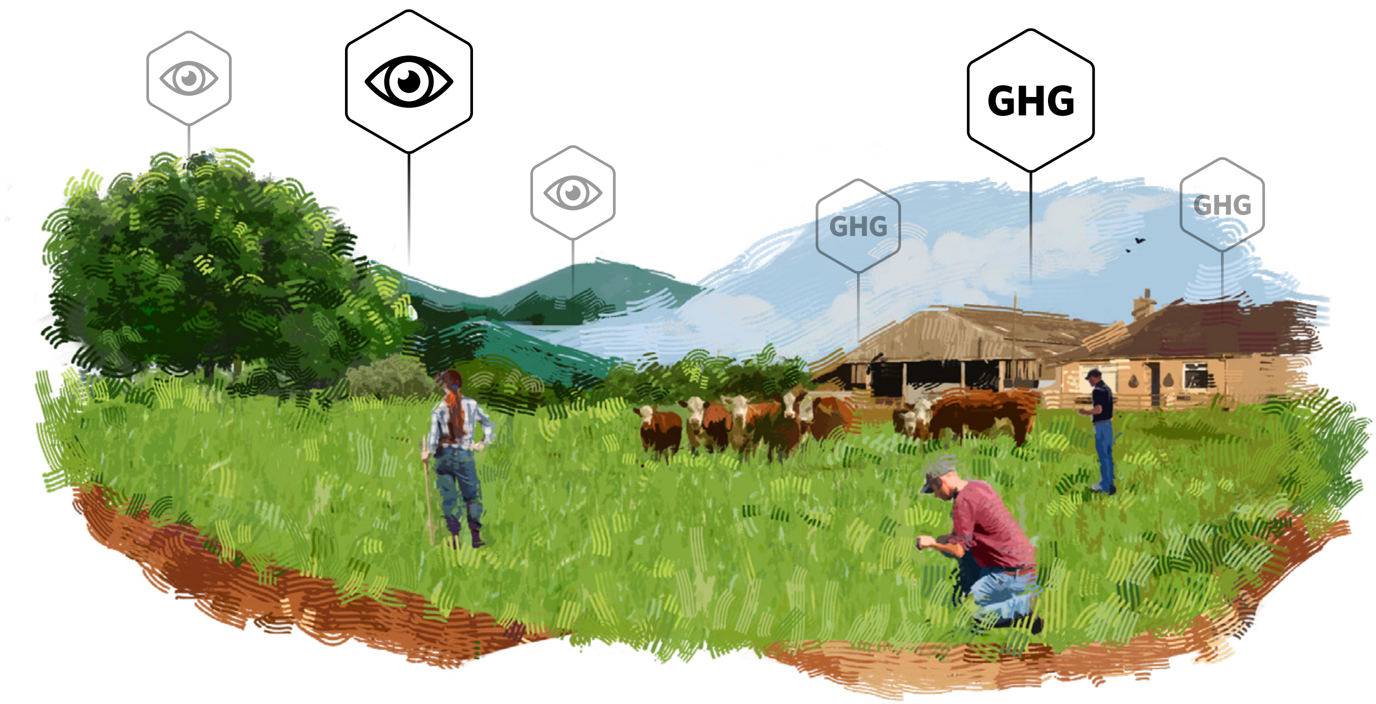


FIGURE 1: Examples of project activities in ALM carbon projects and the GHG pools and sources they impact.

High-quality ALM carbon projects identify and quantify emissions from all pools and sources likely to be affected by the project activity. This list of GHG pools and sources is called the Project GHG Boundary. Once this list is finalized, high-quality ALM carbon projects should leverage scientific best practices to achieve two fundamental tasks:



1.

Monitoring the management practices implemented before and after the project start date.

2.

Quantifying GHG emissions reductions and removals under the baseline and project scenarios.

1. Monitoring Management Practices

Carbon projects effectively represent climate-positive behavior change that is driven by market incentives. It is therefore essential to monitor ALM practices before and after the implementation of a carbon project to provide confidence to a buyer both that a practice change has been made and that the change is a result of their purchase. This documentation is a critical component of a project's demonstration of additionality relative to a business-as-usual baseline scenario.

Credits in high-quality ALM projects are quantified as the net impact of improved management practices on GHG emissions relative to a counterfactual baseline scenario in which the project was not implemented. For most ALM projects, the most credible baseline is usually the continuation of the historical practices implemented in the 3-5 years leading up to the project start date. For example, if a project aims to incentivize the adoption of cover crops to a conventional crop rotation, the baseline scenario should represent the continuation of the conventional crop rotation and its associated GHG emissions without the planting of cover crops.

Detailed data on ALM practices are therefore needed for pre-project years as well as the duration of the project itself. When changes in impermanent carbon pools like SOC are credited, management data beyond a project's crediting period is needed to monitor for potential reversals. The data necessary to achieve these monitoring requirements includes things like:

- Digital field boundaries as fundamental units that represent the specific areas where project activities are implemented. High-quality field boundaries for ALM carbon projects therefore exclude areas where project activities aren't implemented (e.g. roads, water bodies, buildings, etc.)
- Annual records of crops grown for each field boundary, including planting and harvest dates.
- Annual tillage, fertilizer, and irrigation records for each field boundary, including event dates, tillage depths, fertilizer application rates, and irrigation amounts.
- Livestock grazing records for each field boundary, including stocking rates, grazing dates, and manure management practices.

These data can be difficult and costly for land managers to produce. Sometimes they don't even exist. To relieve this burden, many ALM carbon projects use remote sensing tools to provide data that land managers cannot or to independently verify the data they do have. Remote sensing tools use machine learning algorithms and ground-truth datasets to interpret publicly available satellite data and identify specific ALM practices at a fine scale. Many ALM practices can be accurately detected by remote sensing at the field-level, including:

- Crop type (cash crops and cover crops), planting date, and harvest/termination date (Kussul et al. 2017).
- Tillage intensity (inferred by crop residue cover after harvest/termination) (Zheng et al. 2014).
- Irrigation method (flood duration in rice paddies) (Karthikeyan et al. 2020).

Some ALM practices are not reliably monitored by remote sensing, such as:

- Nutrient management (fertilizer type, application rate, application date)
- Grazing management (stocking density, grazing duration)

All remote sensing tools have inherent uncertainties and can occasionally make incorrect conclusions. High-quality ALM carbon projects that use remote sensing tools to fill data gaps for land managers should therefore embed these tools in a larger QA/QC process that ensures errors can be identified and resolved. As part of this process, projects should transparently inform land managers what data is being remotely sensed on their lands and give them the opportunity to review and identify data that may be inaccurate.

TIPS FOR BUYERS: MONITORING

- Ask how geospatial boundary data were obtained and edited to ensure that only the lands implementing the project activities were included in the project area. Ask to see several example boundaries and overlay them on a satellite map to verify that the entire project area appears to be agricultural land.

- Ask how management practices for both pre-project, during-project, and post-project years have been/will be monitored. Where remote sensing tools are used to fill data gaps:

    - Ask for a report on the accuracy of the tools for the data they provide. Have they been tested in the project area? What is their false positive rate? What is their false negative rate?
    - Ask to see the project's QA/QC process for identifying and resolving errors in the application of the remote sensing tools. Ensure that the QA/QC process includes both a way for land managers to contribute their own data and a way to independently verify those data.

2. Quantification of Emissions Reductions and Removals

A core element of all carbon projects is the accurate quantification of the net GHG emissions reductions and removals achieved by a project while conservatively accounting for uncertainty in that number. This project-wide number is the sum of the project's impact on all GHG pools and sources identified in the Project GHG Boundary. Different GHG pools and sources often require different quantification methods to accurately estimate a project's impact. Different quantification methods include different types of uncertainty. High quality ALM carbon projects transparently outline both the quantification methods and types of uncertainty accounted for in all credited GHG sources and pools.

Quantification Method	Types of Uncertainty	SOC Removals	Woody Biomass Removals	Soil N_2O Emissions	Soil CH_4 Emissions
1 **Measure and Model**	• Model prediction error • Sample error • Measurement error	X			
2 **Measure and Remeasure**	• Sample error • Measurement error	X	X		
3 **Model Only**	• Model prediction error • Sample error			X	X
4 **Default Emission Factors**	• Prediction error			X	

TABLE 1: The different quantification methods used to estimate GHG pools and sinks and their associated types of uncertainty in high-quality ALM carbon projects.

1 A Measure and Model approach measures SOC stocks at the start of a project and then models their subsequent changes under both the baseline and project scenarios. Projects should account for **model prediction error, sample error,** and **measurement error.** Periodic re-measurement of SOC stocks should be done to re-calibrate the chosen model over time. See the GHG Modeling section below for more details.

2 A Measure and Remeasure approach measures SOC and woody biomass stocks at the start of a project and again over time in both the project area and baseline control sites. Projects should account for **sample error** and **measurement error**. See the SOC Measurement section below for more details.

3 A Model Only approach models Soil N_2O and CH_4 emissions under both the baseline and project scenarios. Projects should account for **model prediction error** and **sample error**. In-situ measurements of these fluxes are not expected nor required as long as models are appropriately validated (see GHG Modeling section below). Note that this approach is NOT considered best practice for SOC removals.

4 A Default Emission Factor approach quantifies emissions using simple formulas published by the International Panel on Climate Change (IPCC) for use in national GHG inventories. While these formulas often contain some **prediction error**, the data necessary to quantify that error is infrequently reported. Most projects therefore assume this error to be zero, which is acceptable for high-quality projects unless good data is available.

BOX 1: TYPES OF UNCERTAINTY

- Model prediction error resulting from inaccurate model predictions of measured data (e.g. model predictions that are biased or have low precision).
- Sample error resulting from measuring or modeling only a portion of the project area (e.g. sampling one out of every five hectares).
- Measurement error of alternative measurement methods relative to established methods (e.g. in-situ soil spectroscopy of SOC% and bulk density relative to traditional lab analysis).

High-quality ALM carbon projects should use the same quantification methods to quantify emissions and removals under *both* the baseline and project scenarios for the duration of the project's crediting period. Projects that use different quantification methods for baseline versus project scenarios or make assumptions that emissions or removals under one scenario are "conservatively" equal to 0 (e.g. baseline SOC removals = 0) should be considered lower quality. Baseline scenarios should be *dynamic* and reflect the emissions and removals that *would have occurred* during the project years had the project not been implemented. Using the same tools and methods for quantifying emissions and removals under each scenario ensures consistent carbon accounting that maintains the integrity of a dynamic baseline scenario while also reducing the uncertainty in the credits generated by the project (Zhou et al. 2023).

SOC MEASUREMENT

SOC stocks (the mass of organic carbon in the soil) should always be measured both at the start of an ALM project and periodically (roughly every 5 years) over the project's lifetime. The initial measurement represents the shared starting point for the baseline and project scenarios, which diverge from the initial SOC stock once the project starts.

SOC stocks should be measured using a stratified random sampling design. This approach splits a project area into small, homogenous units to reduce the measured variation in SOC stocks within each stratum. Soil samples should be taken and analyzed to enable the subsequent calculation of SOC stocks and changes in SOC stocks. The sampling density (number of samples per unit area) within each stratum should be chosen to balance the tradeoff between sampling costs and reductions in credits due to sample error (see above). The optimal density will depend on the specific geography and the project activities being credited.

SOC stocks at a single point in time are calculated using the following equation:

$$SOC\ Stock = SOC\% \times BD \times (1 - CF) \times Depth$$

- SOC Stock is the mass of SOC per unit area to the specified depth (tonnes/ha).
- SOC% is the percent SOC content of the fine soil portion (<2mm diameter), ideally measured via dry combustion.
- BD is the bulk density of the fine soil portion (g fine soil /cm^3 fine soil). The soil portions (fine vs coarse) represented by bulk density measurements can vary among labs - explicit definition is critical.
- CF is the coarse fragment content by volume of the coarse soil portion (>2mm diameter) (0-1).
- Depth is the depth of the sampled soil core (cm). Depth should always be at least 30 cm and ideally 50 cm. Some ALM practices like no-till can redistribute SOC within the soil profile. Deeper sampling can catch this redistribution and ensure that SOC stock changes aren't mistakenly overstated (Smith et al. 2020).

The current best practice for collecting these data is via the collection of physical soil samples that are transported to an accredited soil lab where they are processed and analyzed. This process is time consuming and expensive and can present a cost barrier to many projects, yet the data are crucial to the integrity of high-quality ALM carbon projects. The research, development, and commercialization of technologies that reduce these costs by measuring this required soil data either in the field or via remote sensing represents a huge opportunity to overcome cost barriers (Smith et al. 2020). Buyers of high-quality ALM carbon credits that aren't satisfied with the current volume of credits available may consider investing in research efforts to drive down SOC measurement costs.

Projects that use Measure and Remeasure approaches for quantifying SOC removals must take care when reporting SOC stock changes to ensure that these changes are due only to changes in SOC% and not bulk density. Changes in bulk density may occur when projects incentivize activities like reduced tillage or improved grazing management that loosen or compact the soil, and a failure to account for these changes can cause SOC removals to be under or overestimated (von Haden et al. 2020). High-quality ALM carbon projects should therefore report SOC stock changes using bulk density corrections, also commonly referred to as an equivalent soil mass.

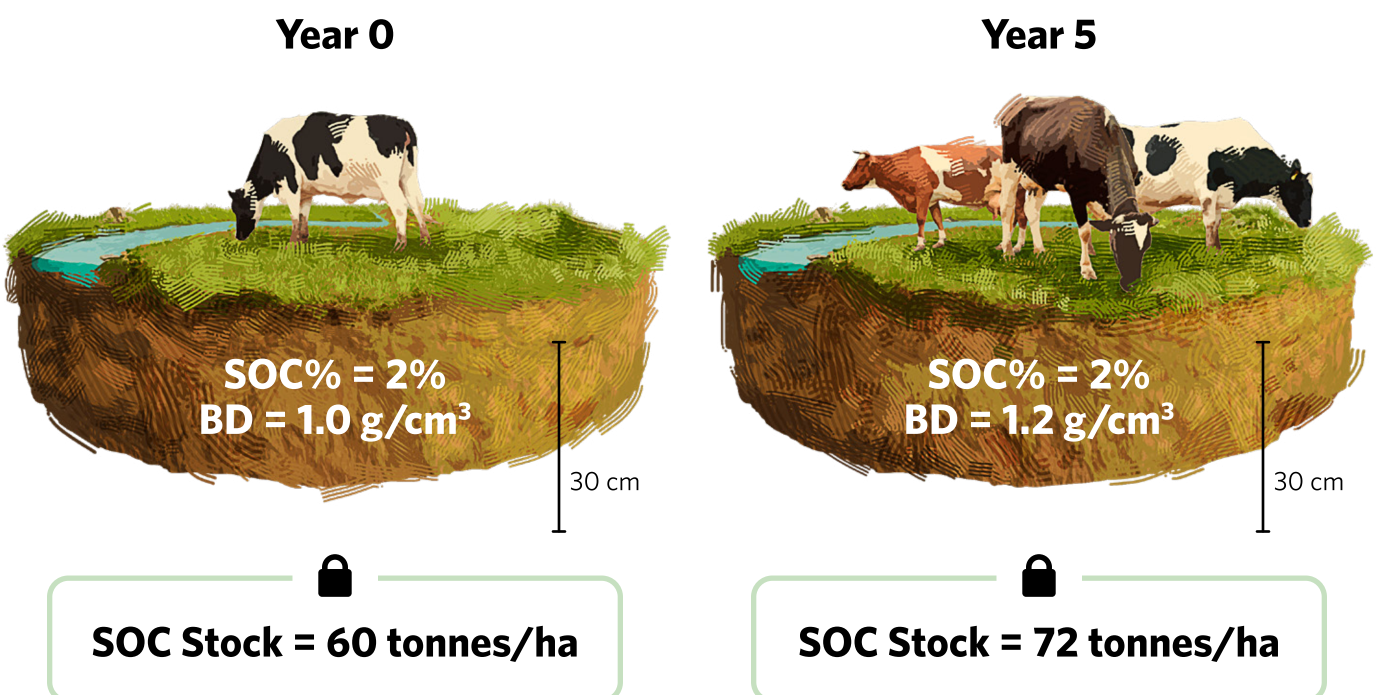


FIGURE 2: This figure shows the perils of failing to account for changes in bulk density in an example improved grazing project (project scenario only). Note how bulk density (BD) has increased in Year 5 due to more livestock while SOC% has remained the same. When SOC stocks are calculated using Equation 1, they are mistakenly found to be higher in Year 5 than Year 0 when, in reality, a larger mass of soil was sampled. It is essential to compare SOC stocks for the same soil mass between years to avoid this error.

GHG MODELING

Models used to simulate the effects of the project activities on GHG reductions and removals should always be calibrated and validated against measured datasets of the same GHGs. Model validation should transparently report model prediction error and propagate that error to subsequent model simulations. High-quality ALM carbon projects will have **publicly available model validation reports** that **include all data used for calibration and validation** and **intuitively display them opposite model predictions as simple scatterplots**. Models used in projects to quantify SOC removals should be validated based on their ability to predict SOC stock changes and not simply SOC stocks.

Very specific ground-truth data are needed to validate models used in high-quality carbon projects. The best data come from long-term studies (>5 years) where repeated measurements of the target GHG source or pool are made over time in paired plots where both the improved project activity and business-as-usual baseline activity are implemented. Most of the studies that meet these criteria are from cropping systems in North America and Europe with limited applications to other project types (Reinhart et al. 2022). Studies that don't meet these criteria often only measure GHG sources and pools at a single point in time, limiting their utility for model validation. Buyers of high-quality ALM carbon credits that aren't satisfied with the current volume of credits available may consider investing in research studies to generate the data needed to rigorously validate process-based GHG models.

ACCOUNTING FOR UNCERTAINTY

High quality projects that quantify multiple sources of uncertainty should conservatively account for the impact of that uncertainty on the number of credits issued to the project. Proper accounting for uncertainty creates a probability distribution around a point estimate of a project's climate impact. The final credit volume issued to a project can then be selected from this distribution to represent a conservative issuance based on the reported uncertainties. For example, Verra VM0042 requires projects to take uncertainty deductions at the 33rd percentile of a project's uncertainty distribution (see figure below). This translates directly to a 33% probability that the project is over crediting and a 67% probability that the project is under crediting. Because the uncertainty distribution is created from the uncertainty in the project's quantification methods, this crediting approach incentivizes projects that reduce uncertainty through steps like reducing model prediction error (improving model validation) or reducing sample error (collecting more samples).

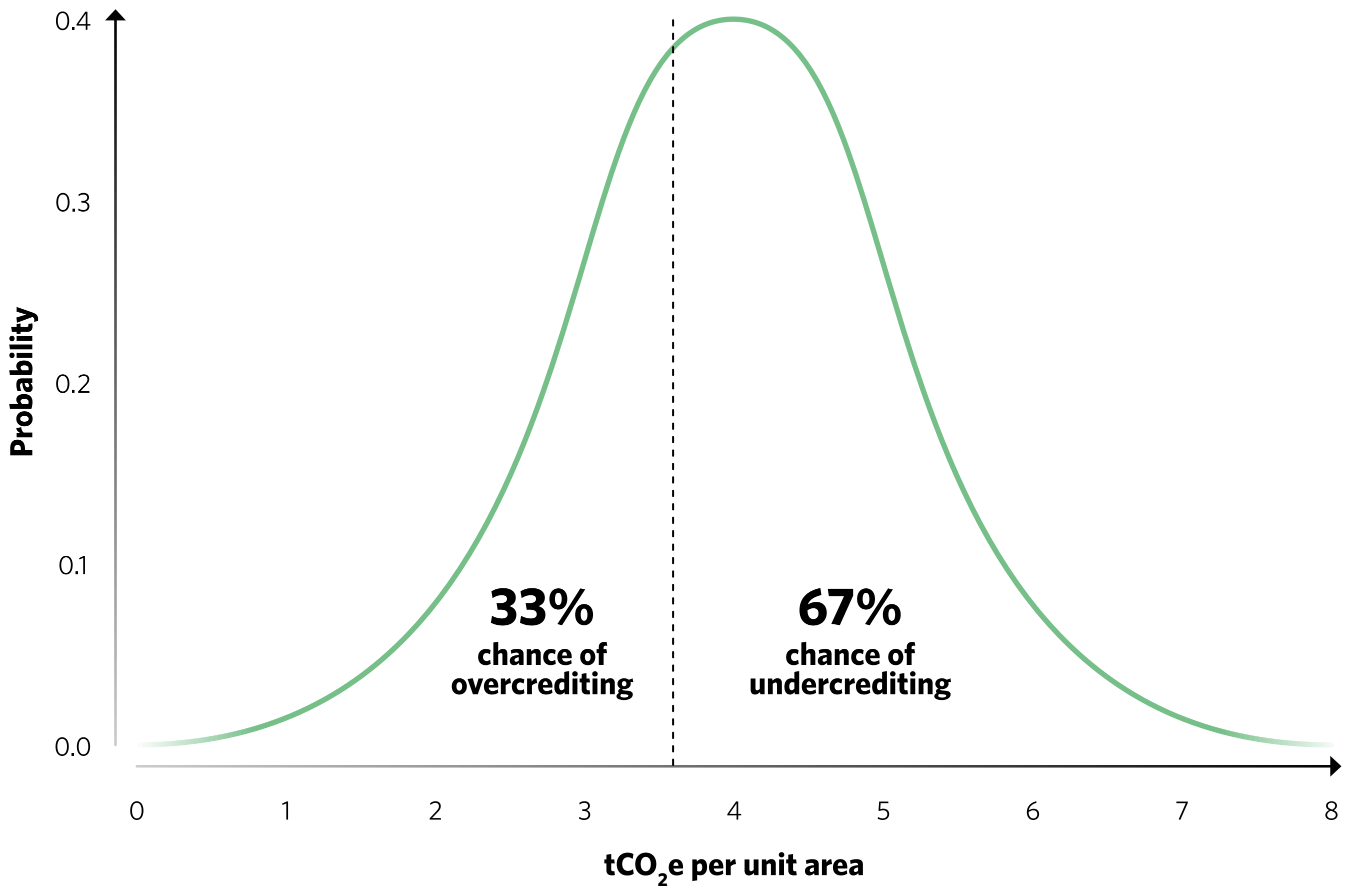
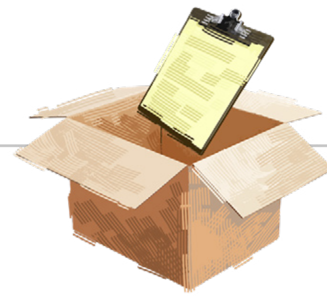


FIGURE 3: Example probability distribution that illustrates how uncertainty should be conservatively accounted for. The project's average credit volume is ~4.1 tCO_2e/unit area, but it is conservatively issued 3.6 tCO_2e/unit area – reflecting a 67% probability that the true climate impact of the project exceeds the credited impact.



TIPS FOR BUYERS: QUANTIFICATION

- Ask for a report summarizing all GHG sources and pools credited by the project, their associated quantification methods, and the types of uncertainty that are accounted for (Table 1)
  - Ensure the same quantification methods are used for both the baseline and project scenarios for each GHG source or pool.

- Ensure that the final credit issuance conservatively accounts for uncertainty by issuing less than the average expected credit volume of the project.

- For projects measuring SOC stocks and stock changes:
  - Ask if the project area has been stratified prior to collecting soil samples.
  - Ask if equivalent soil mass methods were used when calculating SOC stock changes.
  - Ask about sampling density and if sample error is accounted for in the final credit volume.
  - If alternative measurement methods are used, ask what the error in those methods is and if it is accounted for in the final credit issuance.

- For projects modeling GHG emissions:
  - Ask to see the project's model validation report, and ensure it shows a simple scatterplot of model performance for data from previous studies of the project activity.

ALM Methodology Review

Many carbon standards offer methodologies to credit ALM carbon projects, and there is substantial variation in the minimum requirements for the use of scientific tools across ALM methodologies. The table below summarizes the extent to which existing methodologies published by the leading voluntary carbon standards require projects to use the scientific best practices discussed in this article.

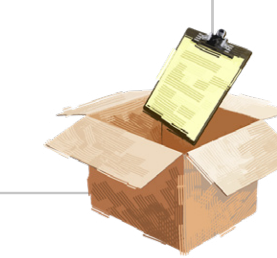
Methodology	Year Published	Requires Best Practices for:				
		Practice Monitoring	Baseline Quantification	SOC Measurement	GHG Modeling	Uncertainty Accounting
VCS VM0022: Quantifying N_2O Emissions Reductions in Agricultural Crops through Nitrogen Fertilizer Rate Reduction v1.1	2013	No	Yes	N/A	N/A	No
VCS VM0026: Methodology for Sustainable Grassland Management v1.1	2021	Yes	No	No	No	No
VCS VM0032: Methodology for the Adoption of Sustainable Grasslands through Adjustment of Fire and Grazing v1.0	2015	Yes	No	No	No	No
VCS VM0042: Methodology for Improved Agricultural Land Management v2.0	2023	Yes	Yes	Yes	Yes	Yes
CAR U.S. Nitrogen Management Protocol v2.1	2021	No	Yes	N/A	No	No
CAR U.S. Rice Cultivation Protocol v1.1	2013	Yes	Yes	No	No	Yes
CAR U.S. Soil Enrichment Protocol v1.1	2022	Yes	Yes	Yes	Yes	Yes
Gold Standard Methodology for Methane Emission Reduction by Adjusted Water Management Practice in Rice Cultivation v1.0	2023	Yes	Yes	N/A	N/A	No
Gold Standard Soil Organic Carbon Framework Methodology v1.0: Activity Module for Increasing Soil Carbon Through Improved Tillage Practices v1.0	2020	Yes	No	No	No	No
Gold Standard Soil Organic Carbon Framework Methodology v1.0: Activity Module for Application of Organic Soil Improvers from Pulp and Paper Mill Sludges v1.0	2022	Yes	No	No	No	No

TABLE 2: A summary of popular ALM methodologies and whether or not they require (Yes/No) projects to follow the best practices discussed in this report. This table is not intended to be an evaluation of all projects developed under a given methodology. Rather, it is intended to identify methodologies whose projects are most likely to be high-quality given the minimum methodological requirements. Some high-quality projects may be developed under less rigorous methodologies if they choose to exceed their minimum requirements.

TIPS FOR BUYERS: METHODOLOGIES

VCS VM0042 v2.0 and CAR U.S. SEP v1.1 require projects to meet current scientific best practices.

Conduct extra due diligence on projects verified under other methodologies to ensure they meet a similar level of rigor.



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Zheng et al. 2014. Remote sensing of crop residue and tillage practices: Present capabilities and future prospects. *Soil and Tillage Research*, 138, 26 – 34.

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