VCS Tool

VT0014

ESTIMATING ORGANIC CARBON STOCKS USING DIGITAL SOIL MAPPING

Version 1.0

26 August 2025

Sectoral Scope 14: AFOLU

This tool was developed by Perennial Climate Inc. and supported by TerraCarbon LLC in collaboration with Verra.

CONTENTS

1 SUMMARY DESCRIPTION

Digital soil mapping (DSM) is the use of computer models to predict soil properties using spatially explicit ancillary variables (McBratney et al. 2003). Numerous studies have demonstrated the ability to quantify soil organic carbon (SOC) using DSM techniques (Castaldi et al. 2019; Fu et al. 2024; Gomez et al. 2008; Ratnayake et al. 2016; Sothe et al. 2022; Szatmári et al. 2021; Venter et al. 2021; Wadoux and Heuvelink 2023; Zhou et al. 2020). Most focus on SOC content, measured as a proportion or percentage of oven-dry soil mass. Others have quantified SOC stock in units of total mass or mass density (e.g., mass of SOC per unit area). These studies encompass a wide range of geographic locations, statistical procedures, and measurement sources, including airborne and satellite remote sensing. However, specific guidance on appropriate calibration, model validation, and uncertainty estimation is needed to support the use of DSM in agricultural land management (ALM) carbon projects to ensure robust and verifiable quantification.

This tool contains protocols for using DSM to generate mapped estimates of SOC when applying ALM methodologies under the Verified Carbon Standard (VCS) Program. The tool specifically addresses:

- DSM model calibration, model validation,[1] and uncertainty estimation.
- the use of physical soil samples for model calibration and model validation.
- selection and processing of remote sensing and other environmental covariates.
- use of DSM to initialize and/or true-up any model that requires an estimate of SOC content, SOC stock, or bulk density (BD).
- use of DSM to predict SOC content and/or stock (i.e., Use Case 1: Measure and Model quantification approaches, or Use Case 2: Measure and Re-Measure).
- development of a DSM Model Validation Report (DSM-MVR) and assessment by a DSM Independent Modeling Expert (DSM-IME; see Appendix 1).

Schematic descriptions of DSM-MVR workflows and DSM-IME assessment are shown in Figure 1.

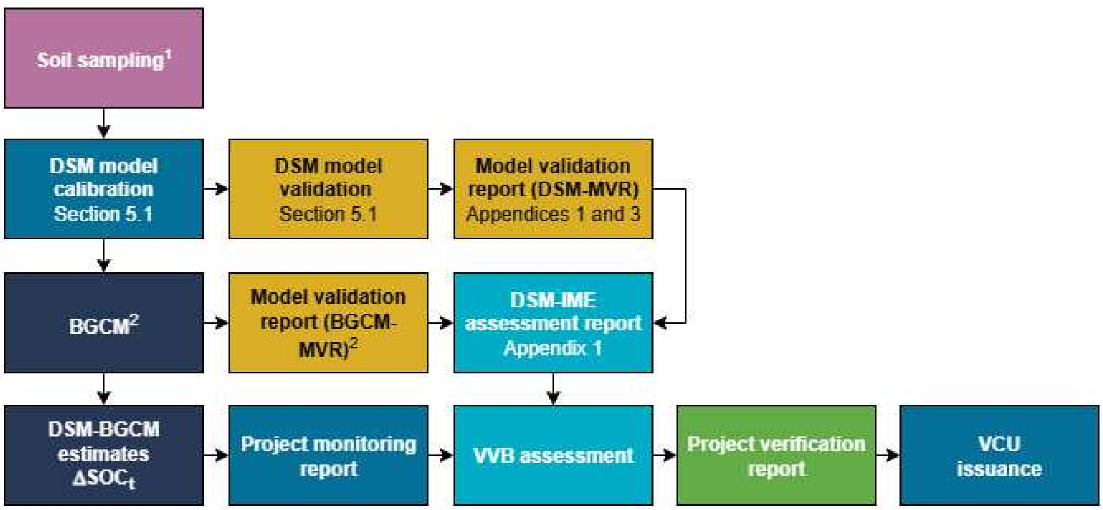
[1] The *VCS Standard, v4.7* defines validation as "… the independent assessment of the project by a validation/verification body that determines whether the project and its GHG statement conforms with the VCS Program rules and evaluates the reasonableness of assumptions, limitations, and methods that support a claim about the outcome of future activities." The tool distinguishes between project validation under the VCS Program and model validation. Model validation, as defined in VCS module *VMD0053 Model Calibration, Validation, and Uncertainty Guidance for Biogeochemical Modeling for Agricultural Land Management Projects, v2.1*, is "the process of evaluating model performance relative to measured values." *VMD0053, v2.1* states that a validated model demonstrates "satisfactory performance in terms of goodness of fit and characterization of model prediction error."

By providing a generalized approach to the quantification of SOC stocks in vegetated or bare agricultural soils, the tool enables model calibration, model validation, and uncertainty estimation to be conducted in compliance with any guidelines established under the applied VCS methodology.

Figure 1. DSM model calibration, validation workflow, and DSM-IME assessment

Use Case 1

DSM is used to initialize and/or true-up any model that requires an estimate of SOC content, SOC stock, or BD.



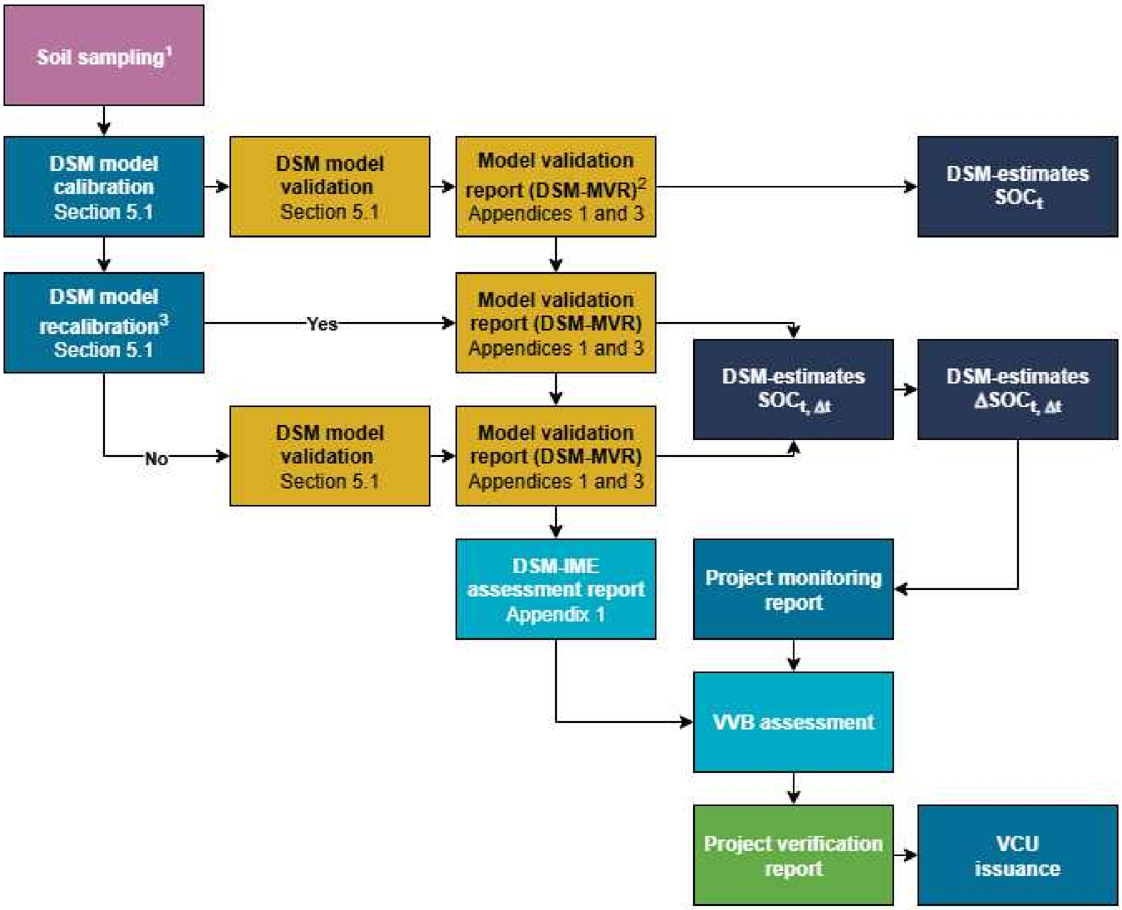
[1]Calibration data may be from samples inside or outside the project area, and calibration data must be from samples within the project area

[2]Refer to calibration and validation requirements for the use of BGCM in the applied methodology

[3]The DSM-MVR is required at every verification event. Updates to the DSM-MVR must occur every time the DSM model is calibrated or validated. The DSM model calibration and validation must be reported in the DSM-MVR at the first project verification event. Subsequent model calibration (recalibration) is optional, and validation must occur at least once every five years.

Use Case 2

DSM is used to generate mapped estimates of SOC stocks at a specified time. DSM predictions at different times are used to compute changes in SOC stocks over time.



[1]Calibration data may be from samples inside or outside the project area, and calibration data must be from samples within the project area

[2]The DSM-MVR is required at every verification event. Updates to the DSM-MVR must occur every time the DSM model is calibrated or validated. The DSM model calibration and validation must be reported in the DSM-MVR at the first project verification event. Subsequent model calibration (recalibration) is optional, and validation must occur at least once every five years.

[3]Optional recalibration for the DSM model: Model parameters may be fixed or updated at every verification event. Regardless of whether it is recalibrated, the DSM model must be validated at the start of the project and at least once every five years.

2 SOURCES

This tool is based on the following VCS methodologies and module:

- *VM0032 Methodology for the Adoption of Sustainable Grasslands through Adjustment of Fire and Grazing, v1.0*
- *VM0042 Improved Agricultural Land Management, v2.1*

- *VMD0053 Model Calibration, Validation, and Uncertainty Guidance for Biogeochemical Modeling for Agricultural Land Management Projects, v2.1*

3 DEFINITIONS

In addition to the definitions set out in the *VCS Program Definitions*, the following definitions apply to this tool.

Biogeochemical model (BGCM)
A model to mathematically describe 1) biological, chemical, and physical processes in soils, or 2) statistical relationships between soil organic carbon and predictor variables

Calibrated model
A workflow that uses digital soil mapping to produce an estimate of soil organic carbon stocks, along with associated uncertainty estimates, for all prediction locations within a project area

Calibration
The process by which a digital soil mapping model learns from data to minimize prediction error. Calibration can be closed-form (e.g., least-squares) or iterative (e.g., machine learning, Bayesian methods). Calibration results in a set of parameters or settings that can be used to generate predictions from the model.

Calibration and validation dataset
A dataset that contains the target variable and covariates used to calibrate and validate the digital soil mapping model.[2] The calibration and validation dataset may contain direct measurements of soil organic carbon (SOC) stock and numerous corresponding environmental and remote sensing variables associated with each SOC stock measurement.

Cluster
A group within a staged sampling design, which is chosen for sampling with a known, non-zero probability

Covariate
An independent variable used to predict the target variable during and after calibration. Covariates may be measured or modeled and may be generated using feature engineering. See Appendix 2 for additional resources related to covariate selection.

Coverage
The percentage of independent model validation measurements that are correctly predicted by a model. Coverage is assessed using a prediction interval by counting the number of model

[2] Calibration and validation are referred to as "training" and "testing" in machine learning. This tool exclusively uses the terms "calibration" and "validation" to ensure consistency with VCS terminology.

validation observations within a given prediction interval. Nominal coverage occurs when the percentage of observations within the prediction interval matches the prediction interval width (e.g., 90% of observations are within the 90% prediction interval at 90% coverage).

Digital soil mapping (DSM)
The use of computer models to predict soil properties using spatially explicit ancillary variables. Soil properties are predicted at prediction locations.

Feature engineering
The process of selecting or developing covariates used in a model. This includes developing new variables, such as biophysical or vegetation indices, conducting quality assessment and data screening (e.g., excluding or processing satellite images with cloud cover and snow), and standardizing data values over time. Outputs from feature engineering can be measured, modeled, or both.

Hyperparameter
A configuration setting that informs the behavior and learning process of a machine-learning or statistical model (e.g., depth of a decision tree, learning rate in gradient descent methods, or sampling characteristics of a Markov chain Monte Carlo procedure). In the context of this tool, hyperparameters also include weights applied to different sets of calibration data during calibration.

Hyperparameter tuning
The process of choosing values for hyperparameters prior to model calibration. When hyperparameters are tuned by evaluating model performance, the data used for hyperparameter tuning must be independent of the calibration and validation sets.

Independent modeling expert (DSM-IME)
An individual or organization with demonstrated competence in digital soil mapping or hybrid approaches using digital soil mapping and biogeochemical models, especially with respect to soil organic carbon stocks and error propagation. The DSM-IME is independent of the project proponent.

Independent sample data
Sample data that are not used for calibration procedures under a given instance of a model. Independent sample data are used for model validation.

Mapped area
The portion of the project area within which digital soil mapping estimates of soil organic carbon stock and stock changes are generated. It may encompass the entire project area or a subset of it (e.g., if other quantification methods are applied to some locations within the project area). The mapped area may include baseline control sites or not.

Missing at random
Missing at random describes one way in which observations can be missing from a dataset. An observation is missing at random when the probability that the observation is missing does not depend on the value of the missing observation.[3]

Model architecture
The structure and design of a machine learning or statistical model that determines how it processes input data and generates predictions (e.g., neural networks, gradient-boosted regression trees, and multiple regression). The components of model architecture include the number of layers or nodes in a neural network; activation functions; whether the model is linear or nonlinear, parametric or non-parametric, frequentist or Bayesian; values for hyperparameters; and the loss function.

Model instance
A calibrated version of a model generated during cross-validation, indexed in the tool using the subscript *k*

Model prediction error
The difference between a model prediction and an independent measured value at a given prediction location

Model validation
The process of evaluating a model's performance by comparing its predictions to independent measured values

Model validation report for digital soil mapping (DSM-MVR)
A document describing calibration and validation procedures and outcomes for the digital soil mapping model used in the project. See Appendix 3: Guidance on Requirements for Model Validation Reports~~Appendix 3: Guidance on Requirements for Model Validation Reports~~.

Prediction location
The geographic point or area for which a prediction is generated by the model. The prediction location refers only to where the prediction is generated, not the volume or depth of soil being represented.

[3] For example, a project proponent may attempt to collect independent sample data using 1000 soil cores. Due to poor weather, changes in planting or harvesting dates, grower dropouts, or laboratory errors, only 985 of these soil cores might actually be available to the project proponent. The missing 15 observations would be missing at random if the probability that the observations are missing is not dependent on the value of the missing observation after controlling for other factors.

Prediction support
The soil volume to a specified depth or depth interval for which a model is calibrated and against which a physical measurement is compared during model validation. The prediction support determines what is being predicted.[4]

Probability sampling
A random sampling process where every unit has a known, non-zero probability of being included in the sample

Standardized prediction error
The prediction error at a given prediction location divided by the predictive standard deviation

Stratum
A homogeneous subgroup of a population selected for the purpose of sampling. Each stratum is homogeneous for a given parameter (e.g., location, weather characteristics, soil type, or tillage system) and differs from other strata in the population. Stratification is used to ensure that subgroups within the population are represented in the sample.

Target date
The date of a given prediction from the calibrated model. The initial target date (t_0) for a prediction location is defined by the date of the first model validation sampling campaign that includes that prediction location in the sampling design.

Target variable
The dependent variable being predicted by a digital soil mapping model (e.g., soil organic carbon (SOC) content, SOC stock, bulk density)

4 APPLICABILITY CONDITIONS

The tool is applicable globally under the following conditions:

1) A calibration dataset and validation dataset are used to calibrate and validate a model of SOC content, SOC stock, or BD. Calibration data may be from inside or outside the project area, but validation data must be collected exclusively within the project area.
2) The project activity is ALM on croplands or grasslands.
3) All calculations are reproducible, and all software, computer code, data, and other dependencies are documented, archived, version-controlled, and available to the DSM-IME, validation/verification body (VVB), and Verra upon request.

[4] For example, if a model is calibrated using soil cores at 0–30 cm depth to predict SOC as a percentage by mass, then all predictions, regardless of location, represent values over that 0–30 cm depth. This is true whether prediction locations are made on a regular 10 × 10 meter grid, a 100 × 100 meter grid, or at arbitrary locations.

The tool is not applicable under the following conditions:

4) The project area has permanent flooding.

5 PROCEDURES

This workflow is a systematic approach for calibrating and validating a DSM model, and for estimating the uncertainty in predictions of SOC stocks and stock changes under the applied methodology. Model validation occurs for every project, using independent sample data. A graphical illustration of the workflow is provided in Figure 2. For simplicity, this process is described for a single time point, *t*, and a single DSM model that generates predictions of SOC stock. In practice, this process may be applied at multiple time points.

The property being validated is always the prediction of SOC stock, even where separate components of SOC stock (SOC content and BD) are independently predicted. The variance of the estimate of the mean change in SOC stock over the duration of the project relative to baseline conditions is used to compute uncertainty and the associated uncertainty deduction under the applied methodology (see Section 5.3).

Multiple localized DSM models may be used for different subsets of the project area. Where multiple localized models are used, the model validation procedure must be conducted in aggregate across the outputs of the localized models for the entirety of the project area. In grouped projects, each time a project activity instance is added to the project, an updated DSM-MVR must be created to demonstrate that the DSM model is valid in the new project areas represented by the new project activity instances.

Estimates of SOC stock generated under the procedures outlined in this tool may be used in two ways:

- **Use Case 1:** DSM is used to initialize and/or true-up any model that requires an estimate of SOC content, SOC stock, or BD. When DSM estimates are used to true-up another model (e.g., biogeochemical models (BGCM)), they are generated throughout the project area at the time of the true-up event. The DSM is validated prior to or at verification (see Figure 1~~Figure 1~~) using the procedures given in this section. Uncertainty of DSM estimates of SOC is propagated through the model (e.g., a BGCM) based on the requirements of the applied methodology. Where Monte Carlo error propagation is permitted, project proponents must use the procedure described in Section 5.1.2.
- **Use Case 2:** DSM is used to generate mapped estimates of SOC stocks at a specified time. DSM predictions at different times are used to compute changes in SOC stocks over time. The model must be calibrated and validated at the start of the project. In

addition, model validation must occur at least once every five years[5] (Figure 1Figure 1). Recalibration requirements are described in Section 5.1.8.

5.1 Model Development

Use the steps below, as illustrated in Figure 2, to develop the model.

1) Assemble the calibration and validation dataset (*X*) to be used for prediction at time *t*. Guidance on the collection of covariate and sample data are detailed in Sections 5.1.5 and 5.2, respectively.

2) Split *X* into *K* calibration and validation sets. The calibration set is used to estimate model parameters and the validation set is used to test model performance.

   a) Multiple procedures for identifying calibration and validation sets are applicable (e.g., a completely independent validation set, leave one sample out, *k*-folds, and geographically dependent cross-validation).

   b) Data from outside the project area may be used for calibration, but all data in the validation set must come from within the project area.

   c) Calibration and validation sets must remain independent (or where cross-validation is being used, conditionally independent). All parameter estimation, including hyperparameter tuning, where used, must not be exposed to observations in the validation set prior to validation. For multi-stage sampling[6] designs, data dependencies must be accounted for in the sampling design and downward bias in model uncertainty estimation must be avoided (see De Bruin et al. 2022).

3) Using the calibration set, calibrate an instance (*k*) of the model.

4) Generate predictions and estimate 90% prediction intervals for the predicted value of SOC stock for prediction location *i* at time *t* for every observation in the validation set.

   a) Prediction intervals for validation locations must be generated in a way that ensures independence of calibration and validation data.

   b) Any procedure that has been documented in at least one peer-reviewed publication in a journal indexed in the Web of Science: Science Citation Index[7] may be used to estimate prediction intervals. Users must select a single method and justify its use.

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[5] Requiring model validation at least once every five years accommodates project proponents that prefer to fix model parameters after calibration and those that prefer to update the calibration over time.

[6] A hierarchical method where sampling occurs in successive stages from larger to smaller units

[7] Available at: https://clarivate.com/academia-government/scientific-and-academic-research/research-discovery-and-referencing/web-of-science/web-of-science-core-collection/science-citation-index-expanded/

5) Repeat steps (3)–(4) *K* times to generate a new model instance for each iteration *k* and assemble a performance dataset for validation. The performance dataset contains pairs of predicted and observed values of SOC stock and the associated 90% prediction interval for each prediction.

   a) The appropriate number of iterations *K* depends on Step (2)(a). Where a completely independent validation set is used, *K* = 1. Where cross-validation is used, *K* is the number of folds in the cross-validation procedure.

6) For every prediction location in the validation set, determine whether the prediction interval for SOC stock at time *t* contains the measured value. When the validation sample falls within the prediction interval, the prediction passes. Otherwise, the prediction fails.

   a) Determine the percentage of validation observations that pass. The model must generate predictions that are within 90% prediction intervals at least 90% of the time, such that at least 90% of tests pass. If the model passes, proceed to step 7. If the model fails, recalibration is required.

   b) Recalibration may require additional sampling, hyperparameter tuning, or other adjustments, but users must avoid fitting the model to the validation set after the validation set is known. Model validation data must remain independent (or where cross-validation is used, conditionally independent).

7) Compute the prediction error for all paired observations in the validation set according to the following equation:

$$\epsilon_{i,t} = \widehat{SOC}_{i,t} - SOC_{obs,i,t} \tag{1}$$

Where:

$\epsilon_{i,t}$	=	Model error for prediction location *i* at time *t* (Mg C/ha)
$\widehat{SOC}_{i,t}$	=	Predicted SOC stock for prediction location *i* at time *t* (Mg C/ha)
$SOC_{obs,i,t}$	=	Observed SOC stock for prediction location *i* at time *t* (Mg C/ha)

8) Determine whether the mean model prediction error is significantly different from zero using a two-tailed, one-sample *t*-test with α = 0.05.

9) Using all paired observations in the validation set, compute the amount of variance explained (R^2) using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \epsilon_{i,t}^2}{\sum_{i=1}^{n}\left(SOC_{obs,i,t} - \overline{SOC}_{obs,t}\right)^2} \tag{2}$$

Where:

R^2	=	Fraction of variance in SOC stocks that is explained by the model (dimensionless)

$\epsilon_{i,t}$	=	Model error for prediction location *i* at time *t* (Mg C/ha)
$SOC_{obs,i,t}$	=	Observed SOC stock for prediction location *i* at time *t* (Mg C/ha)
$\overline{SOC}_{obs,t}$	=	Mean of observed values of SOC stock at time *t* (Mg C/ha)
n	=	Number of prediction locations in the validation set

The amount of variance explained (R^2) must be greater than zero.[8]

10) The model must pass all three of the following model validation:

   a) Coverage is at least 90%.

   b) R^2 is greater than zero.

   c) Model prediction error is not significantly different from zero under a two-tailed, one-sample *t*-test.

For a model that passes these three validation tests, predictions should then be generated over the project area for every prediction location and aggregated over space to determine the arithmetic mean SOC stock at time *t* using the following equation:

$$\overline{\widehat{SOC}_t} = \frac{1}{\sum_{i=1}^{n} A_i} \times \sum_{i=1}^{n} \widehat{SOC}_{i,t} \times A_i \quad (3)$$

Where:

$\overline{\widehat{SOC}_t}$	=	Mean of predicted SOC stock values at time *t* (Mg C/ha)
A_i	=	Area of prediction location *i* within the project area[9] (ha)
$\widehat{SOC}_{i,t}$	=	Predicted SOC stock for prediction location *i* at time *t* (Mg C/ha)
n	=	Number of prediction locations in the validation set

Where new project activity instances are added to the project in different years, the time (*t*) of initial stock measurement will not be equivalent. The target date for the map of initial SOC stock predictions is defined for each prediction location using the first year in which the location is included in the sampling design for these instances.

11) Where the variance of the prediction error of the mean of model predictions is required, estimate the variance at time *t* using any valid procedure that explicitly accounts for the covariance of model prediction errors between prediction locations (see Section 5.3 and Appendix 4). Further guidance on valid procedures to account for covariance of model prediction errors is provided in Section 5.1.1.

12) The mean stock change between times *t* and $t + \Delta t$ is calculated using the following equation:

[8] $R^2 > 0$ indicates that the model provides a more precise estimate than the mean of validation data. See Janssen and Heuberger (1995) and Wadoux et al. (2022) for further justification. Note that this quantity might be negative.

[9] This accounts for the possibility that prediction locations may be of different sizes.

$$\Delta\overline{\widehat{SOC}}_{t,\Delta t} = \overline{\widehat{SOC}}_{t,\Delta t} - \overline{\widehat{SOC}}_{t} \quad (4)$$

Where:

$\Delta\overline{\widehat{SOC}}_{t,\Delta t}$	=	Mean predicted SOC stock change over all prediction locations in the project area between time *t* and time *t* + Δ*t* (Mg C/ha)
$\overline{\widehat{SOC}}_{t,\Delta t}$	=	Mean of model predictions of SOC stock over all prediction locations at time *t* + Δ*t* (Mg C/ha)
$\overline{\widehat{SOC}}_{t}$	=	Mean of model predictions of SOC stock over all prediction locations at time *t* (Mg C/ha)

The mean predicted SOC stock change in the project area between time *t* and time *t* + Δ*t* ($\Delta\overline{\widehat{SOC}}_{t,\Delta t}$) is greater than zero when SOC stock increases between *t* and *t* + Δ*t*, and less than or equal to zero otherwise.

The variance of the estimate of the mean stock change is calculated from the sample variances using the following equation:

$$var\left(\Delta\overline{\widehat{SOC}}_{t,\Delta t}\right) = var\left(\overline{\widehat{SOC}}_{t+\Delta t}\right) + var\left(\overline{\widehat{SOC}}_{t}\right) - 2\rho_{t+\Delta t} \times \sqrt{var\left(\overline{\widehat{SOC}}_{t+\Delta t}\right)} \times \sqrt{var\left(\overline{\widehat{SOC}}_{t}\right)} \quad (5)$$

Where:

$var\left(\Delta\overline{\widehat{SOC}}_{t,\Delta t}\right)$	=	Variance of the estimate of the mean change in SOC stock between times *t* and *t* + Δ*t* (Mg C/ha)[2]
$var\left(\overline{\widehat{SOC}}_{t+\Delta t}\right)$	=	Variance of prediction error of the mean of model predictions of SOC stock at time *t* + Δ*t* (Mg C/ha)[2]
$var\left(\overline{\widehat{SOC}}_{t}\right)$	=	Variance of the prediction error of the mean of model predictions of SOC stock at time *t* (Mg C/ha)[2]
$\rho_{t+\Delta t}$	=	Correlation of the prediction error of SOC stock between times *t* and *t* + Δ*t*

Each of the *var* terms is derived using the procedure from Step (11). The term $2\rho_{t+\Delta t} \times \sqrt{var\left(\overline{\widehat{SOC}}_{t+\Delta t}\right)} \times \sqrt{var\left(\overline{\widehat{SOC}}_{t}\right)}$ is the covariance of the error terms over time.

The variance of the prediction error of the mean of model predictions of SOC stock can be used to propagate uncertainty through other models (e.g., a BGCM) using the Monte Carlo method, as described in VCS methodology *VM0042 Improved Agricultural Land Management*.

13) The mean carbon dioxide removal estimate in soil is calculated using the following equation:

$$CO2_{soil,t,\Delta t} = \left(\overline{\Delta\widehat{SOC}}_{t,\Delta t} - \overline{\Delta\widehat{SOC}}_{bsl,t,\Delta t}\right) \times \frac{44}{12} \quad (6)$$

Where:

$CO2_{soil,t,\Delta t}$	=	Mean estimate of total soil carbon change between times *t* and *t* + Δ*t* net of changes in baseline control sites (t CO_2e/ha)
$\Delta\overline{\widehat{SOC}}_{t,\Delta t}$	=	Mean predicted SOC stock change over all prediction locations in the project area between time *t* and time *t* + Δ*t* (Mg C/ha)
$\overline{\Delta\widehat{SOC}}_{bsl,t,\Delta t}$	=	Mean predicted SOC stock change over all prediction locations in the baseline control area between time *t* and time *t* + Δ*t* (Mg C/ha)
$44/12$	=	Ratio of molecular weight of carbon dioxide to carbon

The variance of the removal estimate in soil is calculated using the following equation:

$$var(CO2_{soil,t,\Delta t}) = \left(var\left(\overline{\Delta\widehat{SOC}}_{t,\Delta t}\right) + var\left(\overline{\Delta\widehat{SOC}}_{bsl,t,\Delta t}\right)\right) \times \left(\frac{44}{12}\right)^2 \quad (7)$$

Where:

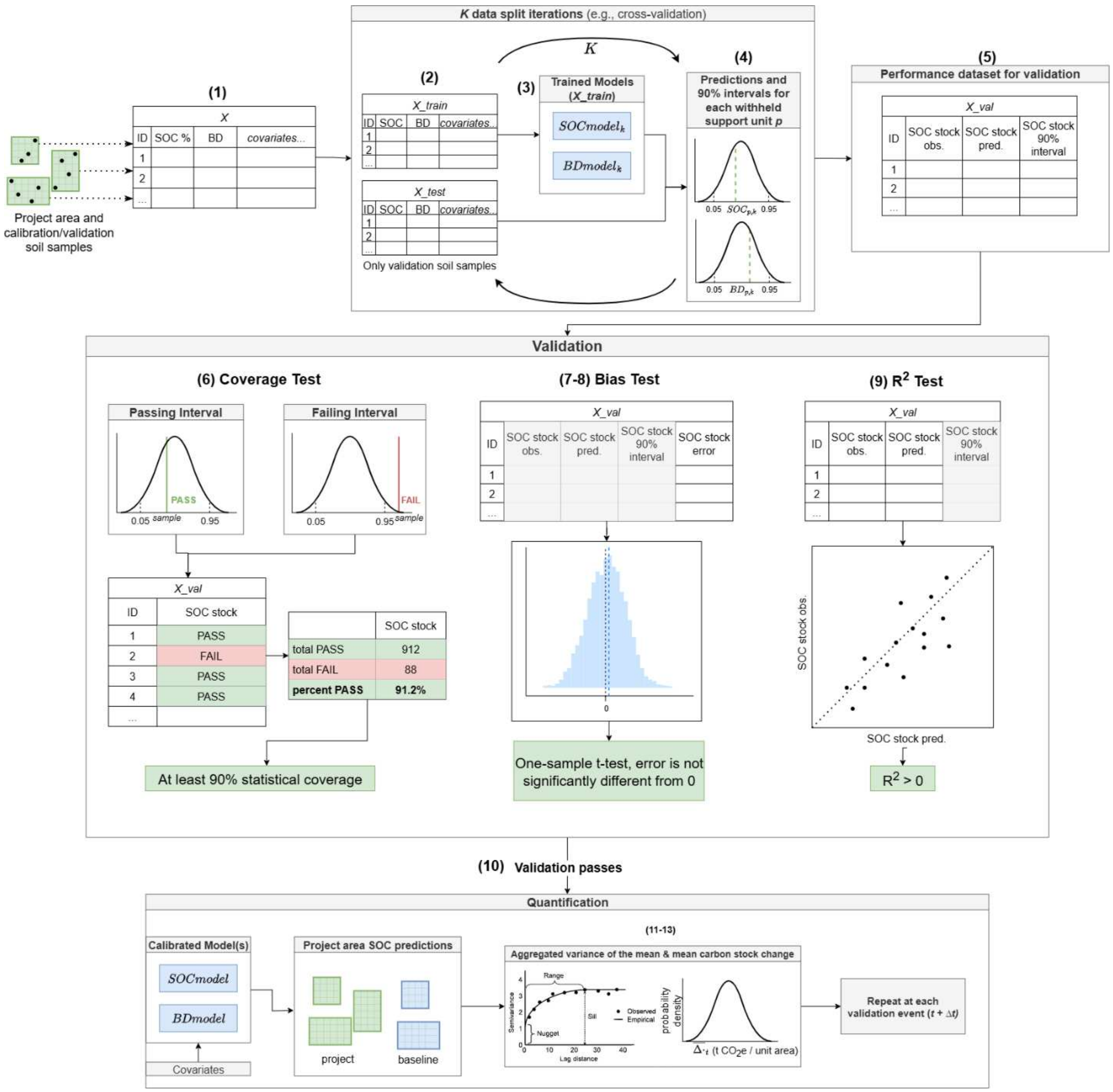
$var(CO2_{soil,t,\Delta t})$	=	Variance of the estimate of carbon dioxide removal in SOC stocks between times *t* and *t* + Δ*t* net of changes in baseline control sites (t CO_2e/ha)[2]
$var\left(\Delta\overline{\widehat{SOC}}_{t,\Delta t}\right)$	=	Variance of the estimate of the mean change in predicted SOC stock between times *t* and *t* + Δ*t* (Mg C/ha)[2]
$var\left(\overline{\Delta\widehat{SOC}}_{bsl,t,\Delta t}\right)$	=	Variance of prediction error of the mean of model predictions of SOC stock at time *t* + Δ*t* (Mg C/ha)[2]
$44/12$	=	Ratio of molecular weight of carbon dioxide to carbon

Where the applied methodology requires estimates of SOC stock within baseline control sites, $\overline{\Delta\widehat{SOC}}_{bsl,t,\Delta t}$ and its variance are calculated by applying Steps (11)–(12) to baseline control sites in addition to the project area.

The variance of the estimate of mean removals is used to compute the uncertainty deduction in compliance with the applied methodology.[10]

[10] For example, the probability of exceedance can be calculated directly from the variance of the estimate of mean removals and may be used with Equation (74) in *VM0042, v2.1* or equivalent equation in the most recent version of *VM0042*.

Figure 2. Model calibration, model validation, and uncertainty estimation flows



5.1.1 Accounting for the Covariance of Model Prediction Errors

Project proponents must use a valid method to account for the covariance of model prediction errors when estimating the variance of the mean of model predictions. In most cases, this will involve a spatially explicit method. The steps below describe how a DSM-IME may determine whether the method used by a project proponent is permissible under the tool. The method developed by Wadoux and Heuvelink (2023) is acceptable without further justification. Regardless of the method applied, the project proponent must provide software or code that demonstrates implementation of the method. This should be compared with the method described in a peer-reviewed publication in a journal indexed in the Web of Science: Science Citation Index[8], and must be confirmed to be accurate.

Where the method used to account for spatial covariance in the variance of the mean of model predictions is not that developed by Wadoux and Heuvelink (2023), the following must be confirmed:

1) **The method itself is valid:** The method must be described in at least one peer-reviewed article[8] where demonstrating the method is the primary focus of the article. The publication must illustrate the method by applying it to the spatially aggregated total or average of some quantity from a map generated by a statistical model.

2) **The method must be valid within this application:** The method must be appropriate for the project's prediction support unit and location. For example, a method designed for use over larger areas, like fields, may not be suitable for soil cores. Where the publication does not explicitly account for the spatial covariance of model errors (e.g., McRoberts et al. 2022), the project proponent must demonstrate that the impact of spatial covariance is minimal. This may be shown using spatial covariance statistics of residual errors (e.g., spatial autocorrelation measures among fields or counties) or other statistical techniques (e.g., as discussed in McRoberts et al. 2022).

5.1.2 Error Propagation Under Use Case 1

Predicted SOC stock in prediction location i at time t ($\widehat{SOC}_{i,t}$) may be used to initialize and/or true-up a model (e.g., a BGCM) in accordance with the applied methodology. The applied methodology dictates requirements for the lowest level unit represented by a single model simulation. In some cases, this unit may be a point represented by a soil sample. In others, the lowest level unit may be an area (e.g., a single polygon representing a sample unit or stratum). Guidance is provided below for both cases.

Where a model is applied on a point basis, procedures for the integration of DSM output data into the model under Use Case 1 follow those described in the applied methodology (e.g., in *VM0042*, guidance on error propagation when applying soil spectroscopy tools for SOC quantification).

1) Initialize the SOC stock (and/or SOC content and BD, where required) by drawing a sample from the predictive distribution for prediction location i at time t. Where the model is initialized using SOC stock, this distribution has a mean equal to $\widehat{SOC}_{i,t}$ and a standard deviation equal to σ_s.

2) Run the model in accordance with the applied methodology.

3) Analytical and Monte Carlo approaches to error propagation are permitted. Where the applied methodology permits Monte Carlo propagation of error, steps (1)–(2) may be repeated for each instance, l, of the Monte Carlo simulation. Compute the total estimate of uncertainty in accordance with the applied methodology.

Where a model is applied on an area basis under the analytical approach to error propagation, the model is initialized using the predictive mean SOC stock. Where a model is applied on an area basis under the Monte Carlo approach to error propagation, the model is initialized using draws from the predictive distribution of the mean SOC stock at time t ($\overline{\widehat{SOC}_t}$) calculated using Equation (3)(3) for the target area (e.g., sample unit or stratum). The variance of this distribution is computed using the methods described in Section 5.3. Uncertainty of model output is calculated in accordance with the applied methodology.

5.1.3 Prediction Locations in the Mapped Area

All prediction locations must be completely contained within the mapped area[11] and must be free of extraneous features. These exclusions do not change the project area.

5.1.4 DSM Model Architecture

Project proponents may use any statistical or machine-learning procedure to predict SOC stocks (e.g., traditional regression, ensemble-based regression trees, neural networks, and other methods in machine learning). Frequentist, Bayesian, parametric, and non-parametric methods are permitted. The selected model architecture may include one or more components. Some examples of multicomponent models are:

- separately generating estimates of SOC content and BD and combining these predictions to estimate SOC stock on an equivalent soil mass (ESM) basis, as described in Appendix 5.
- averaging the outputs of different procedures to arrive at a weighted mean estimate.
- using one method to estimate the mean and another to quantify its uncertainty.
- using localized versions of the model with differing calibration weights to generate predictions for different prediction locations.
- using one method to generate predictions of SOC stock, then using the predicted value of SOC stock as a single predictor in a simple linear regression.

The selected model architecture must be described in at least one peer-reviewed journal article in any field (see examples in Appendix 2).

5.1.5 Covariate Selection / Feature Engineering

Peer-reviewed studies demonstrate that numerous covariates can predict SOC content, SOC stock, and BD. Because additional covariates are likely to emerge as appropriate predictors in the future, there is no fixed positive list of acceptable covariates, and no restrictions on their

[11] For example, pixels on edges, such as field boundaries, are not fully contained within the mapped area. After excluding edge pixels from a 100-hectare field, the field might be 97 hectares. If the prediction locations are 10 m × 10 m pixels, there are 9700 pixels inside the mapped area for the field. The mean SOC stock density within the 9700 prediction locations is assumed to represent the 100-ha field. If the mean SOC stock density in the 9700 locations is 65 Mg C/ha, the total C stock in the field is 6500 Mg C.

types. However, users must ensure that covariates are generated in accordance with the recommendations in Sections 5.1.5.1–5.1.5.3. A set of peer-reviewed publications describing a wide range of covariate features, including the appropriate steps to generate them and ensure their accuracy, is provided in Appendix 2.

5.1.5.1 Quality Control for Covariates Derived from Remote Sensing

Covariates from remote sensing must be processed carefully to remove extraneous features (e.g., cloud cover, shadows, snow, hedgerows, roads, buildings, and waterways). All covariate sources and resolutions must be identical among calibration, validation, and prediction steps. Named and versioned data products must be used consistently. Project proponents must not, for example, use one named data product for calibration and a different named data product for prediction, even where these data products represent the same physical quantity. Similar logic applies to data processing. Where a cloud masking method is applied, the same method must be used consistently during calibration, validation, and prediction. Where optical remote sensing data depend on physical interpretations of reflectance, data must undergo atmospheric correction before further processing.

5.1.5.2 Time-invariant Covariates

Time-invariant (or static) covariates are those for which the data source serves as a fixed representation of these properties (e.g., digital elevation models, long-term climate normals, and prior soil property and class maps) over the project crediting period.

5.1.5.3 Time-varying Covariates

Time-varying covariates depend on the target date of model calibration and prediction (e.g., summaries from optical remote sensing, such as remote sensing indices indicative of vegetation or soil characteristics, weather measurements, including temperature, precipitation, vapor pressure, and humidity, and farm-practice data, such as cover cropping, reduced tillage, and other changes to land management practices). These covariates must maintain the same time interval and temporal relationship with respect to the target prediction date during calibration and prediction phases. Where the model is calibrated using data from a specific period (e.g., days, weeks, or months) leading up to the target date, the same time structure and method must be applied when making predictions. For example, if a covariate represents the three-year mean surface temperature prior to the prediction date, users cannot change this to a two-year mean during prediction unless the model is recalibrated with the new temporal relationship.[12]

[12] Maintaining this consistency ensures the model correctly applies the patterns learned during calibration to new predictions.

5.1.6 Calibration Data

The target variable is SOC content, SOC stock, or BD measured using individual soil cores or composite samples, but the tool permits use of augmented or synthetic calibration data[13] provided that all validation data follow the guidance in Section 5.2.

5.1.7 Treatment of Depth in the DSM Model

The use of a surface-to-subsurface relationship from ancillary depth-profile data is not permitted. The calibrated model must treat soil depth in one of two ways:

1) The calibrated model may treat soil depth as a continuous covariate feature to predict subsurface SOC content, SOC stock, or BD (e.g., Fu et al. 2024; Ma et al. 2021; Sanderman et al. 2018).

2) Alternatively, a project proponent may choose to use independent models to generate predictions at specific soil depths or depth ranges. For example, a project proponent could choose to develop one calibrated model that predicts SOC or BD over the 0–5 cm depth range, and another calibrated model that predicts these properties over the 5–30 cm depth range. The project proponent could then combine model outputs to represent SOC and BD over the 0–30 cm depth range. Where separate models are used, prediction uncertainty from each model must be propagated through all calculations of SOC stock.

5.1.8 Quantification and Calibration at Intermediate Verification Events

Under Use Case 2, the DSM model must be recalibrated[14] (see Section 5.2.3 for sampling requirements for recalibration) when project proponents pursue project verification between model validation events. Model performance metrics (coverage, R^2, and bias) for the recalibration must be reported in an amendment to the DSM-MVR.

5.2 Soil Sampling

Project proponents must follow best practices for the collection and analysis of soil samples as described in the applied methodology. Collection of soil samples must follow procedures outlined in the applied methodology, subject to the following and the requirements in Table 1:

1) All samples must be matched with covariate features that coincide in space and time with the location and sample date.

2) Samples may be depth-aligned to target depths using a method described in at least one peer-reviewed publication appearing in the Web of Science: Science Citation Index (e.g., mass-preserving splines or linear interpolation; Bishop et al. 1999).

[13] For instance, Xie et al. (2022) show that creating synthetic calibration data using predictions from a soil biogechemical model can improve the temporal stability of DSM predictions.

[14] Recalibration reduces dependency on cumulative carbon stock change for correcting systematic errors, if any.

Table 1. Requirements for sampling data used for model validation and model calibration

Collection requirements	Model calibration data	Model validation data
Sample location	Within or outside project area	Within project area or baseline control site only
Location data	Georeferenced coordinates	Georeferenced coordinates
Collection year	Recorded	Recorded
Collection season	Recorded	Same as target date required by the applied methodology[15]
Sample date	May be before project start date	Must be after project start date
Soil depth or depth range	Recorded	Must be at the specific soil depth or depth range required by the applied methodology
Composite samples	May be used[16]	May be used
Accounting for gravel particles in BD estimates	BD estimates with and without correction are permitted	Must follow guidance in applied methodology

5.2.1 Sampling Design

Data used for model validation must be sampled exclusively from within the project area or baseline control site and should be drawn from a probability sample. When a probability sample cannot be acquired, the project proponent must justify treating unsampled units as missing at random in the DSM-MVR. All sampling procedures for project stratification and data collection must comply with the applied methodology.

1) Where the method selected to account for spatial covariance in the variance of mean SOC stock requires a variogram, the project proponent must ensure that inter-point distances in the 0–500 m range are adequately represented among the sample locations (see guidance for the use of geostatistical methods in Section 5.5).

2) The number of strata is governed by the applied methodology and may be defined using estimates of SOC, covariates, potential or realized SOC stock change, or ancillary variables not included in the model.

3) Each prediction location must belong to only one stratum.

[15] For example, this is consistent with general requirements for soil sampling in *VM0042*, which state that sampling must be conducted during the same season.

[16] If calibration data contains a mix of composite samples and individual soil cores, the model must include a covariate or set of covariates that distinguish among sample types.

4) Under Use Case 2, where baseline control sites may be required by the applied methodology, they must be sampled according to the requirements of the applied methodology.

5) There is no fixed minimum number of soil samples for model calibration, recalibration, or validation. In general, larger sample sizes are desirable, but the marginal benefit diminishes when sampling error is small relative to other sources of uncertainty. Accordingly, the appropriate sample size depends on the level of uncertainty in the model and the expected rate of SOC sequestration. The project proponent must report, in the DSM-MVR, the number of samples used for calibration, recalibration, and model validation, and how the sample size was determined. The DSM-IME must determine whether the sample size is:

   a) sufficient for the model to meet the three validation criteria in Section 5.1(10).

   b) aligned with requirements in the applied methodology.

5.2.2 Sampling Requirements under Use Case 1

All sampling and model validation requirements for initial SOC stocks described above apply under Use Case 1. The model (e.g., a BGCM) must be validated according to the applied methodology. Validation of the DSM estimate of SOC stocks follows the procedures specified in Section 5.1. Since estimates of changes in greenhouse gases (GHGs) under this approach depend on the model, there are no additional sampling requirements beyond those necessary to validate the SOC stock estimate at the specified time.

5.2.3 Sampling Requirements under Use Case 2

The DSM model must be validated by the date of the first project verification and at least once every five years (see Figure 1~~Figure 1~~). Model calibration or model validation is required at every project verification event, and must meet the following requirements:

1) There are no spatial sampling design requirements for model calibration.[17]

2) The number of samples used to recalibrate the model must be sufficient to update the calibration for the current target date.

3) Validation of the DSM estimate of SOC stocks follows the procedures specified in Section 5.1.

[17] This is because the tool evaluates model performance on an outcome basis (model validation) by comparing model predictions to independent measured values within the mapped area.

5.3 Computing Variance of the Average SOC Stock

The contribution of spatial correlation in the variance of SOC stock must be addressed. Project proponents may implement the methods described by Wadoux and Heuvelink (2023) using the steps below.

1) Compute the standardized prediction error at every validation prediction location using the following equation:

$$\epsilon_{i,standardized} = \frac{\epsilon_i}{\sigma_i} \quad (8)$$

Where:

$\epsilon_{i,standardized}$	=	Standardized prediction error for prediction location *i*
ϵ_i	=	Prediction error for prediction location *i*
σ_i	=	Predictive standard deviation of the model for prediction location *i*; must be generated by the same process used to evaluate the coverage test described in Section 5.1

2) Compute the spatial correlation function by fitting a variogram to the standardized prediction errors and transforming the variogram's predictions into a correlation function. Section 5.5 provides guidance on fitting variograms.

$$\rho(h) = \frac{sill - \gamma(h)}{sill} \quad (9)$$

Where:

$\rho(h)$	=	Correlation function of the standardized model prediction error at lag distance *h*
$\gamma(h)$	=	Semivariance for a pair of points separated by lag distance *h*
sill	=	Value of the semivariance at the range in the dataset

3) For each Monte Carlo draw, l, randomly select a pair of prediction locations s_l and u_l, and compute the covariance between them using the following equation:

$$cov(\sigma_{s,l}, \sigma_{u,l}) = \sigma_{s,l} \times \sigma_{u,l} \times \rho(|s_l - u_l|) \quad (10)$$

Where:

$cov(\sigma_{s,l},\sigma_{u,l})$	=	Covariance between prediction locations s_l and u_l
$\sigma_{s,l}$	=	Predictive standard deviation of the model at location s for Monte Carlo draw *l*
$\sigma_{u,l}$	=	Predictive standard deviation of the model at location *u* for Monte Carlo draw *l*
$\rho(\lvert s_l - u_l \rvert)$	=	Correlation of model prediction error at the lag distance separating points s and *u* for Monte Carlo draw *l*

4) Compute the variance of prediction error of the mean of model predictions of SOC stock at time *t* using the following equation:

$$var\left(\overline{SOC_t}\right) = \frac{1}{L} \times \sum_{l=1}^{L} \sigma_{s,l} \times \sigma_{u,l} \times \rho(|s_l, u_l|) \qquad (11)$$

Where:

$var\left(\overline{SOC_t}\right)$	=	Variance of the prediction error of the mean of model predictions of SOC stock at time *t*
$\sigma_{s,l}$	=	Predictive standard deviation of the model at location *s* for Monte Carlo draw *l*
$\sigma_{u,l}$	=	Predictive standard deviation of the model at location *u* for Monte Carlo draw *l*
$\rho(\lvert s_l - u_l \rvert)$	=	Correlation of model prediction error at the lag distance separating points *s* and *u* for Monte Carlo draw *l*

5) Confirm that the Monte Carlo simulation generated a precise estimate of the variance. The precision of the variance will increase with the number of Monte Carlo samples (*L*). Project proponents must demonstrate that the variance of the mean carbon dioxide removal estimate in soil has been calculated with sufficient precision such that imprecision in estimates of the terms in Equation (5(5) impacts the uncertainty deduction by less than ±1 percentage point. This can be achieved by repeating the Monte Carlo process many times and showing that the uncertainty deduction fluctuates less than ±1 percentage point.

5.4 Computing Variance of the Change in SOC Stock

The variance of the mean stock change estimate is calculated using Equation (5)(5). This calculation accounts for the covariance term explicitly, using an estimate of $\rho(h)$. This parameter may be estimated in one of two ways following the Monte Carlo procedures outlined in Section 5.3.

1) Where measurements of the standardized prediction error are available at the same model validation locations at more than one time (i.e., there are repeated validation measurements at the same locations), use the following cross-variogram procedure:[18]

$$\gamma_{01}(h) = \frac{1}{2} \times E\left[\left(\epsilon_0(s+h) - \epsilon_0(s)\right) \times \left(\epsilon_1(s+h) - \epsilon_1(s)\right)\right] \qquad (12)$$

Where:

$\gamma_{01}(h)$	=	Semivariance for errors ϵ_0 and ϵ_1 separated by distance *h*
ϵ_0	=	Model prediction error at time 0

[18] Adapted from Equation 20.10 in Wackernagel (2003, p. 147)

ϵ_1	=	Model prediction error at time 1

2) Where measurements of the standardized prediction error are available at more than one time, but not at the same validation locations, use the following pseudo cross-variogram procedure:[19]

$$\pi_{0,1}(h) = \frac{1}{2} \times E\left[\left(\epsilon_0(s+h) - \epsilon_1(s)\right)^2\right] \quad (13)$$

Where:

$\pi_{0,1}(h)$	=	Semivariance obtained with the pseudo cross-variogram for errors ϵ_0 and ϵ_1 separated by distance h
$\epsilon_0(s + h)$	=	Model prediction error at location s at time 0
$\epsilon_1(s)$	=	Model prediction error at location s at time 1

The *E* operator in Equations (12)~~(12)~~ and (13)~~(13)~~ indicates an expected value. This value can be obtained using the arithmetic mean over Monte Carlo draws. The number of Monte Carlo iterations must satisfy the condition that the uncertainty deduction fluctuates by less than ±1 percentage point as described in Section 5.3. After this process has been completed, $\rho_{t+\Delta t}$ can be obtained using Equation (9)~~(9)~~.

5.5 Guidance on Variogram Selection and Fitting

Project proponents must compare multiple variogram functions to ensure that the variogram has been correctly estimated (e.g., spherical, Gaussian, and nugget-only variograms). Publicly available software is available to fit variograms. Project proponents must describe the software and version used in the DSM-MVR. A candidate variogram model should be selected using visual interpretation of the fitted variogram and may include model selection criteria (e.g., Akaike's information criterion or the Bayesian information criterion).

The DSM-MVR must include a plot of the selected variogram and several candidate alternatives and must include numerical values of model selection criteria, where used. Nested variogram models are permitted, where different functions are used to estimate spatial autocorrelation of standardized prediction errors at different lag distances. Nested variograms may be geographically stratified, such that short-distance lags are handled differently in different parts of the project area.

5.5.1 Sampling Guidelines for Variogram Calculations

Sampling guidelines must ensure that distances in the 0–500 m range are adequately represented. Webster and Oliver (1992) and Kerry and Oliver (2007) provide guidance on sample sizes and the spatial proximity of samples that must be followed.

[19] Adapted from Equation 20.18 in Wackernagel (2003, p. 149)

Fitting a variogram involves calculating a distance matrix containing the distances between all pairs of points. The variogram is then fitted to these distances within specific bins, such as 0–10 m, 10–20 m, and so on. A key consideration is determining the number of bins and the width of each bin. This can be approached in various ways, including using bins with an even number of pairs, bins of uniform width, or bins that minimize variation in distance.

If bin intervals are too small, semivariance estimates will be based on few point pairs, leading to imprecise estimates of the variogram. Conversely, if bin intervals are too wide, the reduced number of intervals may limit the ability to accurately estimate the range of spatial correlation. Use the following principles to guide the selection of appropriate bin numbers and widths:

1) Each bin should contain at least 50 pairs of locations (Schabenberger and Gotway 2017).
2) The distance represented by the center of the first bin must be smaller than the estimated range of the variogram.
3) The distance represented by the center of the last bin should be half the maximum distance among all possible locations (Cressie 1985).

For additional guidance related to bin width and number, see Section 3.2.3 in Oliver and Webster (2015).

6 DATA AND PARAMETERS

6.1 Data and Parameters Available at Validation

Data/Parameter	$\widehat{SOC}_{i,t}$
Data unit	Mg C/ha
Description	Predicted SOC stock in prediction location unit *i* at time *t*
Equations	(1)~~(1)~~, (3)~~(3)~~
Source of data	Calibrated DSM model
Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	This is the predicted value from the calibrated DSM model applied to covariates at prediction location *i* at time *t*.
Purpose of data	Calculation of project emissions

Comments	None

Data/Parameter	A_i
Data unit	Area (i.e., ha)
Description	Area of prediction location *i* within the project area
Equations	(3)~~(3)~~
Source of data	Prediction location *i*
Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	The area of each prediction location is used to account for the possibility that not all prediction locations have the same area.
Purpose of data	Calculation of project emissions
Comments	None

Data/Parameter	$\overline{SOC}_t$
Data unit	Mg C/ha
Description	Mean of model predictions of SOC stock over all prediction locations at time *t*
Equations	(4)~~(4)~~
Source of data	Calibrated DSM model
Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	This is the predicted mean value from the calibrated DSM model applied to covariates at time *t*.
Purpose of data	Calculation of project emissions
Comments	None

Data/Parameter	$\overline{SOC}_{t,\Delta t}$
Data unit	Mg C/ha

Description	Mean of model predictions of SOC stock over all prediction locations at time $t + \Delta t$
Equations	(4)~~(4)~~, (6)~~(6)~~
Source of data	Calibrated DSM model
Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	This is the predicted mean value from the calibrated DSM model applied to covariates at time $t + \Delta t$.
Purpose of data	Estimation of SOC stock and changes over time
Comments	None

Data/Parameter	$\overline{\Delta SOC}_{bsl,t,\Delta t}$
Data unit	Mg C/ha
Description	Mean predicted SOC stock change in the baseline control area between time t and time $t + \Delta t$
Equations	(6)~~(6)~~
Source of data	Calibrated DSM model
Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	This is the mean removal estimate in the baseline control area at time t and time $t + \Delta t$.
Purpose of data	Calculation of project emissions
Comments	Equal to zero where baseline control sites are not used.

Data/Parameter	σ_s σ_u
Data unit	Mg C/ha
Description	Predictive standard deviation of the model at location s Predictive standard deviation of the model at location u
Equations	(10)~~(10)~~, (11)~~(11)~~
Source of data	Any valid method to compute the predictive standard deviation

Value applied	N/A
Justification of choice of data or description of measurement methods and procedures applied	The predictive standard deviation is used in combination with the spatial covariance of the standardized prediction error to estimate the variance of the mean using geostatistical methods.
Purpose of data	Calculation of project emissions
Comments	None

6.2 Data and Parameters Monitored

Data/Parameter	$SOC_{obs,i,t}$
Data unit	Mg C/ha
Description	Observed SOC stock at prediction location *i* at time *t*
Equations	(1)~~(1)~~, (2)~~(2)~~
Source of data	Measurement of SOC content and BD from a soil core or composite sample
Description of measurement methods and procedures to be applied	Measurement techniques must follow guidance in the applied methodology.
Frequency of monitoring/recording	DSM model validation must occur by the date of the first project verification and subsequently at least once every five years.
QA/QC procedures to be applied	See section 5.2
Purpose of data	Calibration and validation of the DSM model
Calculation method	The calibration method follows the guidance of the applied methodology
Comments	None

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APPENDIX 1: ASSESSMENT BY INDEPENDENT MODELING EXPERT FOR DIGITAL SOIL MAPPING (DSM-IME)

This appendix describes the stepwise process for the assessment of a DSM model by a DSM-IME.

1) The project proponent must generate a DSM-MVR to demonstrate the validity and use of the DSM model consistent with the guidance and requirements of the tool (see Appendix 3).

2) The VVB must contract a DSM-IME, approved by Verra, to review the DSM-MVR. New DSM-IMEs must fulfill minimum qualifications defined by Verra. New DSM-IME must fulfill minimum qualifications defined by Verra (see Minimum DSE-IME qualifications below).

3) The DSM-IME must assess the DSM-MVR and generate a DSM-IME assessment report that:

    a) assesses the quality of calibration data.

    b) confirms that the calibration procedure meets the requirements stated in Section 5.1.

    c) confirms that the samples used for model validation follow the guidelines in Sections 5.1 and 5.2. The assessment report must explicitly confirm that validation samples were acquired exclusively within the project area, that the depth or depth range of validation samples matches the depth or depth range of the applied methodology, and that any unsampled locations can be treated as missing at random as defined in Section 3.

    d) confirms that the sample size is sufficient, with justification, and that the model passes the three validation tests: coverage, goodness of fit, and bias, as described in Section 5.1(10). Where DSM has been used to initialize and/or true-up a BGCM, the DSM-IME must confirm that the uncertainty propagation procedures in Section 5.1.2 have been correctly implemented.

    e) confirms that the variogram has been properly estimated using the procedures outlined in Appendix 4.

   Project proponents must promptly respond to inquiries and requests for consultation from the DSM-IME, including submission of additional documentation.

4) The DSM-IME assessment report must be submitted to the VVB for approval alongside other project documentation. The DSM-IME must keep the VVB apprised of questions and resolved findings related to the DSM-MVR and should provide documentation to the VVB justifying its recommendation. The VVB has ultimate responsibility for approval of the DSM-MVR. All DSM-

MVRs and DSM-IME assessment reports will be made public alongside project documentation in the Verra registry.

Minimum Qualifications of DSM-IMEs

Verra defines the minimum qualifications that IMEs must fulfill to perform an evaluation of the use of DSM models. To provide an assessment report, the DSM-IME must meet the following criteria:

1) demonstrated competence in quantifying SOC stocks and/or stock changes using DSM or combined approaches (i.e., DSM-BGCM). Specialization in certain practices, land uses, and regional/country expertise may be relevant. The IME must have at least five years of relevant work experience.
2) stated ability to assess DSM model types based on demonstrated use of statistical and/or machine learning procedures for DSM. Prospective DSM-IMEs may demonstrate expertise through peer-reviewed scientific publication(s) appearing in the Web of Science: Science Citation Index, or by submitting relevant project reports.
3) demonstrated ability to assess uncertainty in DSM predictions, including methods to account for spatial covariance in model prediction errors.
4) demonstrated independence from conflict of interest. This must be established by disclosing all relevant organizational and financial affiliations that could potentially undermine the integrity of the DSM-IME review process.
5) recommendation by two references, preferably research scientists with public, private, or government affiliations, including but not limited to academia.

The IME Qualification Form must be used to provide evidence demonstrating that the DSM-IME meets the above criteria.

APPENDIX 2: MODEL ARCHITECTURES AND COVARIATES

More than 1000 peer-reviewed academic journal articles have been written in the field of DSM with an explicit focus on SOC content, SOC stock, or BD and how these quantities change over time. Eighteen influential publications that include a wide range of model architectures and covariates are summarized in chronological order below.

- McBratney, A. B., M. L. Mendonça Santos, and B. Minasny. 2003. "On Digital Soil Mapping." *Geoderma* 117 (1–2): 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4

  Proposes a framework for DSM. This review discusses a wide range of model architectures, including generalized linear models, classification and regression trees, neural networks, fuzzy systems, and geostatistical tools. The authors generalize the state factor framework originally developed by Jenny (1941) by discussing covariates related to soil, climate, organisms, parent material, age, and spatial or geographic position.

- Gomez, C., R. A. Viscarra Rossel, and A. B. McBratney. 2008. "Soil Organic Carbon Prediction by Hyperspectral Remote Sensing and Field Vis-NIR Spectroscopy: An Australian Case Study." *Geoderma* 146 (3–4): 403–11. https://doi.org/10.1016/j.geoderma.2008.06.011

  Combines partial least squares regression with visible and near-infrared spectral data from proximal and spaceborne sensors to predict SOC as a percentage by mass in northwestern New South Wales, Australia. Spaceborne remote sensing was from the NASA Hyperion sensor on the EO-1 spacecraft. This sensor provided coverage of the 400–2500 nm spectral range using a spectral sampling interval of approximately 10 nm.

- Adhikari, K., A. E. Hartemink, B. Minasny, R. Bou Kheir, M. B. Greve, and M. H. Greve. 2014. "Digital Mapping of Soil Organic Carbon Contents and Stocks in Denmark." *PLoS ONE* 9: e105519. https://doi.org/10.1371/journal.pone.0105519

  Uses regression kriging, a geostatistical technique, to predict SOC content, SOC stock, and BD in Denmark. The authors used 18 continuous and categorical predictors related to land use and soils, hydrology, surface topography, climate, and insolation.

- Lacoste, M., B. Minasny, A. B. McBratney, D. Michot, V. Viaud, and C. Walter. 2014. "High Resolution 3D Mapping of Soil Organic Carbon in a Heterogeneous Agricultural Landscape." *Geoderma* 213: 296–311. https://doi.org/10.1016/j.geoderma.2013.07.002

  Uses Cubist, a rule-based regression method, to predict SOC content and BD in cropland areas of France. Covariates include topographic properties derived from a high-resolution LiDAR digital elevation model, geological and land use data, and a map of A-horizon thickness.

- Ratnayake, R. R., S. B. Karunaratne, J. S. Lessels, N. Yogenthiran, R. P. S. K. Rajapaksha, and N. Gnanavelrajah. 2016. "Digital Soil Mapping of Organic Carbon Concentration in Paddy Growing Soils of Northern Sri Lanka." *Geoderma Regional* 7 (2): 167–76. https://doi.org/10.1016/j.geodrs.2016.03.002

  Uses linear mixed models to predict SOC content in rice cropping in Sri Lanka. The study used topographic climatic, biological, and spatial covariates, including satellite remote sensing from the Landsat sensor.

- Hengl, T., J. M. de Jesus, G. B. M. Heuvelink, et al. 2017. "SoilGrids250m: Global Gridded Soil Information Based on Machine Learning." *PLoS ONE* 12: e0169748. https://doi.org/10.1371/journal.pone.0169748

  Uses random forest, gradient boosting, and multinomial logistic regression to map SOC content, SOC stocks, BD, and other soil properties globally to a depth of up to 30 cm. Covariates include numerous climate variables, topographic measurements from a digital elevation model, and land cover information from global satellite products.

- Ramcharan, A., T. Hengl, T. Nauman, et al. 2018. "Soil Property and Class Maps of the Conterminous United States at 100-Meter Spatial Resolution." *Soil Science Society of America Journal* 82 (1): 186–201. https://doi.org/10.2136/sssaj2017.04.0122

  Uses random forest to predict SOC content, BD, and other soil properties in the United States. The model uses a wide range of covariates, including a digital elevation model and derived topographic properties, long-term climate data, hydrological variables, optical remote sensing measurements from the NASA Landsat and MODIS sensors, and previously generated SOC maps and soil data.

- Castaldi, F., A. Hueni, S. Chabrillat, et al. 2019. "Evaluating the Capability of the Sentinel 2 Data for Soil Organic Carbon Prediction in Croplands." *ISPRS Journal of Photogrammetry and Remote Sensing* 147: 267–82. https://doi.org/10.1016/j.isprsjprs.2018.11.026

  Uses partial least squares regression and random forest. The authors applied these architectures to multispectral satellite data from the European Space Agency Sentinel-2 sensor, and to airborne spectral measurements from two hyperspectral sensors: the Airborne Prism Experiment (APEX) and a commercial off-the-shelf sensor from the Norwegian company Norsk Elektro Optikk. These sensors provide coverage throughout the visible, near-infrared, and shortwave infrared spectrum. The workflow was used to predict SOC as a percentage by mass in Germany, Belgium, and Luxembourg.

- Gomes, L. C., R. M. Faria, E. De Souza, G. V. Veloso, C. E. G. R. Schaefer, and E. I. F. Filho. 2019. "Modelling and Mapping Soil Organic Carbon Stocks in Brazil." *Geoderma* 340: 337–50. https://doi.org/10.1016/j.geoderma.2019.01.007

Uses random forest, Cubist, generalized linear model boosting, and support vector machines to predict SOC content in Brazil. Covariates include 74 measurements of surface topography from a digital elevation model, vegetation indices, and climate variables.

- Dvorakova, K., P. Shi, Q. Limbourg, and B. Van Wesemael. 2020. "Soil Organic Carbon Mapping from Remote Sensing: The Effect of Crop Residues." *Remote Sensing* 12 (12): 1913. https://doi.org/10.3390/rs12121913

  Uses partial least squares regression to predict SOC content in Belgium. Covariates were from two remote sensing instruments: APEX and Sentinel-2. APEX is an airborne hyperspectral sensor with coverage throughout visible, near-infrared, and short-wave infrared regions. Sentinel-2 is a multispectral satellite sensor. The study used two spectral indices to examine the impact of crop residue on SOC prediction: the Cellulose Absorption Index (CAI) and the Normalized Burn Ratio 2 (NBR2). The study demonstrates that using CAI to remove pixels with residue coverage can improve the performance of SOC prediction.

- Dvorakova, K., U. Heiden, and B. van Wesemael. 2021. "Sentinel-2 Exposed Soil Composite for Soil Organic Carbon Prediction." *Remote Sensing* 13 (9): 1791. https://doi.org/10.3390/rs13091791

  Uses partial least squares regression to predict SOC content in croplands. The study used Sentinel-2 multispectral satellite data as covariates and created composite images to isolate exposed soil. Composites were assembled using thresholds applied to spectral indices, including the Normalized Difference Vegetation Index (NDVI) and NBR2. This study demonstrates the use of time series filtering-based vegetation phenology to select data for SOC prediction. The authors argue that these methods minimize the influence of crop residues, surface roughness, and soil moisture.

- Heuvelink, G. B. M., M. E. Angelini, L. Poggio, et al. 2021. "Machine Learning in Space and Time for Modelling Soil Organic Carbon Change." *European Journal of Soil Science* 72 (4): 1607–23. https://doi.org/10.1111/ejss.12998

  Uses a quantile regression forest to predict SOC stock in Argentina. Covariates include topographic measurements and properties derived from a digital elevation model, land cover, long-term climate variables, and geological data in addition to measurements from two NASA spaceborne instruments: MODIS and AVHRR.

- Poggio, L., L. M. de Sousa, N. H. Batjes, et al. 2021. "SoilGrids 2.0: Producing Soil Information for the Globe with Quantified Spatial Uncertainty." *SOIL* 7: 217–40. https://doi.org/10.5194/soil-7-217-2021

  Employs a quantile regression forest to predict SOC content, BD, and other soil properties using an approach similar to Hengl et al. (2017). Covariates include more than 400 environmental variables, including long-term climate proxies, bioclimatic regions, geological properties, land use and land cover data, topographic measurements from a digital elevation model, vegetation indices, and optical measurements from spaceborne remote sensing and hydrological variables.

- Sothe, C., A. Gonsamo, J. Arabian, and J. Snider. 2022. "Large Scale Mapping of Soil Organic Carbon Concentration with 3D Machine Learning and Satellite Observations." *Geoderma* 405: 115402. https://doi.org/10.1016/j.geoderma.2021.115402

  Uses a quantile regression forest to predict SOC content in Canada. The analysis uses 40 covariates that include long-term climate data, optical remote sensing summaries, soil properties, topographic measurements from a digital elevation model, and data from a spaceborne synthetic aperture radar (SAR).

- Zhou, Y., C. Chartin, K. Van Oost, and B. Van Wesemael. 2022. "High-resolution Soil Organic Carbon Mapping at the Field Scale in Southern Belgium (Wallonia)." *Geoderma* 422: 115929. https://doi.org/10.1016/j.geoderma.2022.115929

  Uses gradient boosting to predict SOC content for agricultural fields in Belgium. Covariates are NDVI from optical remote sensing, elevation, clay content, precipitation, and organic carbon input from crops.

- Ugbemuna Ugbaje, S., S. Karunaratne, T. Bishop, et al. 2024. "Space-time Mapping of Soil Organic Carbon Stock and its Local Drivers: Potential for Use in Carbon Accounting." *Geoderma* 441: 116771. https://doi.org/10.1016/j.geoderma.2023.116771

  Uses a quantile regression forest to predict SOC stock at multiple points in time in Australia. Covariates include soil properties, topography, weather, and climate variables, in addition to satellite-derived quarterly optical indices. This study applies a time-weighted term to increase the importance of recently acquired covariates and demonstrates how time series covariates can be integrated into a DSM workflow.

- Fu, P., Clanton, C., Demuth, K. M., Goodman, V., Griffith, L., Khim-Young, M., Maddalena, J., LaMarca, K., Wright, L. A., Schurman, D. W., Kellner, J. R. 2024. "Accurate Quantification of 0 – 30 cm Soil Organic Carbon in Croplands over the Continental United States Using Machine Learning." Remote Sensing 16(12), 2217. https://doi.org/10.3390/rs16122217

  Uses an artificial neural network, Random Forest and gradient boosting to predict SOC content in croplands in the contiguous United States. Covariates include long-term physical climate, short-term weather, topographic, edaphic, and remotely sensed variables. This study evaluates three ability of three depth strategies to quantify SOC content over the 0 – 30 cm depth range.

- Kellner, J. R., Clanton, C., Demuth, K. M., Donovan, M., Feng, Y. Katherina, Khim-Young, M., Maddalena, J., Rustowicz, R., Schurman, D. 2025 in press. "Digital Soil Mapping in Support of Voluntary Carbon Market Programs in Agricultural Land." PLoS One.

  Employs a digital soil mapping framework driven by gradient boosting to predict SOC content in the top 30 cm of soil in agricultural land within the contiguous United States. Covariates included optical remote sensing summaries, weather, topographic and edaphic variables, long-term climate proxies, and synthetic aperture radar (SAR). Trained on SOC measurements in 47 states, the model performed accurately at the field level and outperformed four existing public SOC maps. The study used feature engineering to increase sensitivity of SOC prediction to optical remote sensing time series summaries.

APPENDIX 3: GUIDANCE ON REQUIREMENTS FOR MODEL VALIDATION REPORTS

This appendix is available as an HTML supplement that contains an example of the DSM-MVR, showing the required components of the DSM-MVR and demonstrating content that project proponents are expected to submit to a DSM-IME.

The DSM-MVR must contain at least the following information:

1) Demonstration that the model passes all three validation tests in Section 5.1(10)
2) A complete list of covariates, data sources, and procedures used for data processing and feature engineering
3) Justification of selected model architecture
4) The number of samples used for calibration, recalibration, and model validation, and how the sample size was determined
5) Software (including version) used to fit variograms
6) A plot of the selected variogram and several candidate alternatives, including numerical values of model selection criteria where applicable

Examples of covariate raster data used for predictions must be made available as supplements to the DSM-MVR for VVB and/or DSM-IME review upon request.

APPENDIX 4: EXAMPLE UNCERTAINTY CALCULATION

This appendix is available as an HTML supplementHTML supplement demonstrating how to calculate the variance of the mean SOC stock and stock changes following the methods outlined in Wadoux and Heuvelink (2023) and as described in this tool.

APPENDIX 5: GUIDANCE ON EQUIVALENT SOIL MASS CORRECTION

Where the applied methodology requires SOC stock changes on an ESM basis, the project proponent must follow appropriate guidelines in the applied methodology. ESM corrections can be applied to predictions of SOC stock that have been generated on a fixed-depth basis over the target depth range.

The project proponent may use any valid method of ESM correction, that is eligible under the applied methodology. For example, following Fowler et al. (2023), adjusted soil depth can be derived using the equations below and used to calculate a new, ESM-corrected value for $\widehat{SOC}_{i,t}$, here denoted $\widehat{SOC}_{stock,n,i,t}$. The *stock* subscript is redundant with other usages in the tool, but is used here for clarity because these calculations deal with SOC as a decimal percentage by mass and SOC stock separately.

$$M_{t+1} = M_t$$ (equation 2a in Fowler et al. 2023)

$$D_{a,i,t+1} \times \widehat{BD}_{i,t+1} \times \left(1 - k \times \widehat{SOC}_{percentage,i,t+1}\right) = D_{i,t} \times \widehat{BD}_{i,t} \times \left(1 - k \times \widehat{SOC}_{percentage,i,t}\right)$$

(equation 2b in Fowler et al. 2023)

$$D_{a,i,t+1} = D_{i,t} \times \frac{\widehat{BD}_{i,t}}{\widehat{BD}_{i,t+1}} \times \frac{1-k \times \widehat{SOC}_{percentage,i,t}}{1-k \times \widehat{SOC}_{percentage,i,t+1}}$$ (equation 2c in Fowler et al. 2023)

Where:

M_t	=	Mineral soil mass per unit area at time *t*
M_{t+1}	=	Mineral soil mass per unit area at time *t* + 1
$D_{a,i,t+1}$	=	Adjusted soil depth for prediction location *i* at time *t* + 1; used to compute a corrected value of SOC stock
$\widehat{BD}_{i,t}$	=	Predicted value of BD for prediction location *i* at time *t* from DSM
$\widehat{BD}_{i,t+1}$	=	Predicted value of BD for prediction location *i* at time *t* + 1 from DSM
$\widehat{SOC}_{percentage,i,t}$	=	Predicted value of SOC as a decimal percentage by mass at prediction location *i* at time *t* from DSM
$\widehat{SOC}_{percentage,i,t+1}$	=	SOC as a decimal percentage by mass for prediction location *i* at time *t* + 1 from DSM
$D_{i,t}$	=	Soil depth at prediction location *i* at time *t*

Mineral soil mass (*M*) can be measured directly or calculated using the van Bemmelen factor (*k*) or a regional variant (Minasny et al. 2020). The value of the van Bemmelen factor or regional variant must be provided in the DSM-MVR.

The corrected SOC stock for prediction location *i* at time *t* + 1 from DSM for a single-layer fixed depth sample (denoted $\widehat{SOC}_{i,t}$ elsewhere in this tool) is:

$$\widehat{SOC}_{stock,i,t+1} = D_{a,i,t+1} \times \widehat{BD}_{i,t+1} \times \widehat{SOC}_{percentage,i,t+1}$$ (equation 3 in Fowler et al. 2023)

DOCUMENT HISTORY

Version	Date	Comment
v1.0	26 Aug 2025	Initial version