Natural and Working Lands Carbon Inventory: Soils

Proposed 2025 Inventory Update Methods
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Background

Soil is a material that covers most of the land surface and is composed of minerals, organic matter, water, air, and living organisms. Soil organic carbon refers to the carbon component of organic matter present in the soil, which is derived from decaying plant material, root deposits, and other organisms. Soil organic carbon is an important natural resource that sustains many ecosystem services, including nutrient cycling and food production, water filtration and storage, and global climate regulation (Trivedi et al. 2018a).

The Intergovernmental Panel on Climate Change (IPCC) categorizes soil as either being organic or mineral in nature, based on the amount of organic carbon the soil stores as well as factors related to flooding and drainage. Organic soils contain high amounts of organic matter, storing more than 12% organic carbon by weight, and are developed under poorly drained conditions that limit decomposition. In contrast, mineral soils have lower amounts organic matter and usually occur under moderate to well drained conditions. Physical and chemical differences between these soil types requires unique methodological considerations; as such, they are treated separately in the IPCC framework. In California, organic soils are found in the Delta ecoregion, where they have mostly been drained for land use purposes (Deverel et al. 2020). However, organic soils are also found in coastal wetlands outside of the Delta, such as in coastal salt marsh ecosystems. The rest of the state's land area sits on soil that is categorized as mineral.

Across all soil types, soil stores more carbon than plants and the atmosphere combined, and exchanges carbon continuously and dynamically with both these reservoirs over time. Globally, 3,000 gigatons (Gt) of organic carbon is estimated to reside in the top 2 meters of soil, with approximately 716 Gt of that occurring in the top 30 cm (Trivedi et al. 2018a). In California, the 2018 NWL Carbon Inventory estimated that 2,750 MMT of organic carbon, or 51% of carbon in the state's land base, is stored in the top 30 cm of soil across all land types. The NWL Carbon Inventory also estimated that approximately 30 MMT of soil organic carbon was lost from California's lands between 2001-2010 (CARB 2018a). Ongoing changes in this carbon stock can either threaten or enhance the provision of ecosystems services for Californians and impact progress toward achieving carbon neutrality by 2045, making accurate estimates of change critical.

In addition to soil organic carbon, inorganic carbon stored in the form of calcium carbonate is also important in arid landscapes of California (Sharififar et al. 2023). However, assessing changes in soil inorganic carbon stocks remains beyond the scope of the NWL Carbon Inventory for this iteration. This is primarily because IPCC does not provide Tier 1 or 2 methods for estimating change in soil inorganic C stocks, and a paucity of temporal data and limited model options makes the use of Tier 3 methods prohibitive. As the science, datasets, and models for soil inorganic carbon progress, the inclusion of this carbon pool may be reassessed.

State of the Science

Accurately quantifying how soil organic carbon (hereafter called 'soil carbon') stocks vary across space and time is critical for creating robust inventories of ecosystem carbon on natural and working lands. National greenhouse gas (GHG) inventories rely on standardized methods to estimate soil carbon stocks and stock change, which are often aligned with guidelines provided by the Intergovernmental Panel on Climate Change (IPCC). Following IPCC principles, these inventories use tiered approaches, with Tier 1 involving default emission factors and generalized soil and climate data, and Tiers 2 and 3 integrating country-specific data and higher-resolution models or monitoring systems for greater accuracy. Where possible, national GHG inventories attempt to incorporate land use and land cover change data, meteorological data, and management practices, offering a complete yet broad picture of soil carbon dynamics within jurisdictional boundaries. Such methods prioritize consistency and comparability but must often trade accuracy and precision for feasibility (Bellassen et al. 2022), especially in regions that rely on Tier 1 or Tier 2 methods due to limited data access. For reference, Table 1 outlines the general approach used by four different national GHG inventories for mineral soils associated with six land types included in CARB's NWL Carbon Inventory. Organic soils are almost always assessed using Tier 1 approaches due to limited data and model availability (Köck et al. 2013).

The scientific literature relies on the equivalent of Tier 3 methodologies to explore and advance soil carbon inventory capabilities. Methods can generally be classified into either empirical or process-based approaches that aim to provide wall-to-wall assessment of carbon stocks across a landscape (Ugbaje et al. 2024; Singh 2018; Ogle et al. 2010). Both approaches have their own strengths and weaknesses (Table 1). Empirical modeling, commonly referred to as digital soil mapping, uses machine learning or other techniques to generate statistical relationships between measured soil carbon values and environmental or management factors (i.e., covariates) at point locations. These point-based relationships are then used to interpolate values across a map surface (McBratney et al. 2003). Digital soil mapping efforts initially centered on producing static maps representing soil carbon at a single point in time but have evolved in recent years to include space-time mapping techniques (Heuvelink et al. 2021). These advanced techniques integrate temporal data with spatial covariates, enabling soil carbon stocks to be estimated not just spatially, but temporally as well (Yang et al. 2022).

In contrast to digital soil mapping, process-based modeling predicts soil carbon by simulating underlying physical, chemical, and biological processes (Wang et al. 2020; Dondini et al. 2018), rather than relying solely on statistical relationships between observed values and covariates. Many process-based models exist, reflecting the diversity of environmental conditions they aim to represent, the varying levels of complexity required to address specific research questions or objectives, and the scientific community's evolving understanding of processes that govern soil carbon formation (Robertson et al. 2019). Process-based models can, but do not always, vary by land and soil type to account for differences in soil dynamics and management practices. For example, while the simplified process-based model RothC has been used to successfully model soil carbon in forests, grasslands, and croplands alike (Morais et al 2019), wetland soils cannot be modeled using RothC. Wetland soils behave very differently from non-wetland soils, as do organic soils from mineral soils (Smith et al. 2007). The scientific community has responded to these differences by developing and parameterizing models that capture the unique processes that govern carbon cycling under various conditions (e.g., Ward 2024). However, not all conditions are equally represented, with some (e.g., desert soils) requiring additional attention from the modeling community.

Empirical and process-based models have unique strengths and limitations that must be considered when estimating spatial and temporal trends for inventory purposes (Table 1). For example, empirical modeling excels at capturing spatial variability and is designed for implementation across large scales. In contrast, process-based modeling excels at capturing temporal variability and excels at simulating systems in novel conditions. To leverage the unique advantages of both approaches, researchers have combined process-based modeling with empirical modeling in recent years (Bernardini et al. 2024). For example, Xie et al. (2022) incorporated RothC predictions into a digital soil mapping exercise to estimate soil carbon stocks in the southern Jiangsu Province of China. Others have explored this approach as well (Zhang et al. 2024; Xu et al. 2024), all demonstrating improved accuracy when the two approaches are combined.

Table 1: Comparison of empirical and process-based modeling approaches for estimating soil carbon stocks in the primary literature. DNDC = Denitrification Decomposition model, MEMS 2.0 = Microbial Efficiency-Matrix Stabilization model, PEPRMT = Peatland Ecosystem Photosynthesis Respiration and Methane Transport model.

Attribute	**Empirical Modeling**	**Process-Based Modeling**
Spatial variability	Excels at capturing spatial variability	Encounters challenges when upscaling
Temporal variability	Encounters challenges related to insufficient data availability across time	Excels at capturing temporal variability
Ease of implementation across large scales	Designed for implementation across large scales; lower computational requirements	Depending on the method, can be computationally intensive
Eligible covariates/Input parameters	Can ingest any numerical (e.g., precipitation) or categorical (e.g., land use) variable that is dynamic or static	Ingests numerical variables related to set parameters in the model
Mechanistic Representation	Does not simulate mechanisms; relies on correlations and patterns in data.	Simulates mechanisms underlying the system.
Novel Scenarios	Can model systems for which it has data, but struggles in novel conditions and outside of these systems	Can simulate systems in novel conditions and can approximate systems similar but outside areas on which it was trained
Examples	Machine learning algorithms such as random forest; Regression kriging	DayCent, DNDC, RothC, PEPRMT, MEMS 2.0

Table 2: Approaches used to assess soil organic carbon change for IPCC land types in the literature and select national GHG inventories. CWEM = Cohort Wetland Equilibrium model, DNDC = Denitrification Decomposition model, MEMS 2.0 = Microbial Efficiency-Matrix Stabilization model, MIMICS = Microbial-Mineral Carbon Stabilization model, PEPRMT = Peatland Ecosystem Photosynthesis Respiration and Methane Transport model. Note: the list of process-based models presented from the literature is not exhaustive. *Tier depended on forest type.

	Literature	**United States GHG Inventory**	**Canada GHG Inventory**	**Australia GHG Inventory**	**Switzerland GHG Inventory**
Forest land remaining Forest land (mineral soil)	Digital soil mapping; process-based models (Century, RothC)	Tier 2 (Country-specific change factors)	Tier 3 (CBM-CFS3)	Tier 3 (FullCAM model with RothC submodel), Tier 2 & Tier 1*	Tier 2 (Country-specific change factors), Tier 3 for productive forest categories (Digital soil mapping)
Grassland remaining Grassland (mineral soil)	Digital soil mapping; process-based models (DayCent, RothC, MEMS 2.0)	Tier 3 (Daycent) except for gravelly, cobbly soils that used Tier 2	Tier 1 (Default change factors)	Tier 3 (FullCAM model with RothC submodel)	Tier 3 (RothC)
Cropland remaining Cropland (mineral soil)	Digital soil mapping; process-based models (DayCent, RothC, DNDC; MIMICS, MEMS 2.0)	Tier 3 (Daycent) for the majority of annual crops, Tier 2 for remaining crops and gravelly, cobbly soils	Tier 2 (Century to determine country-specific change factors)	Tier 3 (FullCAM model with RothC submodel)	Tier 3 (RothC)
Developed lands remaining Developed lands (mineral soil)	Digital soil mapping	Not assessed	Not assessed	Tier 2 (Country-specific change factors)	Tier 1 (Assumes stocks and change equal zero)
Other land remaining Other land (mineral soil)	Digital soil mapping	Not assessed	Not assessed	Not assessed	Tier 1 (Assumes stocks and change equal zero)
Wetland remaining Wetland (mineral soil)	Digital soil mapping; process-based models (CWEM, PEPRMT, WARMER-2, SUBCALC)	Tier 1 (Default emission factors) for peatlands, Tier 2 (County-specific emission factors) for vegetated coastal wetlands	Tier 2 (Country-specific emission factors)	Tier 2 (Country-specific emission factors)	Tier 1 (Assumes change equals zero)
All land types (organic soil)	Digital soil mapping; process-based models (ECOSSE)	Tier 1, Tier 2	Tier 1	Tier 1	Tier 1

Primary Drivers of Change

Like elsewhere, soil carbon storage across California's diverse landscapes is shaped by the factors of soil formation—climate, organisms, topography, parent material, and time (Jenny 1941). Which factor predominates will depend on the scale of interest. Climate is a dominant driver of soil carbon storage across the state, with temperature and precipitation influencing plant productivity and decomposition, resulting in arid regions like deserts storing less soil carbon compared to wetter regions like forests. Organisms, including vegetation and soil biota, play a role in capturing and cycling carbon within soils (Trivedi et al. 2018b; Jackson et al. 2007). This creates differences in soil carbon storage between vegetation types that can be distinguished from climate and seen at smaller scales (Waterhouse et al. 2024). Topography affects soil carbon by dictating the microclimate, water retention, and erosion across sites, with flatter areas often accumulating more carbon compared to steep terrains that are prone to runoff. In addition, parent material provides the mineral foundation that interacts with organic matter and influences carbon stabilization, with volcanic soils in some regions exhibiting higher carbon storage potential (Wilson et al. 2024). Time reflects the cumulative effects of these processes, with older, highly weathered soils often exhibiting greater carbon storage. Superimposed on these factors are human activities such as agriculture, urban development, and forest management, along with climate-driven disturbances like wildfires, which can further influence soil carbon dynamics across space and time.

Nature Based Solutions Targets

See land type reports for specific AB 1757 Nature-Based Solution targets.

2018 NWL Carbon Inventory Methods

Methods Description

With the exception of croplands remaining croplands, carbon stocks for mineral soils across all land types and conversion scenarios were estimated in the 2018 NWL Carbon Inventory using an IPCC Tier 2 approach (CARB 2018b). Briefly, initial soil carbon values were estimated based on SoilGrids (2017) and stock change factors (Table 17 in CARB 2018b) were applied to different land conversion scenarios following standard IPCC equations (Eqn 20, 21, and 22 in CARB 2018b). This resulted in annualized and total estimates for carbon stock change over the inventory period (2001-2010). Changes in soil carbon stocks for croplands remaining croplands were estimated using the Denitrification Decomposition (DNDC) model (Li et al. 1992).

For drained organic soils, which were constrained to land types in the Delta Ecoregion, soils were assumed to be purely emissive. Losses in carbon over time were determined using global "emission" factors from IPCC using a Tier 1 standard IPCC equation. Results for mineral and drained organic soils were combined for final estimates and extrapolated from 2001-2010 through 2014.

For wetlands, the prior inventory methodology estimated CO_2 and CH_4 emissions from three key wetland types: inland wetland mineral soils (IWMS), rewetted organic soils (ROS), and coastal wetlands. Emissions calculations used an IPCC Tier 1 approach, incorporating land cover data from the California Aquatic Resources Inventory (CARI) with global emission factors to produce final inventory estimates.

Benefits and Limitations

The prior use of Tier 2 methodology for mineral soils allowed for the development of carbon inventory estimates despite CARB staff being limited by information and resources. This is a benefit. In addition, using a Tier 2 approach allowed for conceivably greater accuracy than a Tier 1 approach, which would have used a global reference carbon stock value as input rather than more localized initial stock estimates from SoilGrids. However, Tier 2 methods are inherently broadscale and generalized, and thus do not allow for contextualized estimates of change over time. Moreover, the methods employed previously only captured land use change, and were not able to estimate management or disturbance effects on soil carbon over the inventory period. For drained organic and wetland soils, which used a Tier 1 approach, the same general benefits and drawbacks hold.

The prior use of Tier 3 methodology for croplands remaining croplands offered an opportunity to assess soil carbon stock change using process-based modeling and region-specific information. However, DNDC outputs required post-hoc harmonization with the rest of the inventory and, importantly, DNDC is not an open-source model.

2025 NWL Carbon Inventory Update Proposed Methods

Methods Description

We propose a unified framework for space-time mapping of soil carbon across all land types (Figure 1). The framework aims to combine the strength of process-based models with machine learning algorithms, as has been demonstrated elsewhere (Xie et al. 2022; Zhang et al. 2024). Specifically, process-based models do well at approximating processes that govern temporal change in soil carbon, while machine learning does a good job of capturing spatial change (Ugbaje et al. 2024). Together, the complementary strengths can improve the accuracy of soil carbon predictions across spatial and temporal scales.

The general idea is that this hybrid approach will use carbon estimates from process-based models as training data for digital soil mapping. The process-based model chosen will vary depending on the land type, but each will produce soil carbon estimates for inventory years from 2001-2023. These modeled outputs will fill temporal gaps and provide continuity in the training dataset for machine learning. Calibration of the process-based models will occur at representative sites, and calibrated models may be run on manually selected locations across known environmental/management gradients to address gaps in the machine learning training dataset.

Once the training dataset is compiled, it will be combined with environmental and anthropogenic covariates in a machine learning model that will be developed and then applied to predict the spatial distribution of soil carbon across California. Covariates of interest include those foundational to digital soil mapping, namely soil forming factors (climate, vegetation, topography, parent material, time, and space), as well as anthropogenic factors known to influence soil carbon over time (e.g., land management and disturbance) (Ugbaje et al. 2024). Cross-validation and validation using independent data will be conducted to ensure robustness and generalizability of the model (see Input and Validation Data Section).

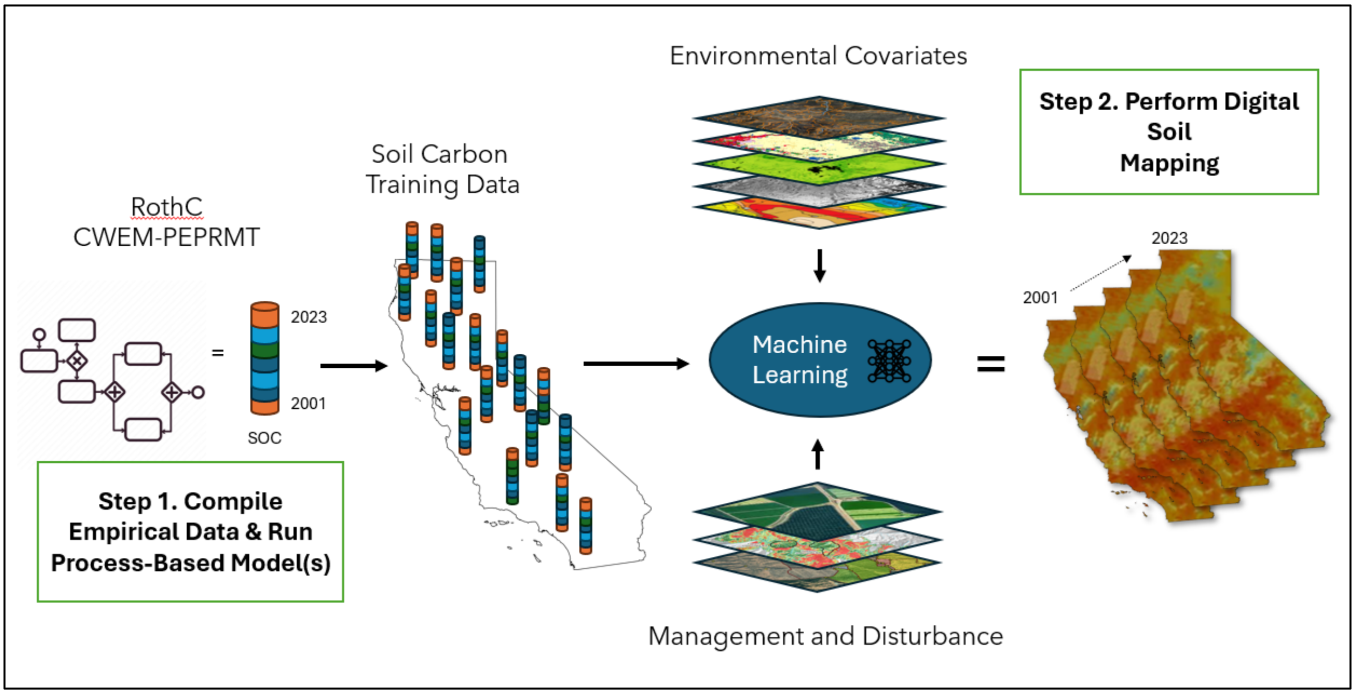

Figure 1: Unified soil framework. The lefthand side shows the generation of training data from empirical data and two process-based models: RothC for grasslands, croplands, and forests and CWEM-PEPRMT for wetlands (Step 1). Those data will be combined with empirical data from other land types and appropriate environmental and anthropogenic covariates in a machine learning model that will be used to predict carbon across California's land types for the inventory period (2001-2023) (Step 2).

Benefits and Limitations

The unified soil framework provides multiple benefits. It combines the strengths of process-based modeling with the strengths of machine learning for digital soil mapping, and in so doing grounds itself in two well-founded approaches (Ugbaje et al. 2024; Zhang et al. 2024; Xie et al. 2022). The framework also allows all lands in California to benefit from a Tier 3 approach, regardless of data availability, and allows for quantification of associated uncertainty. This approach also provides a consistent framework that can improve over time, and logistically, it minimizes issues with estimating Tier 3 land conversion effects across land types. However, overall accuracy of the final map is heavily dependent on the accuracy of the underlying process-based models, and their calibration/validation requires access to field-based measurements.

Input and Validation Datasets

Input datasets for the digital soil modelling include soil carbon training data, environmental covariates, and management/disturbance layers (Table 3). Validation data for the digital soil map will include observations from the World Soil Information Service database in addition to other sources, as available.

Table 3: Input data and proposed sources for digital soil mapping.

Category	Input Data	Proposed Source
Training Data	Direct field measurements	Varied
Training Data	Process-based model carbon output	RothC, CWEM-PEPRMT
Environmental Covariates	Climate: Precipitation, Temperature, Climatic Water Deficit	Cal-Adapt
Environmental Covariates	Vegetation: Landcover, net primary productivity	Landfire, MODIS/Landsat
Environmental Covariates	Topography: Slope aspect, elevation, topographic wetness index	USGS Digital Elevation Model
Environmental Covariates	Parent Material: Soil order, soil texture, pH	gNATSGO
Management & Disturbance Covariates	Fire	CalFIRE Historical Wildland Fire Perimeter
Management & Disturbance Covariates	See individual writeups for land type specific management & disturbance layers	See individual writeups for land type specific management & disturbance layers

Alternative Method for 2025 Update

The alternative methods for soil carbon are described in the individual land type documents.

Criteria Assessment

All decisions regarding proposed updates to the NWL Carbon Inventory were made in relation to standardized criteria set forth by CARB (Table 4). These criteria help to ensure that the methods and data CARB uses are appropriate to meet the goals of the NWL Carbon Inventory, are as rigorous and comprehensive as possible, and are reproducible for others.

Table 4: Criteria used to assess methodological updates for the 2025 NWL Carbon Inventory.

Category	**Criteria Assessment**
Spatial scale • Have accuracy optimized to statewide scales while also providing sufficient accuracy at the county scale • Ensure wall-to-wall coverage with no double counting	This unified method will be done at the statewide scale and is appropriate for county scale aggregation and will include all land types in California.
Temporal scale • Go back as far in time as possible, at least to 2001 • Be as up to date as possible	This unified method will go back to at least 2001 and will provide estimates through as close to present as possible, likely 2023 or one of the surrounding years.
Spatial resolution • Be as spatially explicit as possible, at least to the resolution of ecosystem boundaries • Permit analysis at different stratifications, such as by ownership, management action type, land type, or ecoregion	This unified method will provide a spatial resolution that allows for ecosystem boundaries to be resolved. The exact resolution will depend on a number of factors but will be no greater than 250m and will allow for various categorical analyses.
Temporal resolution • Produce annualized values that can be reported very 3-5 years	This unified method will produce annual values that can be updated and reported every 3-5 years.
Thematic resolution • Include as many carbon pools and fluxes as possible • Capture at minimum aboveground biomass carbon • Be generally consistent with IPCC GHG inventory guidelines	This unified method focuses on soil organic carbon and is consistent with IPCC GHG inventory guidance.
Sensitivity • Be sufficiently sensitive to quantify changes as a result of management and other major drivers of change, including climate change • Prioritize assessing directionality and general magnitude of change through time	This unified method is able to quantify changes in carbon through time that result from management or other major drivers of change.
Practical criteria • Generate transparent, repeatable methods that use free or low-cost tools • Prioritize base data that has reasonable expectation of sustainment and openness for use by state staff • Use models that are publicly available and open source • Use base data that require as little pre-processing for state staff as possible • Use base data that have a proven basis in reality and, where applicable, are validated with error or accuracy	In most cases, these methods use open-source, free datasets and tools that have reasonable expectation of sustainment and openness for use by state staff and others. However, some calibration/validation datasets may have privacy considerations that will be honored to the extent permitted by the law. Base data requires minimal pre-processing and is vetted by data developers.

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