Natural and Working Lands Carbon Inventory: Croplands

Proposed 2025 Inventory Update Methods
January 2025

(photo: California Department of Food & Agriculture, California Agricultural Statistics Review 2022-2023)

For more information, contact:
nwl@arb.ca.gov
Nature Based Strategies Section
Industrial Strategies Division
California Air Resources Board

Table of Contents

Background 3

State of the Science 4

Primary Drivers of Change 6

Nature Based Solutions Targets 6

2018 NWL Carbon Inventory Methods 8

Methods Description 8

Benefits and Limitations 10

2025 NWL Carbon Inventory Update Proposed Methods 11

Methods Description 11

Benefits and Limitations 13

Input and Validation Datasets 15

Alternative Method for 2025 Update 17

Criteria Assessment 18

References 22

Background

California's croplands are an intensively managed landscape serving as an important source of food, economic livelihood, and other co-benefits. Croplands cover 9.5 million acres and include a mix of annual (planted each year) and perennial (producing for multiple years) crops (Landfire, 2013-2021). These crops provide over a third of all vegetables and two-thirds of the fruits and nuts in the United States and make California a global leader in agriculture (State of California, 2020). California's croplands are managed to produce nutritious foods, myriad fibers, and nursery plants which are essential to food security, public health, art and quality of life for all Californians while simultaneously being a key economic driver in our rural communities.

According to the Intergovernmental Panel on Climate Change (IPCC), Croplands consist of "arable and tillable land, rice fields, and agroforestry systems where vegetation structure falls below thresholds" used for the forest land category (Eggleston et al., 2006). Within croplands, the carbon inventory focuses on two main pools of carbon: woody orchard biomass and soil carbon. Woody orchard biomass (hereafter "biomass carbon"), the first main carbon pool, refers to the carbon stock stored in the roots, trunks, and branches of woody perennial crops. Annual crops have herbaceous biomass, but annual biomass is not included in the carbon inventory because it is typically removed from the landscape within a single year. Soil carbon, the second main carbon pool, refers to the organic carbon stock stored in the top 30 centimeters of soil.

Biomass Carbon: Woody orchards play a significant role in California's economy, land use, and carbon storage. Almonds, walnuts, pistachios, and citrus are some of the primary orchard crops, covering millions of acres. According to the United States Department of Agriculture (USDA), almond orchards alone accounted for over 1.6 million acres as of 2022. Orchards are significant carbon reservoirs due to their woody biomass, which stores carbon over decades. However, orchards are subject to changing environmental, regulatory, and market dynamics that influence the extent and age of orchards among California's croplands.

Soil Carbon: Cropland soils are a key belowground carbon reservoir and offer an opportunity to store additional carbon if actively managed for carbon sequestration (Flint et al., 2018). The carbon in cropland soil, measured as soil organic carbon (SOC), is relatively resilient to risks from fire because croplands are heavily managed and generally irrigated landscapes. Despite this resilience, water availability, changes in agricultural practices, fallowing or crop replacement, and conversion to urban development all pose significant risks to the carbon stocks in California's cropland soils. Additionally, farmers in California operate under resource constraints that make adopting new practices a challenge.

State of the Science

Biomass Carbon: Methods to quantify orchard biomass include field measurements, remote sensing data, and machine learning techniques, each with distinct advantages and limitations. Traditional methods include allometric equations which translate field-based tree measurements such as diameter at breast height (DBH) and canopy height to estimates of biomass carbon. Field measurements are time intensive and difficult to replicate over wider spatial extents. Field-derived allometric equations provide high accuracy for site-specific estimates but require extensive field data for calibration across diverse orchard systems covering wide spatial extents (Bazrgar et al., 2024).

Allometric equations can be integrated with advanced remote sensing methods, such as light detection and ranging (LiDAR) and satellite imagery, to scale carbon estimates to larger spatial extents (Xu et al., 2018). LiDAR provides detailed 3D information, allowing for precise biomass mapping and large-scale assessments. However, its high cost and lack of consist time series data limit its applicability for creating periodic temporal inventories. Common limitations of many satellite products include insufficient spatial resolution and temporal frequency. Additionally, many products are proprietary, so purchasing data can be cost-prohibitive. Despite these limitations, LiDAR and high-resolution satellite imagery, such as data from the National Agricultural Imagery Program (NAIP), are widely used to capture key tree structure and biomass-related variables, including height, canopy cover, and volume (Zhang et al., 2014). NAIP, in particular, offers a cost-effective solution with high spatial and temporal resolution, enabling consistent and repeatable measurements over time.

Machine learning approaches utilize diverse datasets like field-based training data, remote sensing imagery, and climatic data to generalize carbon density predictions across different orchard types. Machine learning approaches are sophisticated and offer a means to capture the complexity and heterogeneity of carbon estimates across a cropland landscape. However, machine learning can be computationally intensive. These approaches often demand extensive training data and can suffer from issues with model interpretability (Chen et al., 2018).

Soil Carbon: Carbon inventory methodology aims to capture the complex dynamics of the cropland landscape, but methodology is constrained by the state of the science, models, and data. Small scale assessments of soil organic carbon (SOC), such as in a plot or a field, rely on direct measurements of soil organic carbon sampled with the density and frequency sufficient to capture spatial and temporal variation (Post et al., 2001). This comprehensive methodology can be used to validate carbon offsets. Practice-based SOC estimates, such as using crop residue coverage in a no-till system as a proxy for SOC increases, are another carbon market methodology, but one with considerably more uncertainty (Conant et al., 2011). Neither two approaches are sufficient for measuring cropland SOC at the statewide scale required for California's Natural and Working Lands Carbon Inventory (Table 5).

Methods to quantify SOC at larger spatial scales are more relevant for the NWL Carbon Inventory. Two large-scale approaches include geostatistical upscaling and measurement-based modeling (Conant et al., 2011). Geostatistical upscaling quantifies relationships between measurements of SOC and covariates such as slope, parent bedrock, climate, and plant type and then spatially interpolates estimates of SOC based on maps of the covariates (Viscarra Rossel et al., 2014). The uncertainty in geostatistical upscaling is dependent on the extent and representativeness of underlying field measurements. Measurement-based modeling uses mechanistic models that simulate biogeochemical processes and respond to cropland dynamics like water availability and crop cover. Model calibration is conducted using field measurements of SOC, or measurements derived from peer-reviewed literature. Challenges of measurement-based modeling include model parameterization, validation, and establishing SOC baselines, depending on the extent of available SOC measurements. In general, these large-scale methodologies benefit from improvements in the resolution and frequency of satellite-derived spatial data, which capture geostatistical covariates and model input variables such as climate, topography, and vegetation.

The choice in soil carbon quantification methodology often varies by soil type, according to the suitability of existing models. For example, the intergovernmental panel on climate change (IPCC) recommends differentiating cropland soils into two categories: mineral and drained organic. Mineral soils and the drained organic soils experience different biogeochemical and physical dynamics and are therefore quantified separately.

SOC in cropland mineral soils is often estimated with prevalent process-based models such as The Denitrification-Decomposition (DNDC) model, the Carbon Ecosystem Nutrient Turnover Under Regimes Yielding (CENTURY) model, and the daily timestep CENTURY model, DayCent (Del Grosso et al., 2016; Ding et al., 2023; Lugato et al., 2014). These models can incorporate the biogeochemical processes underlying SOC as well as model the management practices common in agricultural land. DNDC models carbon, nitrogen dynamics, and trace gas emissions including NO_x, NH_3, and CH_4 for cropping systems on short-term and long-term scales. CENTURY, and its daily counterpart, DayCent, models crop growth, carbon, nitrogen, phosophorus, sulfur, and soil water dynamics on time scales of decades to millennia. CENTURY and DayCent differ from DNDC in their conceptualization of nitrification and denitrification, which can lead to differences in the NO_x emission predictions (Li et al., 2014). However, evidence shows both models estimate carbon yield well in nitrogen fertilized systems (Grant et al., 2016).

Despite the application of these process-based models to mineral soils, these models are unable to model the biogeochemical processes of drained organic soils. Instead, these drained organic soils are considered purely emissive, and the carbon lost is quantified by multiplying land area by an IPCC emission factor. This IPCC emission factor framework, albeit simplified, is often implemented by national scale carbon inventories for drained organic soil (Liang et al., 2024).

Primary Drivers of Change

Biomass Carbon: In California, carbon stock changes in orchard woody biomass are driven by various biological and environmental factors. Orchard age and growth cycles play a primary role; as orchards mature, their carbon storage capacity increases, reaching its peak at full maturity when tree biomass is densest. However, growth rates slow over time, and aging orchards may experience higher mortality rates, which can lead to net carbon losses. Management practices also heavily impact carbon storage, with actions like pruning and thinning directly removing biomass and thereby temporarily reducing carbon stock, though these practices can lead to increased growth rates and improved long-term carbon storage potential. Additionally, the decision to remove or replant orchards as markets or environmental conditions change drives carbon in these systems.

Land-use change, agricultural practices, and environmental stressors are additional drivers impacting biomass carbon in croplands. First, Land-use changes away from orchards, such as the conversion of orchards to urban areas, cause immediate losses in woody biomass and associated carbon stocks. Conversely, removal of old orchards that are replaced with newly planted orchards may increase long-term carbon storage but initially produce lower biomass levels, due to the higher planting density seen in recent years. Overall, the economic return on certain orchard crops has led to the expansion of orchard acreage in recent years (Bruno et al., 2021). Second, Healthy soils and regenerative agricultural practices can have a positive impact on woody biomass in orchards by improving soil health, enhancing tree growth, and increasing carbon sequestration. practices such as cover cropping, improve soil structure, and increase organic matter content. These factors contribute to better water retention, nutrient cycling, and overall tree health, allowing orchard trees to grow more vigorously and produce more biomass. Finally, Environmental stressors, including climate-induced drought, increases in soil salinity, extreme temperatures, and pest infestations, pose additional challenges, often reducing orchard health and leading to mortality or decreased growth rates (Medellín-Azuara et al., 2024). These three types of drivers collectively influence orchard carbon stock inventories, making dynamic and species-adaptive methodologies essential for accurately capturing changes across California's orchard landscapes.

Soil Carbon: Many of the dynamics influencing orchard woody biomass also impact soil carbon. The drivers of change to cropland soils are largely influenced by management practices including crop type, crop rotation, tillage, irrigation, and use of cover crops, fertilizer, and residual plant matter. Climatic factors such as temperature and precipitation also impact carbon dynamics but typically have a secondary effect compared to the influence of agricultural management (Wiesmeier et al., 2013). Carbon losses from soil are also caused by fire, soil loss, leaching, and harvest (Lorenz and Lal 2010).

Nature Based Solutions Targets

California's Nature-Based Solutions (NBS) targets aim to foster cropland resilience. Carbon sequestration may be a co-benefit from NBS implementation but is not necessarily the primary goal. Cropland NBS targets include a set of sustainable climate smart agricultural practices and environmental restoration goals (Table 1). For "Healthy Soils Practices," the plan seeks to implement a variety of soil-enhancing techniques across annual and perennial croplands, with specific acre targets of 140,000 acres per year by 2030, expanding to 190,000 acres per year by 2038, and maintaining 190,000 acres per year by 2045. Practices under this approach include compost application, cover cropping, planting of hedgerows and riparian buffers, and no-till methods, which can improve soil health, increase organic carbon content, and reduce erosion. Techniques like whole orchard recycling also contribute by retaining biomass on-site, enhancing carbon storage, and improving soil fertility over the long term.

The conservation aspect targets the protection of annual and perennial croplands, with the acreage conserved gradually increasing from 12,000 acres annually in 2030 to 19,500 acres by 2045. This measure aims to preserve carbon already stored in existing croplands while preventing land-use changes that might otherwise result in emissions. Additionally, the NBS targets include converting conventional croplands to organic systems, aiming for a gradual increase in adoption across croplands: 10% by 2030, 15% by 2038, and reaching 20% by 2045. This shift to organic practices can further enhance soil health and carbon sequestration by reducing chemical inputs and promoting biodiversity within agricultural systems.

In addition to cropland NBS targets, certain NBS targets in developed lands and wetlands will impact cropland areas. In developed lands, an NBS target aims to plant tree buffers between croplands and communities to increase access to greenspace and reduce exposure to agricultural chemicals (Rice et al., 2016; Prosser et al., 2020; Table 2). Wetland NBS targets aim to restore delta wetlands, which overlap with cropland area (Table 2). Rewetted delta cropland may be converted to wetland systems or managed as inundated rice cropland.

Table 1: Nature-based solutions (NBS) targets for croplands established by AB1757.

AB1757 Nature-Based Solutions (NBS)	**2030 Target**	**2038 Target**	**2045 Target**
Healthy soils practices	140K acres/yr	190K acres/yr	190K acres/yr
Conservation	12K acres/yr	16K acres/yr	19.5K acres/yr
Convert systems from conventional to organic	10%	15%	20%

Table 2: Select nature-based solutions (NBS) targets established by AB1757 for wetlands and developed lands which are anticipated to impact croplands.

AB1757 Nature-Based Solutions (NBS)	2030 Target	2038 Target	2045 Target
Developed land: Afforestation between communities and croplands	133 acres/yr	185 acres/yr	230 acres/yr
Wetlands: Restoration	9.2 acres/yr	9.2 acres/yr	9.2 acres/yr

2018 NWL Carbon Inventory Methods

Methods Description

Biomass Carbon: In the 2018 carbon inventory, California Air Resources Board's (CARB) approach to estimating carbon stocks in cropland orchard biomass, categorized as an IPCC Tier 3 method, integrates ground-based data collection with remote sensing and statistical modeling techniques. A key component of CARB's effort was producing species-specific allometric equations which translate orchard type and age to carbon density per area for key orchard species. Developing these allometric equations involved three steps. First, CARB used high-resolution WorldView satellite imagery alongside Google Street View to gather tree measurements, specifically diameter at breast height (DBH), a critical metric for biomass calculations. This data was paired with USDA allometric equations to estimate tree biomass based on DBH values, though these equations traditionally focus on DBH rather than tree age. Second, recognizing this limitation, CARB collaborated with the Wolfskill Experimental Orchards at UC Davis, where a variety of nut and fruit tree species with known ages allowed CARB staff to establish age-specific tree biomass measurements (CARB, 2018). Allometric equations were thus quantified at the tree-level according to the relationship between carbon and tree age. Third, carbon had to be scaled from the tree-level to the orchard field-level, in an estimate of carbon per area. Age-dependent orchard tree density is a critical metric that scales estimates of carbon from the tree-level to the orchard field-level. CARB used high spatial resolution imagery in Google Earth Pro to measure tree density across a range of orchard types and ages. For each orchard age, CARB calculated the average number of trees per hectare, providing a reliable metric to scale biomass estimates from individual trees to larger orchard areas. These three steps produced species-specific allometric equations of carbon per area for key orchard types of almonds, walnuts, pistachios, vineyards, and citrus. The equations, based on both age and tree species, enable more precise biomass calculations, reflecting the unique growth, orchard density, and carbon accumulation patterns of each species.

A second key component of CARB's effort was to develop an estimate of the acreage of each orchard type and the ages of each orchard in croplands statewide. These orchard type and orchard age acreage estimates are necessary to derive a biomass carbon estimate for croplands statewide using the species-specific allometric equations. The National Agricultural Statistics Service (NASS) census was used to derive the county level acreage of each orchard type. Second, CARB developed a method to classify orchard age, using a pixel-based approach that leverages Landsat time series and the NASS Cropland Data Layer (CDL) data. This orchard age classification captures orchard planting and disturbance history, which aids in determining the age of each orchard pixel. This approach was computationally intensive, so CARB was limited to producing an estimate of the distribution of orchard age based on a single year's data; the distribution of orchard age was subsequently assumed to be static over time (USDA NASS, 2023). Subsequent annual updates to estimates of biomass carbon in croplands maintained this static age distribution assumption and only factored changes in acreage derived from NASS census data (CARB, 2018). These data inputs of orchard acreage and orchard age were coupled with the species- and age-specific allometric equations produced by CARB to produce an estimate of carbon for the key orchard species of almonds, walnuts, pistachios, oranges, and vineyards at the county level.

The final component of CARB's approach to estimating carbon stocks in cropland orchard biomass was to produce an uncertainty estimate. Uncertainty was quantified using a Monte Carlo analysis, addressing potential errors from measurements of tree height, DBH, density, and allometric variability. This approach allowed CARB to systematically assess and quantify uncertainties, resulting in robust, spatially refined carbon stock estimates for California's perennial croplands.

<u>Soil Carbon:</u> In the 2018 carbon inventory, mineral soil within croplands was quantified with a blend of tier 2 and tier 3 approaches, using the process-based Denitrification-Decomposition (DNDC) model. DNDC was used to simulate biogeochemical processes according to climate, soil, vegetation, and crop management practices, which served as model input parameters. The model was initialized with a two-year model spin-up and an initial SOC value derived from SoilGrids, which is a 250 m resolution map of SOC (ISRIC, 2018). Stock change for croplands remaining croplands was derived from the difference in DNDC-simulated SOC between inventory time point 1 and time point 2. For cropland changing to a different land type or vice versa, DNDC-derived SOC change was calculated for the cropland half of the period only. SOC change for the other half of the period was calculated using a modified IPCC stock change factor according to the transitioning land type. These IPCC stock change factors were modified according to initial SOC values derived from SoilGrids and thus considered a tier 2 methodology.

In the 2018 carbon inventory, drained organic soils within croplands, or delta soils, were quantified using a tier 1 approach. Like many process-based soil models, DNDC was not suitable for modeling the biogeochemical processes of drained organic soils. Instead, drained organic soils are considered purely emissive, modulated somewhat by climate and land use. Accordingly, the change in SOC was quantified by multiplying the drained organic soil land area by a land type-specific IPCC emission factor, which was 10 tonnes Carbon per hectare per year for cropland. For cropland changing to a different land type or vice versa, land type-specific emission factors were used for the appropriate corresponding half of the inventory time period. Although IPCC just recommends quantifying the carbon emitted from drained organic soils, the remaining carbon stock can be estimated from subtracting the carbon emitted from an initial SOC estimate derived from SoilGrids (ISRIC, 2018).

Changes in SOC for both mineral and drained organic soils were reported for croplands by each crop type for each county. In aggregate, mineral soil covers ~4.5 million hectares, or 97% of California's total cropland area according to the 2023 landfire classification data. The remaining 3% of cropland area consists of drained organic soil, or delta soil. In terms of cropland soil organic carbon (SOC), the top 30 cm of mineral soil contains 245.09 Million Metric Tonnes (MMT) of SOC, quantified in the 2018 NWL carbon inventory. In comparison, the top 30 cm of drained organic soil in the delta is estimated to contain 24.47 MMT of SOC, quantified using an IPCC rate of emission.

Benefits and Limitations

Biomass Carbon: CARB's method for estimating carbon stocks in orchard biomass presents both strengths and limitations. A primary benefit is its use of high-resolution remote sensing combined with ground-truth data, which allows for a refined, orchard-specific understanding of biomass at a regional scale. This approach enables more accurate assessments of carbon stocks that reflect California's unique orchard characteristics, such as species types, tree ages, and planting densities, which are critical for Tier 3 inventories. The use of field data from sources like UC Davis's experimental orchards strengthens the reliability of allometric equations for common species, allowing more precise biomass estimates.

CARB's carbon stock estimation method has several limitations primarily due to data spatiality and temporal assumptions. First, while CARB relies on crop acreage data from the USDA's National Agriculture and Statistics Service (NASS), these census datasets lack spatial specificity. The NASS census and survey programs provide detailed crop information, but their data is presented as aggregate summaries rather than spatially explicit maps. This aggregation includes California's five most common perennial crops—grapes, almonds, walnuts, pistachios, and oranges—while grouping the remaining perennial crops into a single category. As a result, CARB's estimates for carbon stocks, which depend heavily on NASS data, lack the spatial resolution necessary for precise, location-based assessments. Additionally, the census data is only updated every 5 years and often lacks temporal continuity which makes time series using this data difficult.

Additionally, CARB's approach assumes that orchard tree age distribution remains consistent across analysis years. This assumption simplifies the classification process but does not reflect the real-world variability in orchard age distribution over time. By applying the same age distribution across multiple years, CARB may inadvertently overlook important shifts in orchard age structure.

Finally, since CARB combines USDA acreage statistics with a non-spatial age distribution, the resulting carbon stock maps also lack spatial detail. Without spatially explicit data on orchard locations and ages, CARB's final maps present only generalized carbon stock estimates, which can limit their utility for applications requiring fine-scale resolution, such as localized carbon management or targeted climate action planning.

Soil Carbon: A benefit to the previous method used to quantify carbon in mineral soils is the ability of DNDC to simulate carbon and nitrogen biogeochemical processes according to parameterized climate, soil characteristics, crop type, and management variables. However, the DNDC model does not satisfy the California Air Resources Board (CARB)'s open access requirements, because the source code for the model is unavailable and therefore cannot be modified or replicated. Due to this limitation, DNDC can no longer be used for the statewide carbon inventory. Additionally, the version of DNDC used by CARB was primarily designed to estimate nitrous oxide emissions and does not include a robust system for quantifying soil carbon through time.

A benefit to the previous method used to quantify carbon in drained organic soils is consistency with IPCC recommendations. However, the limitation of the IPCC approach is that the simplified quantification of carbon emission is inherently broadscale and generalized. Contextualized estimates incorporating land use and management heterogeneity are not reflected over time.

2025 NWL Carbon Inventory Update Proposed Methods

Methods Description

Biomass Carbon: The proposed method for quantifying carbon in cropland biomass builds on the previous approach but introduces several key improvements to enhance the accuracy and spatial specificity of carbon stock estimates for California's orchards. The core concept remains the same: relying on species-specific allometric equations that use tree age, tree density by orchard age, and orchard acreage data as key inputs. However, the new approach replaces aspatial National Agricultural Statistics Service (NASS) crop acreage data with more recent and spatially explicit data from the California Department of Water Resources (DWR) crop mapping layer (DWR & LandIQ, 2022). The DWR crop mapping layer is available for the years 2014, 2016, 2018, 2019, and 2020-2022. The shift to this data enhances the spatial accuracy of the acreage estimates and reflects a more robust and up-to-date understanding of land use patterns in California's orchards.

A significant change to the updated methodology is the replacement of the previous tree age distribution model with more precise data on tree age from the DWR orchard age layer. For analysis years where DWR's age data is available (2020-2022 and eventually 2023), this layer will be directly used (DWR & LandIQ, 2022). For years when DWR age data is unavailable or incomplete, CARB plans to develop its own in-house age layers based on available data sources and predictive modeling techniques. CARB plans to incorporate the 2023 data once it is released, further refining the spatial and temporal resolution of carbon stock estimates.

Additionally, CARB has expanded its scope to estimate carbon stocks in orchard types previously excluded from the analysis. The previous methodology concentrated on only five orchard crops—almonds, walnuts, pistachios, citrus, and grapes—which together accounted for approximately 91% of the acreage in 2020, according to DWR crop mapping data (DWR & LandIQ, 2023). The updated approach, however, incorporates a wider variety of orchard species, providing a more comprehensive assessment of carbon storage across California's agricultural landscape.   CARB has evaluated several options and plans to assess additional datasets and methods that could potentially be used to estimate the carbon stock of newly added orchards. Current evaluations include canopy height data from META, carbon stock density maps (if deemed suitable for California orchards), and, as a final option, the use of proxy tree species with similar characteristics or functional tree groupings to estimate carbon density.

Overall, the integration of these enhanced data layers reduces reliance on outdated or spatially coarse data sources. CARB's proposed update to quantifying carbon in cropland biomass provides more accurate, timely, and comprehensive carbon stock estimations for California's orchards.

<u>Soil Carbon:</u> The proposed method for belowground carbon quantification is tier 3 and incorporates process-based modeling and digital soil mapping. First, in mineral soils, the open-source, process-based model Roth-C will be used to create a temporal sequence of SOC from 2001 to 2024 at locations which correspond to empirical data points. The empirical data will be measurements of SOC coupled with site characteristics, collected from various academic, private, and non-profit research efforts across the state. Efforts to solicit data are ongoing. Roth-C is also used to model SOC in grasslands and developed land mineral soil, but cropland Roth-C incorporates agriculturally specific inputs. Roth-C will be parameterized with available data on crop cover, crop rotation, climate, soil, and management parameters (Table 3). Inputs such as irrigation, decomposability, and plant biomass inputs according to management recommendations for each corresponding crop type. Roth-C modeling has been shown to be sensitive to changes in climate and management; model parameters can be adjusted to reflect management activity including no-till, cover cropping, and compost application. In drained organic soil, there is no open-source process-based model, so annual SOC will be derived from the IPCC emission factor using empirical measurements as a baseline. The drained organic soil method is not sensitive to management changes other than land use change and therefore offers an opportunity for improvement in future iterations of the NWL carbon inventory.

Second, digital soil mapping will be performed statewide, across all inventory land types, using a knowledge guided machine learning framework. The machine learning process will create a predictive relationship between spatial data of soil forming factors, (e.g. vegetative cover, slope, etc.), disturbance and management factors (e.g. pavement, irrigation, etc.), and the empirically-based temporal sequences of soil organic carbon produced by each land type's soil carbon quantification methodology (i.e. Roth-C for developed lands and croplands, stock change factors for other land types). The output will be a spatially explicit distribution of SOC statewide annually from 2001 to 2024, including through cropland. More details can be found in the proposed update to Natural and Working Lands Carbon Inventory: Soil Methods.

Benefits and Limitations

Biomass Carbon: CARB's updated methodology offers several benefits, including improved spatial accuracy, more precise tree age data, expansion of orchard types, and the inclusion of a Monte Carlo uncertainty analysis. First, spatial accuracy is improved by replacing the previously used NASS crop acreage data with a spatially explicit crop map. This new approach provides more precise data on orchard acreage. The data enables more accurate carbon stock estimates at regional and local scale, improving the overall reliability of the carbon stock mapping. Second, tree age is more accurately estimated by replacing the previously used estimated tree age distribution with an orchard age map, significantly reducing uncertainty. Improved orchard age data better captures an important cropland dynamic in which orchards increase their carbon storage over time. Third, the inclusion of additional orchard species—beyond just almonds, walnuts, pistachios, citrus, and grapes—ensures a more comprehensive estimation of carbon storage across California's agricultural landscape. Finally, the Monte Carlo Uncertainty Analysis will be retained from the previous methodology. This approach accounts for uncertainties in tree height, diameter, density, and age estimations. The Monte Carlo simulations will also consider errors in allometric equations and spatial uncertainties in area estimates. This uncertainty analysis will ensure transparency in the anticipated error from CARB's updated methodology.

CARB's updated methodology to quantify cropland biomass carbon also has several limitations, including a lack of field-level data, inability to account for all climate impacts, and an insensitivity to particular management actions. First, estimates of carbon biomass will not be based on actual field-level data, but are instead derived from orchard type and age. The implication of this approach is that fields with the same age and orchard type will have identical carbon density, regardless of their location. Any regional heterogeneity in the carbon densities of a particular orchard type and age will not be modeled. Second, the current approach does not directly account for the impact of climate change, as allometric equations are held constant and climate variables are not incorporated into the model. Future work to produce periodic updates to allometric equations may be an opportunity to incorporate the effects of climate change into future methodological updates. Finally, the proposed method is not sensitive to management activities that might enhance other biomass carbon stocks within orchards, such as from alley and cover cropping, and planting windbreaks and hedgerows.

Soil Carbon: The process-based model Roth-C has several benefits. Of the models assessed, Roth-C is the most long-standing model with decades of applications across different cropland and climate scenarios. While Roth-C emphasizes carbon inputs at the expense of more complex, updated processes captured by MEMS 2.0 and DNDC, a strength of Roth-C is its simplified design and inputs, the latter of which can be populated entirely using readily-available data. All models were also assessed for sensitivity to cover crop rotation, no and reduced till, and compost application. Roth-C can be sensitive to management changes by management-derived modifications to inputs. For example, rotational cover cropping can be incorporated by changing monthly biomass inputs. Roth-C has also been specifically calibrated in mediterranean climates. Additionally, Roth-C methodology is used in the grasslands and developed lands components, fostering model consistency throughout the NWL carbon inventory.

The blend of process-based modeling via Roth-C and digital soil mapping via the machine learning framework leverages the strengths of each approach. Process-based modeling incorporates biogeochemical processes into the estimation of SOC and is sensitive to changes in management (e.g. compost application). Digital soil mapping interpolates empirical data points using known drivers of SOC heterogeneity, facilitating data-driven estimates of SOC statewide, despite inconsistencies in data availability between land type. Finally, the statewide implementation of the belowground methodology unifies the SOC analysis across land types and fosters inventory consistency.

The limitations of the current version of Roth-C include its simplicity and inability to model all NBS strategies. For example, Roth-C utilizes a simplified understanding of soil carbon dynamics by splitting carbon pools into groups based on their relative decomposability. Similarly, Roth-C does not incorporate nitrogen cycling dynamics, which limits the model's ability to reflect changes in fertilizer application. Despite this limitation, Roth-C can be calibrated to improve accuracy at larger spatial scales. Additionally, Roth-C will not necessarily be sensitive to the implementation of hedgerows and riparian buffers, although this limitation applies to all models assessed.

The digital soil mapping process also has limitations, such as the need for significant computational resources and expertise in machine learning. Another limitation will be a lack of empirical SOC measurements in certain systems. If certain crop types or management approaches are undersampled compared to others, drivers of change may not be well represented in the machine learning algorithm. Despite these limitations, the hybrid approach has the potential to provide high-resolution spatio-temporal maps of SOC in California, integrating and assessing the effects of NBS Implementation. Further analysis of the benefits and limitations of soil carbon quantification methodology can be found in the proposed update to Natural and Working Lands Carbon Inventory: Soil Methods.

Input and Validation Datasets

Biomass Carbon: The input and validation datasets for CARB's updated orchard carbon stock estimation method are designed to incorporate both remote sensing data and ground-based measurements. Input datasets are well defined and selected to enhance the accuracy and spatial resolution of carbon stock predictions (Table 3). Validation datasets are still being vetted and compiled. Several candidate validation dataset sources have been identified and are listed below.

Biomass Carbon Input Datasets: Biomass carbon input datasets include the DWR Crop Cover Data, the DWR Orchard Age layer, and CARB's orchard allometric equations. The DWR Crop Cover dataset replaces the previous NASS crop acreage data. The California Department of Water Resources (DWR) crop mapping data provides detailed, spatially explicit information on orchard crops across California for the years 2014, 2016, 2018, and 2019-2022. This data helps map out orchard acreage and species, offering higher precision for carbon stock estimations compared to the broader NASS statistics. The DWR Orchard Age layer data is CARB's shift from using a generalized tree age distribution model to relying on actual orchard age data from the DWR orchard age layer, available for 2020-2022. This layer provides more accurate information on the age of orchards, which is a critical parameter for carbon modeling. When DWR data is not available, CARB plans to develop its own orchard age layer in-house. Finally, the orchard allometric equation data are species-specific allometric equations of carbon per orchard area were developed by CARB in previous iterations of the NWL carbon inventory (CARB, 2018).

Biomass Carbon Valiadtion Datasets: Biomass carbon validation datasets may include ground-truth measurements, remote sensing validation, and comparisons to past carbon stock estimates. For ground-truth measurements, validation of the carbon estimates will rely on ground-based measurements of tree DBH, height, and other structural characteristics. This data comes from field surveys conducted by CARB staff in previous inventory methods, including the use of tools like tree diameter tapes and hypsometers, as well as the established tree age data from sources like the UC Davis Wolfskill Experimental Orchards. For remote sensing validation, CARB can cross-reference the output of their carbon stock predictions with independent remote sensing data, such as high-resolution satellite imagery like Google Earth and Landsat. These images can be used to assess the accuracy of tree density and orchard age and crop classification. Finally, comparisons to past carbon stock estimates can be used to validation the model output against historical carbon stock estimates from the older CARB methodology, which relied more heavily on USDA data and less accurate static age assumptions. This allows CARB to assess improvements in model accuracy and spatial resolution.

Table 3: Input datasets used for the quantification of woody orchard biomass.

Dataset	Developer	Temporal Resolution	Spatial Resolution	Citation
Crop cover and orchard age	Department of Water Resources (DWR)	Annual or every 2 years	Object-based	(DWR & LandIQ, 2022)
Orchard allometric equations	California Air Resources Board (CARB)	Once	Aspatial	(CARB, 2018)
Canopy height 2020	Meta & World Resources Institute (WRI)	Once	1 m	(Meta & WRI, 2023)

Soil Carbon Input Datasets: The input datasets for soil carbon quantification will be used to parameterize the Roth-C model and scale soil carbon estimates throughout croplands statewide through the digital soil mapping described in the proposed update to Natural and Working Lands Carbon Inventory: Soil Methods (Table 4). Climate data used to parameterize Roth-C will be derived from Cal-Adapt and aligned with the data used across different land types (Thomas, 2018).

Soil Carbon Validation Datasets: Roth-C will also be calibrated using empirical data. Empirical data will consist of measurements of SOC coupled with site characteristics, collected from various academic, private, and non-profit research efforts across the state. Efforts to solicit data are ongoing.

Table 4. Input datasets used to for quantification of soil carbon.

Dataset	Developer	Temporal Resolution	Spatial Resolution	Citation
Crop cover	Department of Water Resources (DWR)	Annual	Object-based	(DWR & LandIQ, 2022)
Spatial CIMIS, Reference ET	DWR	Daily	2 km	(DWR, 2024)
Lit review: plant residue and decomposability, compost application	Various authors	Varied	Likely aspatial	TBD
Management recommendations: Irrigation, compost application	DWR; University of California Cooperative Extension (UCCE); Various authors	Varied	Likely aspatial	TBD
gNATSGO: % clay and initial soil organic carbon	Natural Resources Conservation Service (NRCS)	Single map produced from temporally variable samples	10 m or 30 m	(Soil Survey Staff, 2023)

Alternative Method for 2025 Update

<u>Biomass Carbon:</u> The alternative method for quantifying biomass carbon is to use the National Agricultural Statistics Service (NASS) cropland data layer to derive orchard type and acreage along with a static estimation of the distribution of orchard age (USDA NASS, 2023). This orchard age distribution was previously calculated by CARB staff for a single year based on a time series of satellite imagery coupled with manually collected samples of orchard age (CARB, 2018). These data inputs would be coupled with CARB's allometric

equations to derive an estimate of carbon for the key orchard species of almonds, walnuts, pistachios, oranges, and vineyards at the county level. Additionally, the orchard species with undefined allometric equations will be estimated using allometric equations for proxy tree species with similar characteristics. This alternative methodology is anticipated to have higher error compared to the proposed updated methodology, so associated error will be reported to provide transparency.

Soil Carbon: The alternative method for quantifying belowground carbon in mineral soils is to use a tier 2 method, applying the previously modified IPCC stock change factors to an initial SOC estimate derived from gNATSGO (Soil Survey Staff, 2023). The alternative method for drained organic soil is to use the tier 1 method, multiplying drained organic soil land area by the IPCC emission factor. The estimated carbon emission can then be subtracted from an initial SOC estimate derived from gNATSGO to yield the resulting SOC estimate.

Criteria Assessment

Biomass and Soil Carbon: All decisions regarding proposed updates to the NWL Carbon Inventory were made in relation to standardized criteria set forth by CARB (Table 5). 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 5: 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	These methods will be done at the statewide scale and is appropriate for county scale aggregation and will include all croplands in California.
Temporal scale • Go back as far in time as possible, at least to 2001 • Be as up to date as possible	These methods will go back to 2014 due to data limitation and will provide estimates through 2023. Alternate methodology will be used for estimates prior to 2001.
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	These methods will provide a spatial resolution of 30m. It will allow for various categorical analyses.
Temporal resolution • Produce annualized values that can be reported very 3-5 years	These methods will produce values for roughly every 2 years that can be updated and reported every 3-5 years, depending on data availability
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	These methods capture the primary pools of carbon in croplands, including aboveground biomass carbon stored in orchards and vineyards. They are 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	These methods quantify changes in carbon through time that result from management or other major drivers of change. The biomass carbon pool will be sensitive to changes in crop type and age and the soil carbon pool will be sensitive to management provided management tracking data is available
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.

Soil Carbon: For soil carbon in croplands, a process-based model is being proposed as a component of the unified soil framework. Because of this, additional criteria were considered by CARB staff for model suitability. These criteria encompass the broader inventory requirements but are tailored to evaluate model specifications (Table 6). Many of the prevailing models for cropland soil are not open source, which restricted options for the NWL inventory to a more limited list. Model options which were either open-source or potentially open-source, include MEMS 2.0 and Roth-C, and were evaluated for this proposal (Table 6). We provide the comparison of DNDC and DayCent to add further context.

Table 6: Process-based model candidates for quantifying soil organic carbon (SOC) in cropland mineral soils.

Model Name	**DNDC**	**Roth-C**	**MEMS2.0**	**DayCent**
Must fit context of specific landscape type	Yes	Yes	Yes	Yes
Is the model scalable?	Yes	Yes	Yes	Yes
Can this model do future projections needed for scoping plan?	Yes	Yes, minus coupled nutrient dynamics	Yes	Yes
Does the model include the major drivers of change in this system and key ecosystem processes?	Yes	Includes climate, soil, and plant type, but no nutrient cycling	Yes	Yes
Is this model sensitive to climate change	Yes	Yes	Yes	Yes
Can this model estimate the impacts of management/NBS actions?	Yes	Yes, simplified	Some, not all	Yes
Does the model output carbon stocks and/or GHGs?	Yes, both	Yes, Carbon	Yes, Caron	Yes, both
Is the model validated and have a basis in reality?	Yes	Yes	Yes	Yes
Can this model be run on a regular basis to develop updates and incorporate improvements?	No due to lack of publicly available source code	Yes	No due to lack of publicly available source code	No due to lack of publicly available source code

Is this an open-source model that we can modify and share without restriction?	No	Yes	No	No
Is this a mature model with a scientific track record?	Yes	Yes	Emerging	Yes
Are people currently using this model and is there a current user base?	Yes	Yes	Limited	Yes
Will this model require a lot of work to make usable for CARB's purposes, or is it ready off the shelf?	Ready off the shelf; Requires GHG/carbon calibration; unable to be modified	Ready off the shelf; Requires carbon calibration; modification possible	Not off the shelf ready, could require model development; unable to be modified	Ready off the shelf; Requires GHG/carbon calibration; unable to be modified
Do we have sufficient off the shelf data to parameterize, calibrate, validate (w/ uncertainty statistics) and run this model through time, or will this require new or highly processed data by CARB staff?	Yes, Parameterization is complex; Calibration and validation needed	Yes, simplified parameterization requirements; Calibration and validation needed	No, soil organic matter fractionation data required	Yes, Parameterization is complex; Calibration and validation needed
Can CARB staff run this model within our current timeframe for deliverables	No, this would require a contract	Yes	No	No, this would require a contract

References

Bazrgar, A. B., Thevathasan, N., & Gordon, A. (2024). Allometric equations for estimating aboveground biomass carbon in five tree species grown in an intercropping agroforestry system in southern Ontario, Canada. Agroforestry Systems, 98, 739–749. *https://doi.org/10.1007/s10457-023-00942-z*

California Air Resources Board (CARB). (2018). Technical Support Document for the Natural & Working Lands Inventory. Accessed at: https://ww2.arb.ca.gov/sites/default/files/2022-11/2022-sp-appendix-i-nwl-modeling.pdf

California Department of Water Resources (DWR). (2024). California Irrigation Management Information System (CIMIS), Reference Evapotranspiration Data. Accessed at: https://cimis.water.ca.gov/SpatialData.aspx

California Department of Water Resources (DWR) & LandIQ. (2022). Statewide Crop Mapping. Accessed at: *https://data.cnra.ca.gov/dataset/statewide-crop-mapping*

Chen, L., Ren, C., & Zhang, B. (2018). Estimation of forest above-ground biomass by geographically weighted regression and machine learning with Sentinel imagery. Forests, 9, 582. *https://doi.org/10.3390/f9100582*

Conant, R. T., Ogle, S. M., Paul, E. A., & Paustian, K. (2011). Measuring and monitoring soil organic carbon stocks in agricultural lands for climate mitigation. *Frontiers in Ecology and the Environment*, *9*(3), 169-173.

Del Grosso, S. J., Gollany, H. T., & Reyes-Fox, M. (2016). Simulating soil organic carbon stock changes in agroecosystems using CQESTR, DayCent, and IPCC Tier 1 methods. *Synthesis and modeling of greenhouse gas emissions and carbon storage in agricultural and forest systems to guide mitigation and adaptation*, *6*, 89-110.

Ding, W., Chang, N., Zhang, G., Kang, J., Yi, X., Zhang, J., Zhang, J., Wang, L. and Li, H. (2023). Soil organic carbon changes in China's croplands: A newly estimation based on DNDC model. *Science of The Total Environment*, *905*, 167107.

Eggleston, H. S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). 2006 IPCC guidelines for national greenhouse gas inventories.

Flint, L.E., Flint, A.L., Stern, M.A., Mayer, A., Silver, W., Franco, F., Byrd, K., Sleeter, B., Alvarez, P. and Creque, J. (2018). Increasing soil organic carbon to mitigate greenhouse gases and increase climate resiliency for California. *California's fourth climate change Assessment, California Natural Resources Agency. Publication number: CCCA4-CNRA-2018-006 http://climateassessment. ca. gov/techreports/agriculture. html*.

Grant, B. B., Smith, W. N., Campbell, C. A., Desjardins, R. L., Lemke, R. L., Kröbel, R., McConkey, B.G., Smith, E.G. and Lafond, G. P. (2016). Comparison of DayCent and DNDC models: case studies using data from long-term experiments on the Canadian prairies. *Synthesis and modeling of greenhouse gas emissions and carbon storage in agricultural and forest systems to guide mitigation and adaptation*, *6*, 21-57.

High Resolution Canopy Height Maps by WRI and Meta was accessed on DATE from Google Earth Engine.

High Resolution Canopy Height Maps (CHM). Source imagery for CHM © 2016 Maxar. Accessed DAY MONTH YEAR.

ISRIC. (2018). SoilGrids-global gridded soil information, s.l.: s.n.

LANDFIRE: LANDFIRE Existing Vegetation Type layer. (2013 - 2021). U.S. Department of Interior, Geological Survey. [Online]. Available: https://landfire.gov/version_download.php [Accessed: February 3, 2021]. LANDFIRE: LANDFIRE Biophysical Setting layer. (2013 - 2021). U.S. Department of Interior, Geological Survey [Online]. Available: https://landfire.gov/version_download.php [Accessed: February 3, 2021]. California Multi-Source Land Ownership (ownership18_2), October 15, 2018. CAL FIRE-FRAP. https://frap.fire.ca.gov/mapping/gis-data/ [Accessed: August 17, 2021].

Li, C., Six, J., Horwath, W. R., & Salas, W. (2014). *Calibrating, validating, and implementing process models for California agriculture greenhouse gas emissions*. California Environmental Protection Agency, Air Resources Board, Research Division.

Liang, Z., Hermansen, C., Weber, P. L., Pesch, C., Greve, M. H., de Jonge, L. W., ... & Elsgaard, L. (2024). Underestimation of carbon dioxide emissions from organic-rich agricultural soils. Communications Earth & Environment, 5(1), 286.

Lugato, E., Panagos, P., Bampa, F., Jones, A. and Montanarella, L. (2014), A new baseline of organic carbon stock in European agricultural soils using a modelling approach. Glob Change Biol, 20: 313-326. *https://doi.org/10.1111/gcb.12292*

Medellín-Azuara, J., Escriva-Bou, A., Gaudin, A. C., Schwabe, K. A., & Sumner, D. A. (2024). Cultivating climate resilience in California agriculture: Adaptations to an increasingly volatile water future. *Proceedings of the National Academy of Sciences*, *121*(32), e2310079121.

Meta and World Resources Institute (WRI). (2023). High Resolution Canopy Height Maps. Accessed at: https://meta-forest-monitoring-okw37.projects.earthengine.app/view/canopyheight

Post, W. M., Izaurralde, R. C., Mann, L. K., & Bliss, N. (2001). Monitoring and verifying changes of organic carbon in soil. *Climatic change*, *51*(1), 73-99.

Prosser, R. S., Hoekstra, P. F., Gene, S., Truman, C., White, M., & Hanson, M. L. (2020). A review of the effectiveness of vegetated buffers to mitigate pesticide and nutrient transport into surface waters from agricultural areas. *Journal of environmental management*, *261*, 110210.

Rice, C. P., Bialek, K., Hapeman, C. J., & McCarty, G. W. (2016). Role of riparian areas in atmospheric pesticide deposition and its potential effect on water quality. *JAWRA Journal of the American Water Resources Association*, *52*(5), 1109-1120.

Soil Survey Staff. (2023). The Gridded National Soil Survey Geographic (gNATSGO) Database for California. United States Department of Agriculture, Natural Resources Conservation Service. Accessed at: *https://nrcs.app.box.com/v/soils*

State of California, California Department of Food and Agriculture, California Agricultural Statistics Review, 2019-2020 (2020). *https://www.cdfa.ca.gov/Statistics/PDFs/2020_Ag_Stats_Review.pdf*.

Thomas, N. M. (2018). Cal-Adapt: linking climate science with energy sector resilience and practitioner need. *A Report for California's Fourth Climate Change Assessment*.

United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS). (2023). Cropland Data Layer. Accessed at: nassgeodata.gmu.edu/CropScape/

Viscarra Rossel, R. A., Webster, R., Bui, E. N., & Baldock, J. A. (2014). Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. Global Change Biology, 20(9), 2953-2970.

Xu, Q., Man, A., Fredrickson, M., Hou, Z., Pitkänen, J., Wing, B., Ramirez, C., Li, B., & Greenberg, A. J. (2018). Quantification of uncertainty in aboveground biomass estimates derived from small-footprint airborne LiDAR. Remote Sensing of Environment, 216, 514–528. *https://doi.org/10.1016/j.rse.2018.07.022*

Zhang, G., Ganguly, S., Nemani, R., White, M., Milesi, C., Hashimoto, H., Wang, W., Saatchi, S., Yu, Y., & Myneni, M. (2014). Estimation of forest aboveground biomass in California using canopy height and leaf area index estimated from satellite data. Remote Sensing of Environment. *https://doi.org/10.1016/j.rse.2014.01.025*