Natural and Working Lands Carbon Inventory: Grasslands

Proposed 2025 Inventory Update Methods
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For more information, contact:
nwl@arb.ca.gov
Nature Based Strategies Section
Industrial Strategies Division
California Air Resources Board

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Background

For the NWL Carbon Inventory, grasslands are defined as ecosystems dominated by herbaceous plants, primarily grasses, grass-like plants (sedges and rushes), and forbs, with less than 10% tree/shrub cover. This includes areas that are actively managed to maintain or enhance the herbaceous plant community, areas that are used as rangeland and irrigated pasture, and areas that are managed with agroforestry practices, so long as they do not meet the definition of forest land. Highways and roads that run through grassland are counted as developed lands.

Grasslands are an important part of California's landscape, covering close to 10M acres and supporting critical ecosystem services. Most of the carbon in grasslands is stored belowground in the soil organic carbon (SOC) pool (Bai and Cotrufo 2022). Aboveground carbon is found primarily in a transient herbaceous biomass pool that is subject to growth and decomposition over annual timescales. Carbon stocks of grasslands are highly influenced by factors such as soil type and climate, creating strong variation across the landscape (Liu et al. 2021; Carey et al. 2020a). Interannual variation for aboveground carbon is also quite large (Larsen et al. 2015), while changes in soil carbon stocks tends to happen more slowly over time.

State of the Science

National greenhouse gas (GHG) inventories use a combination of Intergovernmental Panel on Climate Change (IPCC) tiers to estimate carbon stock changes for grassland remaining grasslands and grassland converted to/from other land types. For instance, the US GHG Inventory uses a Tier 3 Forest Inventory and Analysis (FIA) method to estimate aboveground biomass stock changes with forest land converted to grassland. The US GHG Inventory also uses a Tier 3 approach that relies on the DayCent biogeochemical model for soil carbon in most cases; in those cases where the Tier 3 approach is not applicable, such as when grasslands are converted to forest, a Tier 2 stock-change factor approach is used. The Canadian GHG Inventory also uses a Tier 3 Century model approach to estimate changes in soil carbon with conversion from grassland to cropland, but relies on a basic Tier 1 approach for grassland remaining grassland. For the Australian GHG Inventory, grassland carbon stock changes are estimated using a Tier 3 Full Carbon Accounting Model (FullCAM) comprised of three submodels, including RothC for soil. Switzerland also uses RothC as a Tier 3 process-based model for soil carbon of mineral soils. As a final example, the United Kingdom uses a Tier 3 empirical model for aspatial soil carbon stock changes associated with mineral soils and a Tier 2 method for organic soils.

The scientific literature takes an equally varied approach to estimating carbon stocks and stock changes in grasslands, but all methods would be considered Tier 3 in the IPCC framework. Aboveground biomass carbon is often determined through an empirical modeling approach whereby relationships between field biomass data and predictor variables are used to interpolate values across a landscape (Wang et al. 2022). Net primary productivity (NPP), which can help provide an estimate of aboveground biomass in grassland systems, is frequently reported using remote sensing products of NDVI or similar vegetation indices that are validated with field measurements. Soil carbon methods can be classified into either empirical or process-based approaches (Singh 2018). The empirical approach uses digital soil mapping to spatially predict carbon by establishing a statistical relationship between field/laboratory data and environmental covariates, which is then applied to interpolate values across a map surface (McBratney et al. 2003; Veloz et al. 2022). In contrast, a process-based model approach predicts carbon by simulating underlying physical, chemical, and biological processes (Wang et al. 2020), rather than relying solely on statistical relationships between observations and environmental covariates. Many process-based models exist for soil carbon, ranging from models that represent coupled plant-soil dynamics (e.g., Daycent) to those that represent simplified soil organic matter dynamics (e.g., RothC). While these models are often deployed at the project or field scale, they can be scaled up using various approaches for regional and national estimates (Jordon et al. 2022; Morais et al. 2019).

Primary Drivers of Change

Primary controls on aboveground and belowground carbon dynamics are tightly coupled and depend on the scale of interest (Bai and Cotrufo 2022; Singh et al. 2018). Across California grasslands, spatial and temporal variation in net primary productivity (NPP) is most strongly influenced by climate. Specifically, the amount and timing of precipitation as well as minimum and maximum values of air temperature have been shown to be particularly important (Alexander et al. 2023; Lui et al. 2021; Lui et al. 2022). Variables of moderate but lesser importance include topographic and edaphic properties such as available water holding capacity (Lui et al. 2021). Grazing management also has a moderate influence; seminal work by Bartolome et al. (2007) demonstrates the critical role of grazing management in shaping interannual variation in NPP through its effects on residual dry matter (RDM). Other management practices that are often much smaller in scale, such as compost addition and oak plantings, have varied effects on aboveground productivity of grasslands at the state level (Carey et al. 2020b).

Variability of soil carbon across California's grasslands is strongly influenced by climate and soil mineralogy, with minimum air temperature and pedogenic pools of iron/aluminum identified as lead drivers (Wilson et al. 2024; Veloz et al. 2022; Carey et al. 2020a). Vegetation dynamics, such as perennial grass cover, invasion by exotic annuals, and encroachment by woody shrubs, are known to influence soil carbon as well, with the magnitude varying depending on the context (Carey et al. 2020a; Koteen et al. 2011). In California's semi-arid climate, contemporary management practices such as prescribed grazing and compost amendments are not expected to drive strong per acreage sequestration rates (Booker et al. 2013; Biggs et al. 2021); still, healthy soils practices can protect and, in some cases, restore soil carbon (Matzek et al. 2020), with larger effects occurring in more mesic areas containing higher clay content and iron/aluminum oxides (Wilson et al. 2024; Carey et al. 2020b). While many grasslands in the western US experience ongoing overuse, with considerable consequences for bare ground, erosion, and thus soil carbon, California's grasslands tend to have low amounts of bare ground as well as low erosion potential (USDA 2018; Salls et al. 2018). Spatial and temporal patterns of soil carbon are, however, likely influenced by past land use given that many grasslands were previously tilled for flax or other crops. The degree to which legacy effects of cultivation produce signals across the landscape has yet to be determined.

Nature Based Solutions Targets

In April 2024, the Governor's Office released a set of ambitious nature-based solution targets to strategically harness the power of California's lands to fight the climate crisis. Nature-based solutions are land management practices that increase the health and resilience of natural systems, which supports their ability to serve as a durable carbon sink. Five of the 81 targets released include action on California's grasslands (Table 1), and it is a goal of the NWL Carbon Inventory to be able to be sensitive to these interventions going forward.

Table 1: Nature-Based Solution Targets for grasslands as defined in *California's Nature-Based Solutions Climate Targets*. Acreage targets for beneficial fire and other fuels reduction activities are shared among grasslands, shrublands, and forests.

AB 1757 Nature-Based Solution (NBS)	2030 Target	2038 Target	2045 Target
Restoration (incl. healthy soils practices)	55.1K acres/yr	55.1K acres/yr	55.1K acres/yr
Conservation	33K acres/yr	33K acres/yr	33K acres/yr
Beneficial Fire	800K acres/yr	1.2M acres/yr	1.5M acres/yr
Other fuels reduction activities	700K acres/yr	800K acres/yr	1M acres/yr
Oak woodland afforestation	52.9K acres/yr	52.9K acres/yr	52.9K acres/yr

2018 NWL Carbon Inventory Methods

Methods Description

In the CARB 2018 NWL Inventory, grasslands were mapped using Landfire EVT vegetation classifications for 2001 and 2010 (CARB 2018).

<u>Biomass Carbon</u>: Aboveground biomass carbon for grasslands was estimated using a Tier 3 method. MODIS annual NPP data (2000–2010) was determined at a 1 km spatial resolution using the MOD17A3 product, which was calibrated with field measurements by NASA. Above- and belowground biomass was estimated from the NPP values using a root-to-shoot ratio of 4.224 paired with a biomass carbon constant. To quantify uncertainty in carbon stock changes, Monte Carlo methods were used as described in Gonzales et al. (2015).

<u>Soil Carbon</u>: Grassland soil carbon stocks were previously estimated using an IPCC Tier 2 approach. For mineral soils, which underlie most grasslands statewide, initial soil carbon values were estimated based on SoilGrids (2017) and stock change factors (Table 17 in CARB 2018) were applied to different land conversion scenarios following standard IPCC equations (Eqn 20, 21, and 22 in CARB 2018). This resulted in annualized and total estimates for carbon stock change over the inventory period (2001-2010). For drained organic soils,

which were constrained to grasslands 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.

Benefits and Limitations

Biomass Carbon: The prior methodology was straightforward and easy to implement. It offered high temporal resolution with moderate spatial resolution. However, grassland productivity can vary greatly within small spatial scales, which the MODIS-based imagery would have struggled to detect (Liu et al. 2019).

Soil Carbon: 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 within grasslands over the inventory period. For drained organic soils, which used a Tier 1 approach, the same general benefits and drawbacks hold.

2025 NWL Carbon Inventory Update Proposed Methods

Methods Description

Biomass Carbon: CARB proposes to estimate aboveground biomass carbon using a remote sensing approach following methods of Liu et al. 2021. First, to take advantage of complementary resolutions of different satellites, MODIS and Landsat images will be fused using a spatial and temporal adaptive reflectance fusion model (STARFM; Goa et al. 2006). CARB staff will then apply a LUE model previously used on California grasslands to quantify absorbed photosynthetically active radiation accumulated during the growing season (cumulative APAR; Liu et al. 2021). Cumulative APAR values will be compared with field-based biomass clipping data to estimate net primary productivity (NPP). This will allocate the fraction of NPP that goes into aboveground biomass from the rest that goes to roots and exudates. Finally, estimates of NPP will be validated using eddy covariance flux towers stationed at various grassland sites throughout California. Above- and belowground carbon will be partitioned using allometric equations from Gao et al. (2024).

Soil Carbon: We propose a unified framework for space-time mapping of soil carbon across all land types, which is described in detail in the Soil Methods Document. For grasslands specifically, we propose to use the RothC model (Coleman et al. 1996) to generate point-based estimates of soil carbon over time that will be integrated into this framework. RothC is well-suited for simulating soil carbon dynamics in semi-arid grassland soils (Farina et al. 2013; Martí-Roura et al. 2011), accounting for decomposition processes and organic matter turnover under varying conditions. Briefly, the model partitions soil organic matter into distinct pools, each with different turnover rates, and uses inputs such as climate, soil texture, and management information to predict changes in soil carbon stocks over time. The model will be calibrated to account for the effects of grazing management (livestock density) and fire (presence/absence) by adjusting model parameters based on observed data at representative sites. Model parameter and input data uncertainty will be estimated via Monte Carlo simulations.

Once the RothC model is appropriately calibrated and used to generate location-specific estimates across California's diverse grasslands, the resulting dataset will be combined with other land types in the machine learning approach described in the Soil Methods Document. In addition to traditional environmental covariates, grassland-specific anthropogenic covariates for the machine learning portion of the framework will be incorporated, starting with a gridded layer for livestock density (Robinson et al. 2014) as well as an annually updated spatial map of fire (CalFIRE Historical Wildland Fire Perimeters).

Benefits and Limitations

Biomass Carbon: Light-use efficiency models are frequently used for estimating plant productivity and biomass via remote sensing of grasslands (Wang et al. 2022; Clementini et al. 2020). In California, the fusion remote sensing LUE approach has precedence (Liu et al. 2021), and it complements prior inventory methods used by CARB (CARB 2018; Gonzales et al. 2015). This approach also takes advantage of complementary resolutions of different satellites, offering improved spatial resolution from the last inventory. Importantly, it allows NPP to be accurately estimated in grazed landscapes, which constitute most grasslands statewide. MODIS derived NPP, however, has limitations in capturing productivity in dry regions and under drought conditions. This may lead to an underestimation of aboveground biomass in dry regions and years.

Soil Carbon: See the Soil Methods Document for benefits and limitations of the unified soil inventory framework. The RothC model used for grasslands in this framework offers its own benefits and drawbacks, which will be discussed here. RothC is an open-source biogeochemical model that performs comparatively well against its competitors despite its simplified structure (Smith et al. 1997). It's a model that has been widely used to predict soil carbon in many land types across the world (Batlle-Aguilar et al. 2011), including grasslands, and is able to represent grassland management regimes. It is well-suited for regional applications (Falloon et al. 2006) and was successfully applied as the soil carbon model in both Australia's and Switzerland's national GHG inventory. The benefits of RothC's simplistic structure may also create limitations, as it is unable to capture complex feedbacks with other system components like plant growth or nitrogen availability. It is also not widely used in the United States, with scientists and practitioners alike commonly opting for the more complex DayCENT model.

Input and Validation Datasets

The input data for the proposed remote sensing approach for estimating biomass carbon include both satellite and field-based measurements (Table 2).

Table 2: Remote sensing input data and proposed data sources based on Liu et al. 2021.

Category	Input Data	Proposed Source
Satellite Imagery	Red and near-infrared reflectance layers	MODIS (Vermote & Wolfe 2021) and Landsat (EROS 2021)
Field Measurements	Grass biomass clippings	Literature estimates and UCANR collaborators

Input data required to run the RothC model can be adjusted to simulate management factors by altering organic matter inputs and climate variables (Table 3). For example, irrigation can be simulated by modifying rainfall or evaporation values to reflect increased soil moisture, and grazing and fire can be represented by changing the quality and quantity of organic matter inputs from above and belowground (i.e., root) sources.

Table 3: RothC input parameters and proposed data sources. The RothC model will be calibrated at point locations associated with long-term experimental or monitoring sites. Site-specific data collected from field measurements will be used for model input where possible. *Evaporation = open pan evaporation, which can be derived from dividing potential evapotranspiration by 0.75.

Category	Input Data	Proposed Source
Climate	Precipitation (mm)	Site-specific or Cal-Adapt
Climate	Temperature (C)	Site-specific or Cal-Adapt
Climate	Evaporation* (mm)	Site-specific or Cal-Adapt
Soil	Clay content (%)	Site-specific or gNATSGO
Soil	Initial soil carbon stock (t C ha^{-1})	Site-specific or gNATSGO
Organic Matter Inputs	Plant residue input (t C ha^{-1})	Site-specific or MODIS/Landsat fusion model
Organic Matter Inputs	Plant residue decomposability	Site-specific or literature estimates
Organic Matter Inputs	Manure input (t C ha^{-1})	IPCC excretion factors based on livestock density
Organic Matter Inputs	Soil cover (binary)	Site-specific or MODIS/Landsat fusion model

Input data needed for the digital soil mapping portion of the unified soils framework is described in Soil Methods Document.

Calibration and validation datasets have yet to be secured for grasslands. However, there are numerous long term experimental sites, monitoring sites, and published datasets that will be considered and pursued for calibration/validation of the NPP biomass estimates, the RothC model, as well as the digital soil map. These include those from UC Reserves (McLaughlin, Jepson Prairie, Sedgwick, Hastings) as well as: the Ameriflux Network, Sierra Foothill Research and Extension Center, Loma Ridge Global Change Experiment, Jasper Ridge Global Change Experiment, San Joaquin Experimental Range, Hopland Research and Extension Center, Pepperwood Preserve, Swanton Pacific Ranch, Land Trusts (Peninsula Open Space Trust, Big Sur Land Trust, Santa Lucia Conservancy, Sonoma Land Trust, TNC, MALT), and private lands.

Alternative Method for 2025 Update

<u>Biomass Carbon</u>: The alternative method for aboveground carbon will use the Rangeland Analysis Platform that is managed by the USDA Agricultural Research Service (ARS). This tool uses Landsat to provide 16-day and annual aboveground biomass estimates for rangeland ecosystems in the United States, including grasslands (Jones et al. 2021).

<u>Soil Carbon</u>: The alternative method for soil carbon will be the same as the prior inventory methods.

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	These methods will be done at the statewide scale and is appropriate for county scale aggregation and will include all grasslands 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 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	These methods will provide a spatial resolution well beyond the resolution of ecosystem boundaries, between 30m-250m resolution, depending on the carbon pool. It will allow for various categorical analyses.
Temporal resolution • Produce annualized values that can be reported very 3-5 years	These methods 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	These methods capture the primary pools of carbon in grasslands, including aboveground biomass carbon. 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 are 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.

For grassland soils, a process-based model is being proposed as part of the unified soil framework. Because of this, additional criteria were considered by CARB staff for model selection specifically. These criteria encompass the broader inventory requirements that are tailored to consider model specifications and support model selection (Table 5).

Many of the prevailing process-based models for grassland soil are not open source, which restricted options for the NWL Carbon Inventory to a more limited list. Model options which were either open-source or potentially open-source, including MEMS 2.0 and Roth-C, were evaluated for this proposal. We provide a comparison with DayCent, a widely adopted process-based models for grasslands in the US, to add further context.

Table 5: Process-based model candidates for quantifying soil organic carbon (SOC) in grassland mineral soils, evaluated according to California Air Resources Board (CARB) model criteria.

Model Name	**RothC**	**DayCent**	**MEMS 2.0**
Must fit context of specific landscape type (grasslands)	Yes	Yes	Yes
Is the model scalable?	Yes	Yes	Yes
Can this model do future projections needed for scoping plan?	Yes	Yes	Yes
Does the model include the major drivers of change in this system and key ecosystem processes?	Yes, minus coupled nutrient dynamics	Yes	Yes
Is this model sensitive to climate change?	Yes	Yes	Yes
Can this model estimate the impacts of management/NBS actions?	Yes, simplified	Yes	Not all
Does the model output carbon stocks and/or GHGs?	Yes, C stocks	Yes, both	Yes, C stocks
Is the model validated and have a basis in reality?	Yes	Yes	Yes
Can this model be run on a regular basis to develop updates and incorporate improvements?	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?	Yes	No	No
Is this a mature model with a scientific track record?	Yes	Yes	Emerging
Are people currently using this model and is there a current user base?	Yes	Yes	Limited
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 calibration	Ready off the shelf, requires calibration	Not off the shelf ready, could require model development
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, simplified parameterization requirements	Yes, parametrization is complex	No, soil organic matter fractionation data required
Can CARB staff run this model within our current timeframe for deliverables	Yes	Yes	No

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