Natural and Working Lands Carbon Inventory: Developed Lands

Proposed 2025 Inventory Update Methods
January 2025

(Photo: Renee Schiavone/Patch Photo Archive, patch.com)

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

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Background

The California Air Resources Board (CARB) defines developed lands differently compared to the Intergovernmental Panel on Climate Change's (IPCC) settlements category. According to CARB, developed lands encompass energy, transportation, residential, commercial, and production infrastructure of any size. This definition includes all roads, power lines, and structures, including those that extend into other land types. In comparison, IPCC settlements are "all developed land, including transportation infrastructure and human settlements of any size, unless they are already included under other land-use categories" (Penman et al., 2003). CARB's use of "developed lands" is an update to the previous 2018 inventory, which used IPCC's "settlements" term. CARB's updated use of "developed lands" is more comprehensive and ensures categorizing any area associated with human development as developed lands takes precedence over other land type classifications. The term "developed lands" is a better fit for this designation compared to the term "settlements" which emphasizes areas which are inhabited.

Developed lands are critical to supporting resilient economies, communities, and natural or greenspace systems of California. California's developed lands cover approximately 6.8 million acres, consisting of urban, suburban, and rural landscapes. 88% of developed lands are privately owned, and the remainder are owned by government at the federal (7.8%), state (1.1%), and local (3%) levels as well as a small portion owned by non-profits (0.2%). Economically, most jobs and residences are located in developed areas. Developed lands are also home to communities that derive myriad benefits from integrated greenspace, including reduced stress, improved social cohesion, and urban cooling (California Natural Resources Agency, 2022).

Carbon in developed lands come in diverse forms and are subject to various environmental and social stressors. The natural and working land carbon pools in developed lands are comprised of herbaceous and woody vegetation in grasses, shrubs, and trees, as well as carbon stored in soil. These carbon stocks can take many forms, including riparian habitats, public parks, greenways, private yards, urban gardens, street trees, park trees, and residential trees (California Natural Resources Agency, 2022). The developed lands within communities vary greatly from their more wildland counterparts. In communities, developed lands have a high diversity of exotic plant species and are some of the most intensively irrigated and managed landscapes. Climate change, however, threatens the resilience of these plants and carbon pools with exposure to increased temperature and drought (Esperon-Rodriguez et al., 2022). Additionally, negative associations of trees with safety risks and management costs may produce a disincentive for increasing greenspace in developed areas (Egerer et al., 2024). The distribution of urban greening is also a key equity issue, with research documenting higher income neighborhoods receiving increased exposure to greening and greening-derived benefits compared to lower income counterparts (Zhuang et al., 2023; Myers et al., 2023).

State of the Science

Quantification methodology for carbon in developed land systems typically separates carbon into biomass and soil carbon pools. Biomass pools (hereafter labeled *Biomass Carbon*) encompass the carbon stored in the roots, stems, and leaves of vegetation, which includes grasses, shrubs, and trees. Carbon stored in trees in the biomass pool is often the only component estimated because tree carbon is the largest reservoir, is relatively persistent, and more easily mapped using field inventories and remote sensing methods (Ayhan et al., 2020). The soil carbon pool (hereafter labeled *Soil Carbon*) refers to the soil organic carbon (SOC) stored in the top 30cm of the soil surface.

<u>Biomass Carbon:</u> The approach towards biomass carbon quantification in developed lands depends on the scale of the assessment and the availability of data. Carbon inventories in developed lands can use IPCC stock change factors and crown cover growth rates, regionally averaged carbon density estimates, or detailed assessments integrating landcover mapping, spatial tree height, tree species data, and tree allometry (Nowak et al., 2013, Robinson et al., 2023; Mitchell et al., 2018). More sophisticated methodology couples liDAR and multi-spectral data to delineate individual trees, but this approach is challenging due to complex and heterogeneous land cover, artificial tree shapes, and mixed species composition present in developed lands (Nowak et al., 2013, Lee et al., 2024). Another approach uses a machine learning-based regression model to extrapolate carbon storage based on variables like spectral bands, vegetation indices, and structural features, but this approach requires sufficient field-measurements as training data (Lee et al., 2024). These challenges coupled with data limitations lead to inventories often using IPCC tier 1 or tier 2 methodology to quantify biomass carbon in developed lands (Pasher et al., 2014).

<u>Soil Carbon:</u> The approach towards soil carbon quantification in developed lands focuses on quantifying soil organic carbon (SOC) stored in the top 30 cm of soil. 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. For both mineral and drained organic soils, data-limited assessments typically rely on an IPCC tier 1 or tier 2 approach, which utilizes soil carbon stock change factors applied to an initial estimate of SOC. The stock change factor approach is a useful estimate, but drastically simplifies the heterogeneity of land use and paved surfaces found in developed land areas. Popular process-based models for estimating SOC, such as the Denitrification-Decomposition (DNDC) model and the Carbon Ecosystem Nutrient Turnover Under Regimes Yielding (CENTURY) model are typically calibrated for other systems such as croplands and grasslands, and are not widely implemented in developed lands.

If field measurements, remote sensing data, and maps of features such as topography and vegetation cover are available, more sophisticated methodology can be used to quantify soil carbon in developed lands. Digital soil mapping is one approach that has been implemented in developed lands, using environmental variables such as topography and climate, including those with factors specific to developed lands (e.g. functional zoning, size and history of settlements) to help predict SOC based on statistical relationships formed with empirical samples (Vasenev et al., 2014). As remote sensing has evolved, similar efforts to map SOC have relied on remotely sensed spectral variables integrated into digital soil mapping efforts (Sodango et al., 2021). Central to these methodological options are empirical measurements of soil organic carbon in developed lands, which are not as commonly collected compared to empirical measurements in other land types.

Primary Drivers of Change

<u>Biomass Carbon:</u> Drivers that result in the expansion or removal of greenspace and tree cover impact the amount of biomass carbon. Abiotic stressors like climate change, in the form of increased temperature and changes in precipitation affect the resilience of trees in developed lands (Esperon-Rodriguez et al., 2022). Management factors are also an important driver of change, given the proximity of developed lands trees to surrounding communities. For example, trees in developed lands are often irrigated, pruned, or sometimes removed if they pose a risk to safety or infrastructure. Unlike forests, natural regeneration and standing dead biomass rarely occur in developed lands. Additionally, the creation of defensible space around houses and other structures and clearing vegetation from roads and power lines are key actions recommended for wildfire mitigation that lead to decreases in carbon (Syphard et al., 2014).

<u>Soil Carbon:</u> Land use history and development are important drivers impacting soil carbon in developed lands. Development can physically disturb soil, increase additives, and/or seal soil with pavement, impacting the amount of carbon stored belowground. Soil carbon can also be altered by adjacent urbanization even if not directly disturbed (Pouyat et al., 2002). Climate variables such as temperature and moisture, as well as vegetation type, are also an important influence on soil carbon (Pouyat et al., 2006).

Land use change is an important driver in both biomass and soil carbon systems. The expansion of developed lands into other land types can cause complex changes to carbon stocks. For example, developing grassland or wetland areas may reduce vegetation and soil carbon with the increase in paved surfaces. However, in some cases the expansion of residential areas can lead to increased tree planting and the creation and stewardship of adjacent parks and greenspace. In terms of soil carbon, efforts to quantify soil carbon have shown certain cities to have a slight increase in SOC pools after urban development had occurred (Pouyat et al., 2006). Conversely, although less prevalent, land use change from developed land back to another land type will also impact the amount of carbon stored both above and belowground.

Nature Based Solutions Targets

One of CARB's goals in updating the NWL carbon inventory is to develop methodology which is sensitive to the impact of California's Nature Based Solutions Climate targets (Table

1). These targets identified several nature-based solutions (NBS) targets for developed lands. The acreage targets set goals in terms of acreage/year and include afforestation between communities and croplands, which helps reduce community exposure to pesticides, conservation, which helps preserve existing greenspace, and urban and community greening which aims to expand tree cover and greenspace in developed lands. The NBS targets are more specific yet still compatible with AB2251 which previously established a target for 10% increase in urban canopy cover by 2045. In addition to increases in tree cover, mitigation of wildfire risk is also an emphasis of the developed lands nature-based solutions, reflected in the acreage-based target for reducing community wildfire risk by increasing defensible space, as well as the percentage-based targets aiming to decrease fire ignition caused by vehicles and treat roads functioning as evacuation routes. Lastly, there is a tree-based target for increasing the number of trees in communities. These targets are intended to foster resilience in not only within developed land greenspace, but also within the communities living in developed lands. An outcome of the implementation of nature-based strategies may be a change in carbon stocks on developed lands. NWL carbon inventory methodology aims to capture such effects where possible.

Table 1: Nature-based solutions established by AB1757 for developed lands.

AB 1757 Nature-Based Solution (NBS)	2030 Target	2038 Target	2045 Target
Afforestation between communities and croplands	133 acres/yr	185 acres/yr	230 acres/yr
Conservation	17.3K acres/yr	17.3K acres/yr	17.3K acres/yr
Urban and community greening and forestry	34.7K acres/yr	34.7K acres/yr	34.7K acres/yr
Reducing community wildfire risks	11K acres/yr	11K acres/yr	11K acres/yr
Decrease wildfire ignition caused by vehicles	10%	20%	30%
Treat priority roads that function as evacuation routes	50%	70%	100%
Urban and community greening and forestry	200K trees/year	200K trees/year	200K trees/year

2018 NWL Carbon Inventory Methods

Methods Description

Biomass Carbon: The previous inventory methodology quantified biomass stored in trees for "settlements" using a baseline carbon values derived from forest inventory data, allometric equations, and tree cover (California Air Resources Board, 2018). The baseline carbon value was regionally-stratified and calculated according to methodology outlined by Bjorkman et al. (2015). Changes from the baseline carbon value are inferred from changes in tree canopy cover, which were estimated using a manual point-density assessment of aerial imagery. The methodology is classified as IPCC tier 3, because it relies on extensive, localized data. However, the method relies on measured changes in canopy cover to drive changes in carbon, rather than modeling changes in tree height as a driver, as implemented in other tier 3 approaches.

Soil Carbon: In the previous carbon inventory, mineral soil within "settlements" was quantified using tier 2 IPCC methodology. An initial SOC value derived from SoilGrids, which is a 250 m resolution map of SOC (ISRIC, 2018) was multiplied by the IPCC stock change factor corresponding to the appropriate land use and land change category. For developed lands changing to a different land type or vice versa, SOC change was calculated by applying a shift in the stock change factor.

In the previous carbon inventory, drained organic soils within "settlements", or delta soils, were quantified using a tier 1 approach. 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. For developed land 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).

Benefits and Limitations

Biomass Carbon: The benefit of the 2018 inventory method's biomass carbon quantification was the localized, data-driven approach (Bjorkman et al. 2015). Additionally, high resolution aerial imagery is a valuable dataset with the capacity to detect change in canopy cover. An overarching limitation of the 2018 inventory approach is its use of the IPCC's "settlements" term, and its restriction of carbon analysis to census-designated urban areas. Another limitation to the previous method is the point-based estimate of canopy cover, which is a manual, time-consuming process that uses a small sample of points as a proxy for canopy change. Additional limitations include attributing changes in carbon to changes in canopy cover only, which does not necessarily reflect growth in tree height and trunk diameter, as well as the tree inventory, which was small and not proportionally representative of all street, park, and private yard tree types.

Soil Carbon: The benefit of the previous method's soil carbon quantification is consistency with IPCC recommendations. However, the limitation to using a stock change factor is producing a very coarse estimate of carbon that does not incorporate the heterogeneity of landcover (i.e. sealed/unsealed) we know exists in the developed lands and drives changes in carbon.

2025 NWL Carbon Inventory Update Proposed Methods

Methods Description

The designation boundary and the methodological quantification boundary of developed lands are different and have important implications for the proposed methodology. The designation of developed lands within the NWL Carbon Inventory includes all energy, transportation, residential, and industrial infrastructure. In addition to urban areas, exurban, rural, and wildland roads, power lines, and infrastructure are all designated as developed lands. The delineation of this area will require joining spatial maps of energy infrastructure, roads, night time light emissions, and building footprints. Any carbon within the delineated boundary of developed lands will be attributed to developed lands. In contrast, the carbon quantification methodology of developed lands is limited by data availability and methodological robustness. The methodology proposed here is applicable to census-delineated urban areas only, where the necessary data is available and the method is expected to be most effective. Developed land carbon which falls outside the methodological quantification boundary will be quantified using the best corresponding land cover methodology and then attributed to developed lands following the carbon quantification process.

Biomass Carbon: The proposed methodology for biomass carbon is tier 3 and builds upon the prior methodology (Figure 1). First, data from the urban forest inventory will be ingested into iTree which will use underlying allometry to determine the corresponding carbon content for each tree. Carbon content will be connected to corresponding canopy cover using a mix of species-specific crown radius formulas derived from literature and canopy cover derived from the United States Forest Service (USFS) tree cover dataset and National Agriculture Imagery Program (NAIP) imagery. As was done for the 2018 NWL Carbon Inventory, the collection of data points matching canopy cover to carbon content will be synthesized regionally according to climatic zone. Second, the resulting regional carbon density (carbon/area of tree cover) will be applied to the corresponding area of tree cover for each region, mapped by the United States Forest Service (USFS) tree cover dataset. The result will yield a spatial estimate of carbon stored in trees, informed by the inventory species sampled in each region. This updated methodology will be performed for each year the USFS tree cover dataset is available, which is 2012, 2018, and 2022.

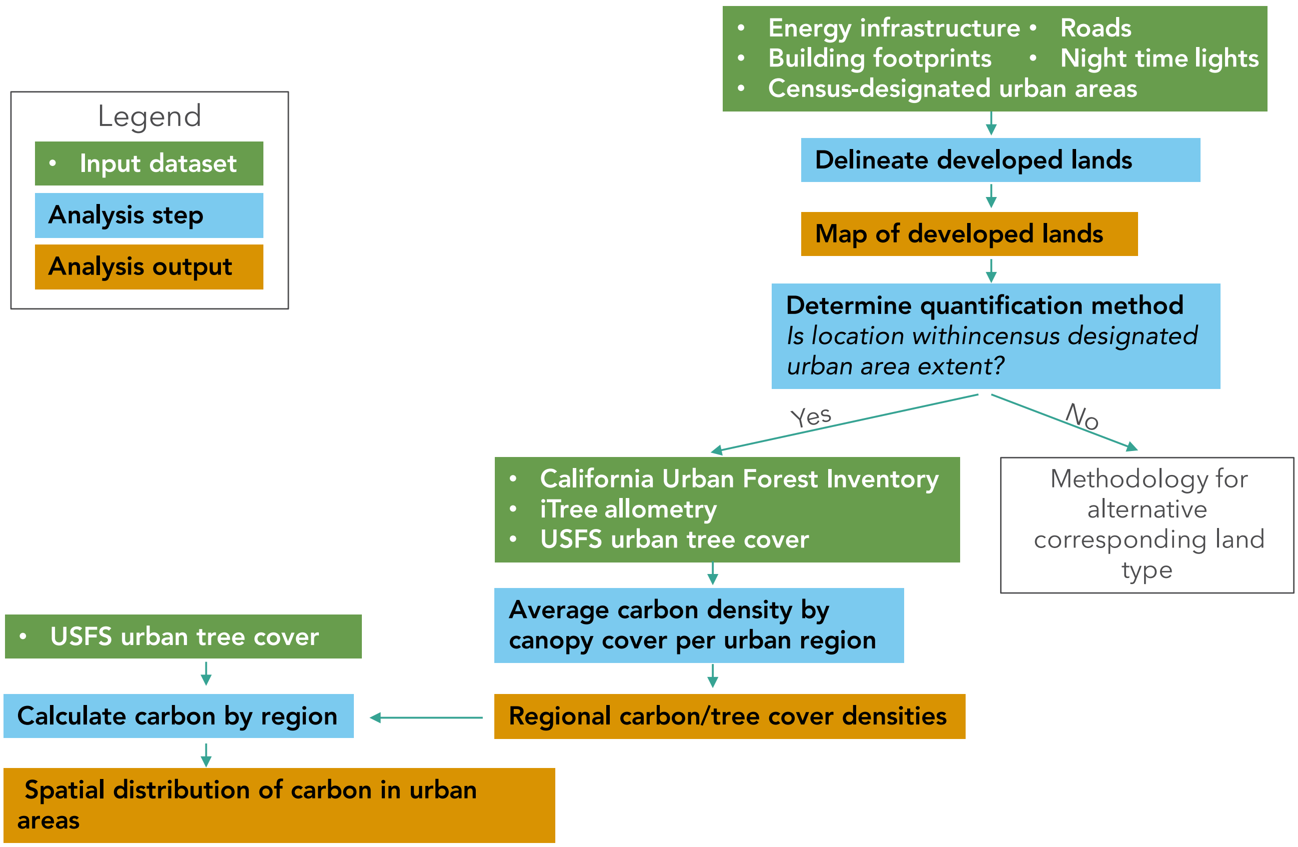

Figure 1: Schematic of proposed methodology to delineate developed lands and quantify biomass carbon.

Soil Carbon: The proposed methodology for soil carbon is tier 3 and incorporates landcover classification, process-based modeling, and digital soil mapping. First, landcover will be mapped in a hierarchical classification scheme using 1m USFS tree cover data, National Agriculture Imagery Program (NAIP) imagery, and National Land Cover Database (NLCD) percent impervious data (Figure 2). The resulting landcover classes will be tree cover, non-tree vegetative cover, bare soil, and pavement.

Second, for mineral soils, an empirical model called Roth-C will be used to create a temporal sequence of soil organic carbon from 2001 to 2024 at locations within the developed landscape which correspond to empirical data points. RothC is a simplified process-based model which accounts for decomposition processes and organic matter turnover under varying conditions. 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. Roth-C will be parameterized according to climate data, soil attributes, and vegetative cover corresponding to the appropriate landcover class. The use of Roth-C is subject to the availability of empirical samples within developed lands. If CARB is unable to obtain any empirical samples, then Roth-C will not be used in the developed land type. Drained organic soils are not appropriately modeled using Roth-C, so changes in soil organic carbon will be estimated using IPCC Tier 1 methodology by applying a stock change factor to an initial SOC estimate derived from the gridded National Soil Survey Geographic Database gNATSGO.

Third, digital soil mapping will be performed statewide using a knowledge guided machine learning framework. The machine learning process will create a predictive relationship between spatial data of soil forming factors, (i.e. vegetative cover, slope, etc.), disturbance and management factors (i.e. pavement, irrigation, etc.), and the empirically-based temporal sequences of soil organic carbon produced by each land type's soil carbon quantification methodology (e.g. Roth-C for mineral soils in developed lands, stock change factors for drained organic soil in developed lands). The output will be a spatially explicit distribution of SOC statewide annually from 2001 to 2024, including through developed land.Details about the third step, the unified framework for space-time mapping of soil carbon across all land types, is described in detail in the proposed update to Natural and Working Lands Carbon Inventory: Soil Methods.

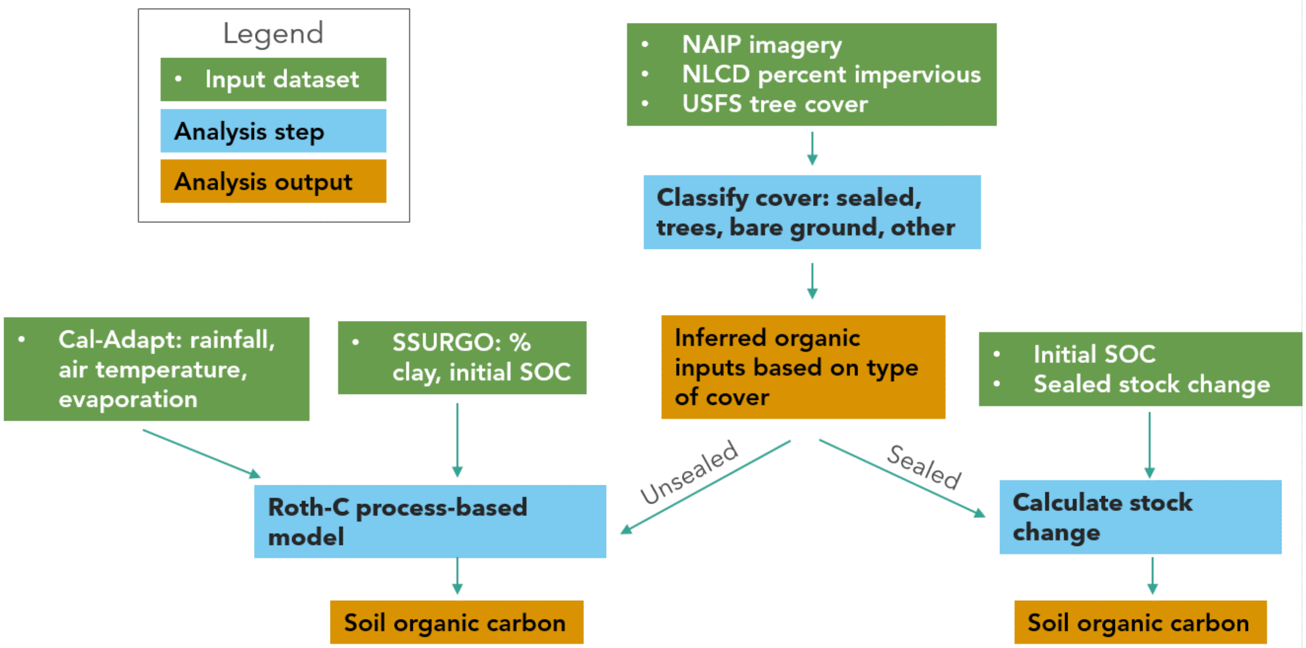

Figure 2: Schematic of the first and second step of proposed methodology to quantify soil organic carbon in developed lands. An exception to this methodology applies to drained organic soil SOC which will be estimated using IPCC stock change factors.

Benefits and Limitations

Biomass Carbon: An overarching benefit of the updated inventory approach is expanding the scope to all "developed lands," which is more comprehensive than the previous scope focused on IPCC-defined "settlements." CARB's new developed lands approach ensures any area associated with human development will be categorized within developed lands, more accurately capturing the impact of development on the landscape. Overall, the benefits of the proposed biomass carbon quantification method are due to an improvement in available data. First, the number of urban trees inventoried has increased 8-fold compared to what was used in previous inventories. Second, the availability of 1m resolution tree cover enable an exact quantification of tree cover change, rather than relying on an arduous point-based method that produced a low accuracy estimate of tree cover change. The proposed method will be sensitive to NBS strategies that aim to increase tree cover.

A limitation to the proposed biomass carbon quantification method is the reliance on tree cover as a proxy for carbon growth, which may not capture tree growth resulting from increased height or trunk diameter. Additionally, urban field inventories overrepresent street trees, which are often different species compared to the comparatively under-sampled trees that grow on private land in yards and gardens in developed land. In terms of NBS strategies, this proposed method will be unable to distinguish between drought-tolerant and grass vegetation and is not sensitive to increases in number of trees, only tree cover. Finally, the tree cover mapping using NAIP is a computationally expensive and complex effort that only has a few years of data. The extent of the data is also restricted to census-delineated urban areas. Future efforts will work to decrease these limitations.

<u>Soil Carbon:</u> There are several benefits to the proposed soil carbon quantification method. First, the proposed method differentiates between sealed and unsealed soil, which is a driving factor for SOC in the developed landscape. Additionally, discerning tree cover from non-tree vegetation introduces vegetative functional diversity that is otherwise ignored in lower tier methods. Second, 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 a time series derived from a simplified understanding of biogeochemical processes. The model also ensures the estimation of SOC and is sensitive to changes in management (i.e. 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 soil carbon methodology unifies the SOC analysis across land types and fosters inventory consistency.

The main limitation to the proposed soil carbon quantification method is a result of data limitations. One limitation is the inability to map landcover class at high resolution and high accuracy. The current approach will produce proportional estimates within a 30m cell. Efforts to improve accuracy and resolution of landcover mapping, built from improved remote sensing datasets, can help improve future inventory methodology. Another potential limitation is a lack of empirical SOC measurements in the developed landscape. If developed lands are under sampled compared to other land types, the drivers of change in developed lands may not be well represented in the knowledge-based machine learning algorithm. However, the methodology will include an uncertainty assessment which will account for any underlying biases resulting from data limitations.

Input and Validation Datasets

Biomass Carbon: The input datasets for the biomass carbon quantification will be used for developed lands within census-designated urban areas (Table 2). The datasets used to delineate developed lands beyond census-designated urban areas are currently being vetted. Additionally, exploration of potential validation datasets is ongoing. The quantification of carbon for 2012 will be compared to previous estimates (Bjorkman et al., 2015).

Table 2: Input datasets used for biomass carbon quantification in developed lands.

Dataset	Developer	Temporal Resolution	Spatial Resolution	Citation
Tree Cover	US Forest Service (USFS)	2012, 2018, 2022	1 m	(EarthDefine et al., 2022)
California Urban Forest Inventory	Cal Poly State University	Single database compiled from multiple years	Point samples	(Urban Forest Ecosystem Institute, 2022)
National Agriculture Imager Program (NAIP) 4-band imagery	United States Department of Agriculture (USDA)	Every 2 years	60 cm	(USDA, 2022)
iTree allometric equations	i-Tree	N/A	N/A	(i-Tree, 2023)

Soil Carbon: The input datasets used for the soil carbon quantification methodology consist of measurements of tree cover, percent impervious, 4-band aerial imagery, and soil characteristics including percent clay and initial SOC (Table 3). The climate data used to parameterize Roth-C will be from Caladapt and uniformly used throughout the entire inventory. Validation and calibration data in the form of empirical measurements of SOC are critical for justifying the use of Roth-C over simpler methods relying on stock change factors. The data on tree cover, percent impervious, and 4-band imagery will be used to scale estimates of SOC throughout developed land in the digital soil mapping effort described in the proposed update to Natural and Working Lands Carbon Inventory: Soil Methods. Efforts to locate validation and calibration data are ongoing.

Table 3: Input datasets used for soil carbon quantification in developed lands.

Dataset	Developer	Temporal Resolution	Spatial Resolution	Citation
Tree Cover	US Forest Service (USFS)	2012, 2018, 2022	1 m	(EarthDefine et al., 2022)
National Land Cover Database (NLCD) percent impervious	United States Geologic Survey (USGS) and Multi-Resolution Land Characteristics Consortium (MRLC)	Annual	30 m	(USGS & MRLC, 2019)
National Agriculture Imager Program (NAIP) 4-band imagery	United States Department of Agriculture (USDA)	Every 2 years	60 cm	(USDA, 2022)
Gridded National Soil Survey Geographic Database (gNATSGO) percent clay and initial SOC	Natural Resources Conservation Service (NRCS)	Single map produced from temporally variable samples	30 m	(Soil Survey Staff, 2023)

Alternative Method for 2025 Update

Biomass Carbon: The alternative method for quantifying biomass carbon is to use the carbon estimates produced in 2012 by Bjorkman et al. (2015) and scale it according to changes in tree cover between the 2012 1m tree cover data and the 2018 and 2022 1m tree cover data.

Soil Carbon: The alternative method for quantifying soil carbon is to use the same tier 2 stock change factor approach used in the prior inventory.

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 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 developed land 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 2010 due to data limitation and will provide estimates through 2022.
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 1m -30m 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 values at the interval of tree canopy data 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 developed lands, including aboveground biomass carbon stored in trees. 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 tree cover 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.

<u>Soil Carbon:</u> For soil carbon in developed lands, 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 5). Process-based models are not commonly used in soil carbon estimation in developed lands. Instead, studies typically use either stock change factors or digital soil mapping approaches (Eggleston, 2006; Vasenev, 2014). Many process-based soil carbon models are built for other land types such as croplands or grasslands, and therefore require inputs that are not relevant to developed lands. Roth-C is a simplified process-based soil carbon model which can be parameterized according to the conditions found in developed lands. Roth-C was the only model evaluated due to its simplicity and its use in other landscape types.

Table 5: The process-based model candidate for quantifying soil organic carbon (SOC) in developed lands, evaluated according to California Air Resources Board (CARB) model critera.

Model Name	**Roth-C**
Must fit context of specific landscape type	Simplified enough to fit
Is the model scalable?	Yes
Can this model do future projections needed for scoping plan?	Yes
Does the model include the major drivers of change in this system and key ecosystem processes?	Sealed soil would not be modeled with Roth-C
Is this model sensitive to climate change	Yes
Can this model estimate the impacts of management/NBS actions?	Change in vegetation type, compost addition
Does the model output carbon stocks and/or GHGs?	Just SOC
Is the model validated and have a basis in reality?	Yes
Can this model be run on a regular basis to develop updates and incorporate improvements?	Yes
Is this an open-source model that we can modify and share without restriction?	Yes
Is this a mature model with a scientific track record?	Yes- in a variety of other landscape types
Are people currently using this model and is there a current user base?	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 carbon calibration; modification possible
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; Calibration and validation needed and may be a limiting factor
Can CARB staff run this model within our current timeframe for deliverables	Yes, depending on data availability
Must fit context of specific landscape type	The simplicity of this model lends itself to use in other landscape types, but it is not typically implemented in developed land soil, which is generally understudied compared to soil in other land types.

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