Technical Support Document for the Natural & Working Lands Inventory

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Prepared by:
Air Quality Planning and Science Division of
The California Air Resources Board

Acknowledgements

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1 – Inventory Framework

1A – The Carbon Cycle

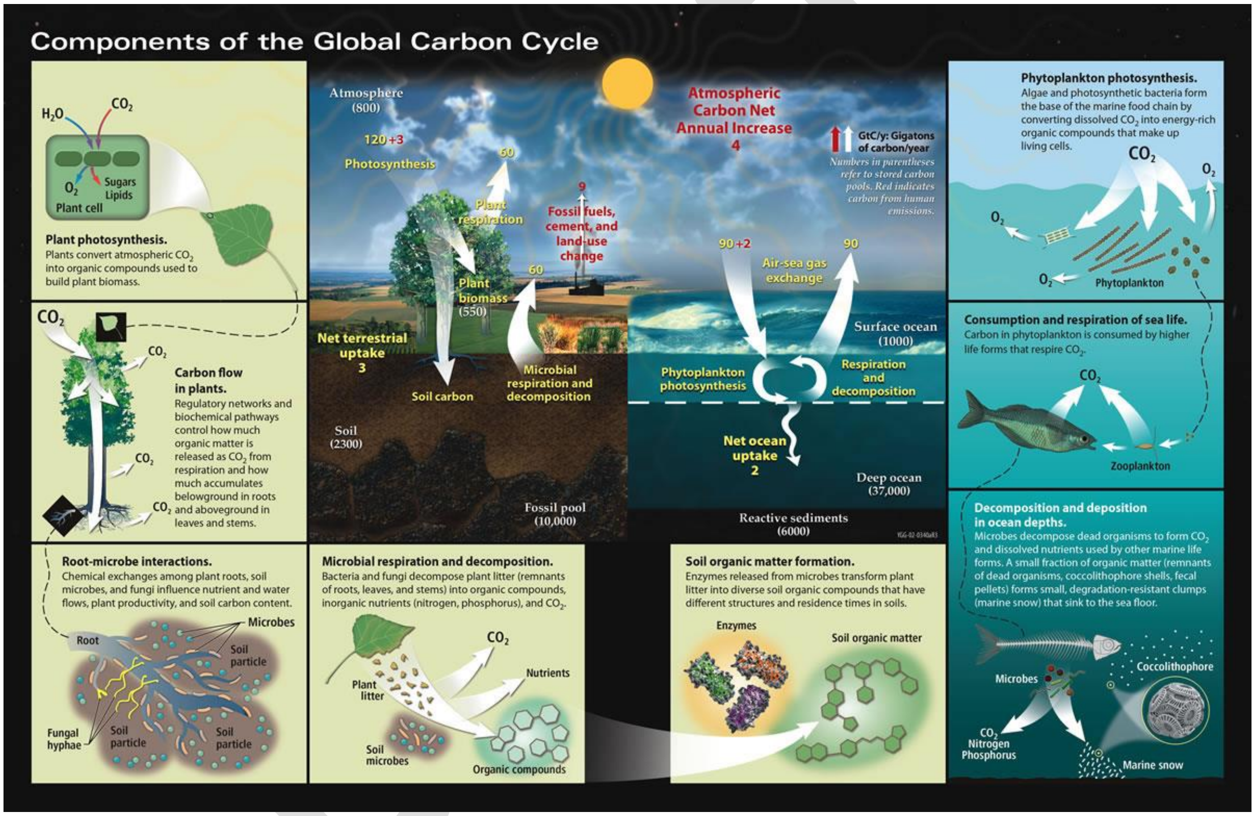

Figure 1. The Earth's carbon cycle (Riebeek & Simmon, 2011).

The Earth's carbon cycle is the exchange of carbon between the Earth's five main carbon pools: the atmosphere, biosphere (plants, animals, algae, bacteria, and other life forms), pedosphere (soils), hydrosphere (oceans and other water bodies), and lithosphere (rocks and Earth's deeper geological layers) (Riebeek & Simmon, 2011). Carbon is cycled between these pools via both natural and anthropogenic processes (**Figure 1**). Carbon flows from the atmospheric pool to both the biosphere and hydrosphere via photosynthesis conducted by plants, photosynthetic bacteria, and algae. During photosynthesis, light energy is captured by chlorophyll in the cells of a photosynthetic organism and used to convert water, carbon dioxide (CO_2), and minerals into oxygen and energy-rich sugar (**Figure 2**). Plants and algae use sugars as an energy source for cellular respiration, a process which releases carbon back to the atmosphere as CO_2 and produces the energy molecule adenosine triphosphate (ATP).

Gross Primary Production (GPP) is the total amount of energy stored as a result of the photosynthetic process and is generally expressed as mass of carbon per unit area per unit time (e.g. 100 grams carbon meter^{-2} year^{-1}). About half of GPP is respired; the remaining sugars are used to build tissues. These tissues constitute the biosphere's non-animal biomass and, as those tissues die, dead biomass. GPP minus plant respiration is termed Net Primary Productivity (NPP), which is comprised of the total amount of living and dead biomass produced per unit area per unit time. The carbon in plant tissues is sequestered and does not transfer to other pools until it is released rapidly through disturbance (e.g. wildfire) or slowly through decomposition. Decomposition moves carbon from the biosphere to both the atmosphere and pedosphere. Carbon is released to the atmosphere via this pathway as microbes, fungi, and other decomposer organisms breakdown the organic molecules of dead biomass and release CO_2. Similarly, this process transfers carbon to the pedosphere as soil organic matter (SOM) when the organic molecules of dead biomass leach into the soil. SOM can release carbon back to the atmosphere as CO_2 when the soils are disturbed (e.g. tilled for agriculture) or experience a natural disturbance, such as a wildfire. Carbon in the pedosphere can move to the lithosphere pool when tectonic subduction forces one tectonic plate under another and it becomes part of the Earth's mantle or when geological processes convert high carbon density SOM into fossil fuel deposits. Carbon moves out of the lithosphere during volcanic eruptions, when it is deposited on the Earth's surface and becomes part of the pedosphere, or is released to the atmosphere as a gas. Anthropogenic extraction of fossil fuels from the lithosphere and the fuels' subsequent combustion also moves carbon to the atmosphere.

1B – IPCC Defined Carbon Pools and Flows for Greenhouse Gas Accounting

The goal of greenhouse gas (GHG) accounting is to estimate the amount of carbon dioxide and other GHGs that are being transferred from one carbon pool to another, with special focus on the amount of GHGs removed from and released to the atmosphere in a given inventory period. The concept of pools, or reservoirs, is useful to track the fate of carbon that is moved from one pool to another as a result of human disturbance and/or activity. The United Nations Framework Convention on Climate Change (UNFCCC) defines carbon pools, or carbon reservoirs, as "components of the climate system where a GHG or a precursor of a GHG is stored" (UNFCCC, 2014). The pools defined by the IPCC for landscape GHG accounting in the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories ("the IPCC Guidelines"), Volume 4 – Chapter 1 include: the Above-Ground Live (AGL) (trunks, stems, foliage) and Below-Ground Live (roots) vegetation pools; the dead organic matter (DOM) pools (standing or downed dead wood, litter); and the soil organic matter (SOM) pool. Natural and Working Lands (NWL) carbon and greenhouse gas inventories also give special consideration to a forest biomass pool called Harvested Wood Products (HWP), which are defined as all wood material, including bark and small branches, that leave a harvest site (IPCC, 2006l).

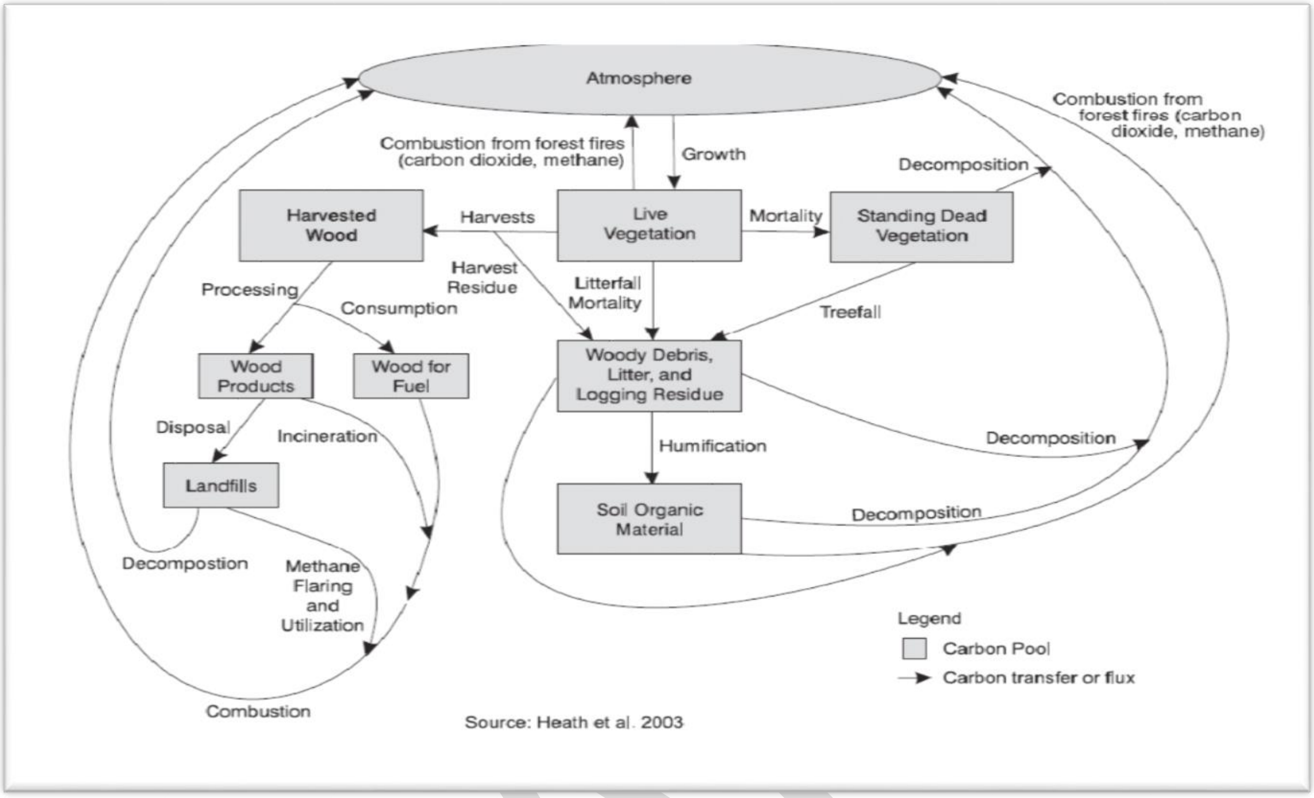

Figure 2. Carbon transfer pathways from IPCC defined reservoirs.

Over time, carbon is cycled between these different pools, including the atmosphere, via photosynthesis, respiration, decomposition, disturbance, and combustion (**Figure 2**). For example, when a tree is harvested, a portion of its carbon is transferred from the live tree pool to the harvested wood product pool, and another portion to the dead organic matter pool. Similarly, during a fire some of the carbon contained in the above-ground live or dead organic matter pools is combusted and released to the atmosphere as CO_2, other GHGs, particulate matter, and criteria pollutants, while the remaining carbon remains on the land surface in the form of unconsumed fuel, killed vegetation, cinders, or ash.

The NWL inventory aims to quantify the amount of carbon stored in each of the aforementioned pools, as well as the amount of carbon being moved from one pool to another in a given inventory time period.

1C – Land Use Categories

The 2006 IPCC Guidelines defines six broad land-use categories for GHG accounting: Forest Land, Cropland, Grassland, Wetlands, Settlements, and Other Land (**Table 1**). The IPCC Guidelines states that definitions of land-use categories may incorporate land cover type, land use, or a combination of the two. For convenience, the categories are referred to as land-use categories.

Table 1. Land-use category definitions (IPCC, 2006c).

Land-Use Category	Definition
Forest Land	All lands with a minimum of 10% woody vegetation cover, including shrubs
Cropland	Cropped lands, including rice, orchards, vineyards, field crops, and agro-forestry systems that fall below the 10% woody vegetation threshold for Forest Land
Grassland	Rangeland, pasture, and other non-grass vegetation that fall below the 10% woody vegetation threshold for Forest Land
Wetlands	Areas used for peat extraction and land that is covered or saturated by water for all (perennial wetlands) or part of the year (seasonal wetlands)
Settlements	All developed land, including transportation infrastructure and settlements
Other Land	Bare soil, rock outcroppings, ice, and all land areas that do not fall into any of the other five categories

Land-use categories are further disaggregated into land-use change categories in order to quantify the magnitude and direction of carbon flows from one pool to another (**Table 2**). The term "land-use change" is sometimes a source of confusion. In IPCC usage, the term applies to any situations where significant changes in land carbon stocks occur, irrespective of human or natural agency, or actual changes in land-use.

Table 2. IPCC codes for land-use and land-use change categories (IPCC 2006).

IPCC Land-Use Category	Category Code	IPCC Category
3B1 Forest Land	3B1a	Forest Land remaining Forest Land
	3B1bi	Cropland Converted to Forest Land
	3B1bii	Grassland Converted to Forest Land
	3B1biii	Wetlands Converted to Forest Land
	3B1biv	Settlements Converted to Forest Land
	3B1bv	Other Land Converted to Forest Land
3B2 Cropland	3B2a	Cropland remaining Cropland
	3B2bi	Forest Land Converted to Cropland
	3B2bii	Grassland Converted to Cropland
	3B2biii	Wetlands Converted to Cropland
	3B2biv	Settlements Converted to Cropland
	3B2bv	Other Land Converted to Cropland
3B3 Grassland	3B3a	Grassland remaining Grassland
	3B3bi	Forest Land Converted to Grassland
	3B3bii	Cropland Converted to Grassland
	3B3biii	Wetlands Converted to Grassland
	3B3biv	Settlements Converted to Grassland
	3B3bv	Other Land Converted to Grassland
3B4 Wetlands	3B4ai	Peatlands remaining Peatlands
	3B4aii	Flooded Land remaining Flooded Land
	3B4bi	Land converted for Peat Extraction
	3B4bii	Land Converted to Flooded Land
	3B4biii	Land Converted to Other Wetlands
3B5 Settlements	3B5a	Settlements remaining Settlements
	3B5bi	Forest Land Converted to Settlements
	3B5bii	Cropland Converted to Settlements
	3B5biii	Grassland Converted to Settlements
	3B5biv	Wetlands Converted to Settlements
	3B5bv	Other Land Converted to Settlements
3B6 Other Land	3B6a	Other Land remaining Other Land
	3B6bi	Forest Land Converted to Other Land
	3B6bii	Cropland Converted to Other Land
	3B6biii	Grassland Converted to Other Land
	3B6biv	Wetlands Converted to Other Land
	3B6bv	Settlements Converted to Other Land

Land-use types are used in the IPCC GHG accounting architecture to define the magnitude and direction of carbon flow from one pool to another (**Figure 3**) and are disaggregated by climate domain (Boreal, Temperate, and Tropical), ecological zone, management regime, and other factors. For example, when Forest Land is converted to Settlements, carbon flows out of the soil organic matter pool and into the atmosphere due to soil disturbance from excavation and other development activities. The amount of carbon transferred is dependent on factors such as the initial carbon stock in a pool, the type of flow that is causing the carbon transfer (e.g. wildfire or land-use conversion), and the aforementioned land-use type disaggregation factors.

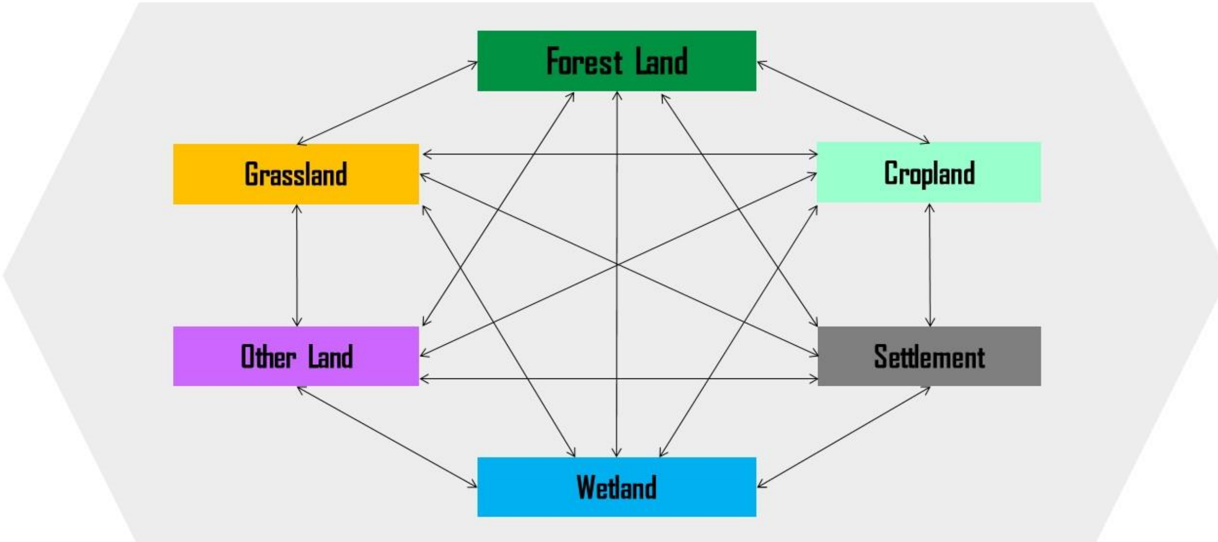

Figure 3. IPCC land-use and land-use change categories.

Land-use and land-use change as defined by the 2006 IPCC Guidelines was mapped with the LANDFIRE existing vegetation type (EVT) raster datasets for all inventory periods (IPCC, 2006c) (Ryan & Opperman, 2013). Each of the 239 EVTs were mapped to an IPCC category – 132 to Forest Land, 46 to Cropland, 25 to Settlements, 17 to Grassland, 15 to Other Land, and 4 to Wetlands – according to the methodologies detailed in California Air Resources Board contract agreements 10-778 and 14-757 (**Figure 4**).

Using this methodology to identify land-use and land-use change for the State of California resulted in inventory time-steps being defined by the availability of LANDFIRE product vintages for the Forest and Other Natural Lands (FONL) and Soil Carbon sections of the Agriculture, Forestry, and Other Land-Use (AFOLU) inventory. Higher quality data were available for the Urban Forests and Cropland Woody Biomass sections, hence these inventories did not use LANDFIRE to define land-use and land-use change and consequently have inventory time-steps that differ from the aforementioned FONL and Soil Carbon sections.

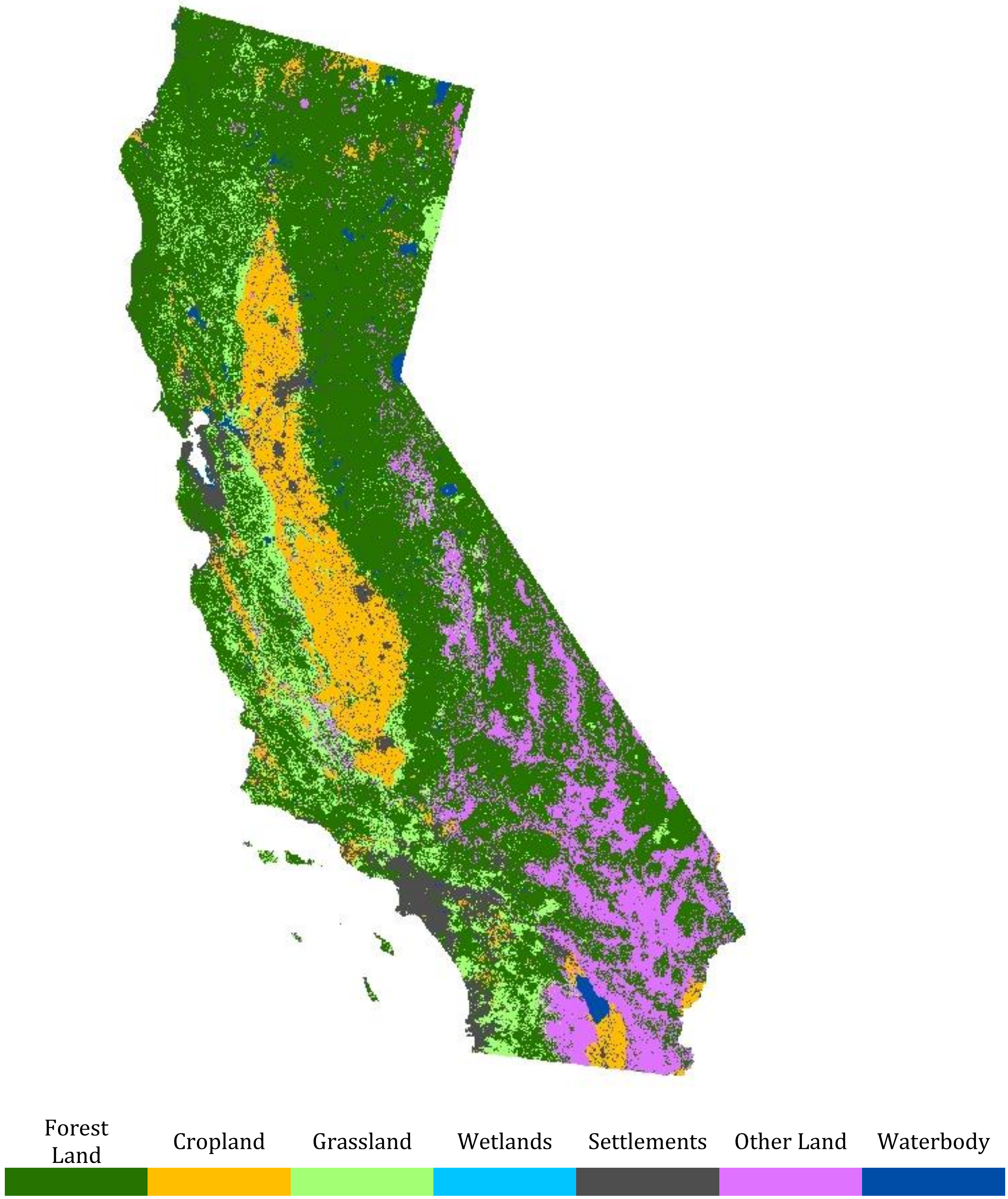

Figure 4. Distribution of land-use categories in 2014 for the State of California.

1D – Approaches and Methods

The 2006 IPCC Guidelines for National Greenhouse Gas Inventories provides three framework options for inventory reporting: (1) the stock-change approach (SCA) reports changes in ecosystem carbon stocks and wood products in the reporting country, including imported wood products, (2) the production approach (PA) reports changes in ecosystem carbon stocks and wood products produced in the reporting country (changes in wood products exported from the producing country are also reported, while products imported to the reporting country are not counted), and (3) the atmospheric flow approach (AFA) accounts for carbon fluxes to/from the atmosphere for lands and wood products pools, including imported products. Each option prescribes specific system boundaries.

California Air Resources Board (CARB) staff uses the AFA because the system boundaries are most consistent with how emissions from anthropogenic sources are accounted for in the GHG inventory. The AFA includes in its estimate the exchange of carbon with the atmosphere due to changes in carbon stocks in forests and other natural lands, and carbon releases to the atmosphere associated with harvested wood products.

The IPCC also provides two accounting methods for estimating the exchange of carbon between the atmosphere, biosphere, and other pools (IPCC 2006): (1) the gain-loss method (sometimes described as process-based) subtracts carbon losses from carbon gains to estimate the net balance of additions to and losses from a pool, and (2) the stock-difference method estimates the difference in the carbon stock of a pool at two points in time. CARB staff use the stock-difference method because stock estimates are derived from data collected in the state. The gain-loss method entails sophisticated land-atmosphere exchange process models, which require extensive resources to develop, calibrate, validate, and maintain. Process models have advantages in that they can account for both stocks and flows in ways that capture inter-annual variability.

1E – Tier of Methodology

IPCC provides three methodology tiers in its GHG inventory guidance. Lower tiers are less resource intensive and are designed for ease of use whereas higher tiers are generally regarded as more accurate but require significantly more resources to produce. A combination of tiers can be used for different sections of the inventory. This allows an inventorying jurisdiction to create a complete inventory while simultaneously providing greater accuracy for key sectors or sectors for which higher quality data is available.

The tiers are defined by the IPCC as follows (IPCC, 2006a):

Tier 1 methods are designed to be the simplest to use, for which equations and default parameter values (e.g. emission and stock change factors) are provided in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Country-specific activity data are needed. Globally available activity data sources are available, although such sources are often spatially course.

Tier 2 methods use the Tier 1 methodological approach but utilizes country-specific emission and stock change factors for the most important land-use and livestock categories. Higher resolution temporal and spatial data is often used to correspond with factors for specific regions and specialized land-use categories.

Tier 3 features custom measurement systems and/or models repeated over time and driven by high-resolution activity data and disaggregated at the sub-national level. Such systems may include comprehensive field sampling repeated at regular time intervals and/or GIS-based systems of age, class/production data, soils data, and land-use and management activity data, integrating several types of monitoring. Pieces of land where a land-use change occurs can usually be tracked over time, at least statistically. In most cases these systems have a climate dependency, and thus provide source estimates with inter-annual variability. Models should undergo quality checks, audits, and validations and be thoroughly documented.

Wherever possible, higher tier methodologies were used to create the NWL inventory. The decision tree for inventory creation (**Figure 5**) outlines the process CARB staff used when deciding on an inventory tier for each sector.

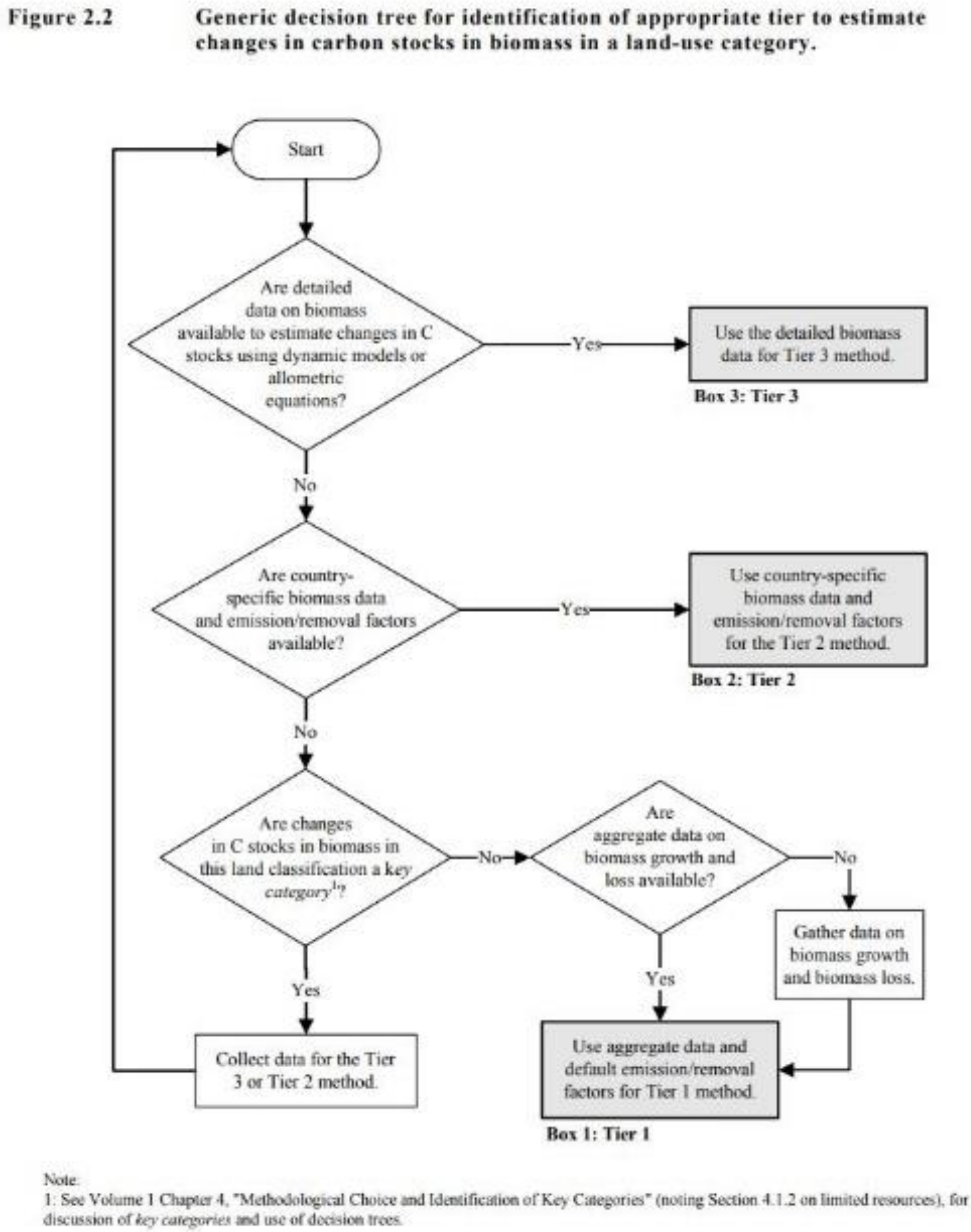

Figure 5. Generic decision tree for identification of appropriate IPCC methodology tier to estimate changes in carbon stocks.

1F – Disturbance

IPCC provides guidance for reporting ecosystem carbon stock changes associated with natural and anthropogenic conversions between land categories. Ten of the twenty-eight conversion categories (**Table 2**) implicitly involve anthropogenic disturbance. These include conversions to cropland or settlements and typically involve clearing land of extent vegetation. In addition, IPCC provides guidance for reporting ecosystem carbon stock changes associated with the removal of forest carbon via tree harvest (IPCC category 3D1 – Harvested Wood Products) and biomass burning on land (IPCC category 3C1 – Emissions from Biomass Burning). Greenhouse gases associated with land biomass burning include CO_2, CH_4, and N_2O. Harvested wood products include wood destined for fuel use. GHG accounting guidance is also provided for carbon persisting in solid form in wood products and emissions associated with wood carbon losses during manufacture (such as mill residues combusted for heat and power) and decay upon disposal at the end of product life.

Disturbance data sources include land use/land cover changes revealed through time series in the LANDFIRE Existing Vegetation Type (EVT) geospatial product, and the LANDFIRE disturbance product DISTYEAR. The DISTYEAR product georeferences areas where fires, harvests, and other events occurred in a given year.

2 – Forest and Other Natural Lands

2A – Background

This document follows the analysis for forests and other natural lands (FONL) in 2001-2010 by reporting changes in carbon stocks for the 2010-2012 period. A principal difference between the two analysis periods is the magnitude of the time interval. Due to the duration of the 2001-2010 period, a large number of disturbance events (namely fire) accumulated in the spatial data and figured prominently in stock change estimates. The 2010-2012 period exhibited less disturbance and a reduced contribution by fire to overall disturbance. The lack of disturbance contributed to greater stock gains in lands that remained in forest cover, compared to the 2001-2010 period. Sources and methods used for 2010-2012 are the same as in 2001-2010, with one exception. During the initial 2010-2012 analysis, quality assurance checks using state timber harvest data suggested that forest harvest activity was under-represented in the LANDFIRE disturbance activity raster product for the analysis period. In order to improve stock change attribution to disturbance processes, state Timber Harvest Plan (THP) geodata were used to fill data gaps in the LANDFIRE disturbance dataset.

2B – Methodology

2B.1 – Forests and Other Lands Biomass

ARB estimates for biomass, carbon stocks and stock change on forests and other lands for 2010 – 2012 are based on sources and methods developed under a contract with the University of California– Berkeley (Battles, et al., 2013), reported in Gonzalez et al. (2015), and developed further under a follow-up contract (Saah, et al., 2016). The methods combine geospatial vegetation and disturbance activity data with tabular data from georeferenced forest plots, reference databases and literature. Thirty meter resolution geospatial data from the federal LANDFIRE program (Ryan & Opperman, 2013) include vegetation species composition (existing vegetation type, EVT and vegetation order [tree, shrub, or grass/herbaceous-dominated]) and structure (canopy height class EVH, and canopy cover class EVC) for 2010 and 2012, and disturbance activity (fire, harvest, thinning, etc.) throughout the 2010 – 2012 period. Field data include biomass densities (Mg ha^{-1}) calculated from regional allometric equations for the above- and below-ground live tree and standing dead tree pools, and modeling of understory vegetation, down dead and litter pools in 3,623 georeferenced forest plots maintained by the Forest Inventory and Analysis (FIA) program of the USDA Forest Service (Battles, et al., 2013). Biomass densities for shrub-dominated lands were compiled from field data reported in the LANDFIRE reference database (LFRDB) and in published literature. For land types dominated by non-woody vegetation such as grassland, wetlands, and sparsely vegetated lands, biomass densities were derived from NPP estimated from the Moderate Resolution Imaging Spectroradiometer (MODIS product MOD17A). ARB refinements to the methods include accounting for carbon increments associated with live tree growth undetected by the satellite-derived LANDFIRE products, post-harvest carbon persisting in wood products, and development of default biomass densities for croplands and selected categories of developed lands.

Biomass densities (Mg C ha^{-1}) and total biomass (Mg C $pixel^{-1}$) in forests and other lands for 2010 and 2012 were estimated at 30 meter spatial resolution using regression equations designed to predict biomass and carbon stocks as functions of LANDFIRE vegetation attributes EVT, EVC and EVH (Gonzalez, et al., 2015). Stock rasters for 2010 included adjustment for growth in 2001-2010, as described in the Technical Documentation for California's Forest and Other Natural Lands Carbon and Emission Inventory for 2001-2010 (CARB, 2017a). The method assumes the carbon content of biomass is 0.47 g C g^{-1} biomass (± 0.0235 g C g^{-1} biomass) (Gonzalez, et al., 2015). In order to report carbon stocks and change by IPCC categories, LANDFIRE EVTs for California (n = 168) were assigned to IPCC land categories. One hundred and thirty-two EVTS were assigned to the Forest Land category. Of these, eighty-nine were tree-dominated and forty-three were shrub-dominated types, according to the LANDFIRE attribute vegetation Order. The remaining thirty-six EVTs were assigned to the Grassland (17), Other Land (15) and Wetlands (4) categories.

Raster subtraction was used to estimate stock change in the AGL and Total pools (live and dead pools combined, not including soil carbon) for the 2010 - 2012 analysis period. For many areas dominated by trees in both 2010 and 2012, LANDFIRE data did not report changes in forest canopy height or canopy cover. The "non-detection" of forest canopy growth is due in part to the ordinal nature of LANDFIRE canopy cover and height classes. For canopy cover, LANDFIRE defines ten classes that increase in even steps of 10%, while LANDFIRE defines five canopy height classes of 0-5, 5-10, 10-25, 25-50, and >50 meters. If over the analysis period the average height or cover at a location changed but did not cross into the next class, the method would record no change in biomass. Because tree growth occurs slowly relative to the span of the analysis period, the method can underestimate biomass changes due to growth within a cover or height class. Consequently, the method is sensitive to abrupt changes associated with disturbance while less sensitive to slow changes associated with growth, particularly in mature forests. Tree re-measurement data reported in FIA database version 6.0 (released October 2, 2014) indicated that over a decade, live tree biomass increased statewide on average by 6% (Gonzalez, et al., 2015). In order to account for the carbon increment associated with live tree growth in areas dominated by trees in both 2010 and 2012 and where LANDFIRE did not detect change, an adjustment factor representing growth increment over two years (**Equation 1**) was applied to the 2012 above-ground live stocks. The adjusted 2012 rasters for AGL and Total were used together with the 2010 rasters to evaluate stock change (**Figure 6**). Stocks and stock changes were tabulated by IPCC reporting categories.

Equation 1: Derivation of a two-year growth increment based on a decadal growth rate

$$\mathrm{f(t)} = ae^{kt}$$

Where:

$\mathrm{f(t)} = \mathit{Value\ at\ time\ t}\ (106)$
$\mathrm{a} = \mathit{Initial\ value}\ (100)$
$k = \mathit{Growth\ rate}$
$\mathrm{t} = \mathit{Elapsed\ time}\ (9\ \mathit{years})$

Solving for k:

$\frac{106}{100} = e^{k9}$
$\mathrm{a} = \mathit{Initial\ value}\ (100)$
$\ln 1.06 = k9 \ln e$
$\frac{\ln 1.06}{9} = k$
$0.00647 = k$

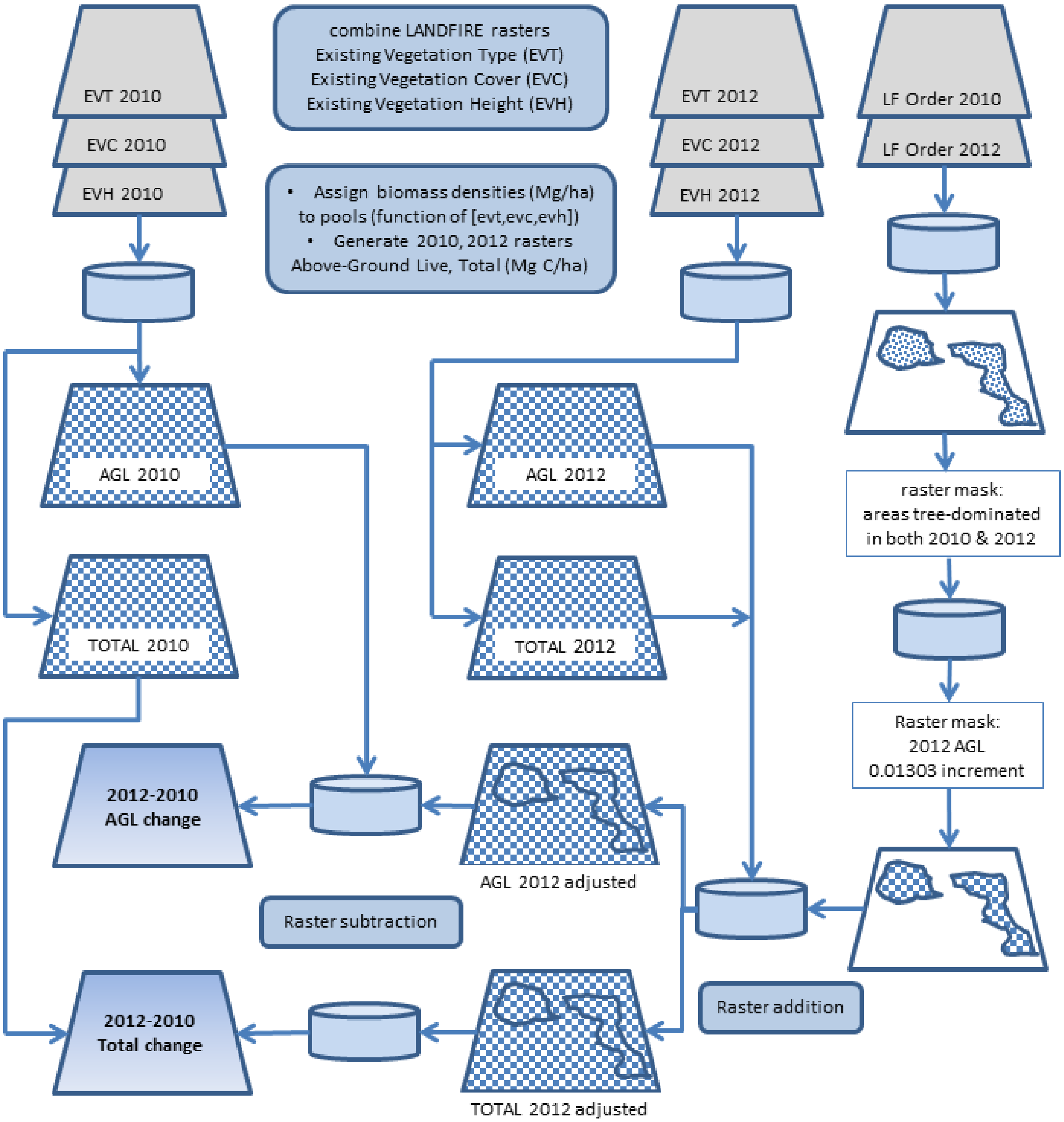

Figure 6. Workflow diagram (stock change attribution not shown).

2B.2 – Stock Change Attribution: Introduction

IPCC inventory guidelines provides for stock change attribution by selected disturbance types. These include biomass burning (IPCC category 3C1) and wood harvest (IPCC category 3D1). LANDFIRE geospatial data on disturbance activity was used to locate areas where fires and harvest related activities occurred during 2010-2012. LANDFIRE harvest activity geodata was augmented with data extracted from the state Forest Practice Geographical Information System (CALFIRE, 2017). Completed harvests contained in the Forest Practice GIS were selected and rasterized based on overlay and inspection with the AGL stock change raster. The additional harvest footprints were merged with the LANDFIRE harvest activity geodata. LANDFIRE fire categories include wildfires (Wildfire), prescribed wildland burning (Rx fire), and Wildland Fire Use (WFU). Harvest related categories include Clearcut, Thinning, Harvest, Mastication and Other Mechanical. Stock changes were attributed by spatial overlay of disturbance areas upon the stock change raster layers. There were areas where fire and harvest "footprints" spatially overlapped, potentially confounding stock change attribution. Moreover, wildfires were spatially extensive, whereas harvest-related activities had limited spatial extent. More information on the spatial extent of wildfires is discussed in the *2C – Data Sources* section (**Figure 7**) and the *2D – Results* section (**Table 3**). In order to attribute stock change to a single disturbance type and to avoid double counting, a calculation priority was applied: Clearcut > Harvest > Other Mechanical > Thinning > Mastication > Wildfire > WFU > Rx fire (Saah, et al., 2016). The prioritization scheme principally served to avoid under-reporting stock changes attributed to harvest activities, for locations that would otherwise have been attributed to fire.

2B.3 – Stock Change Attribution: Fire (IPCC 3C1)

Attributing stock change to fire is complicated by the fact that fire differentially propagates and consumes live and dead vegetation, depending on environmental conditions such as fuel moisture levels, fuel loads and configuration, topography, and weather. In intense forest fires, large amounts of dead woody debris and litter are consumed. In the process, some trees are killed (either by crown torching or by cambium destruction from intense heat at the ground surface) while others survive. Fires in shrub lands and grasslands typically consume nearly all above-ground biomass. Post-fire landscapes therefore feature barren areas, unburned dead fuels, killed trees, patches of intact or surviving vegetation, and re-emergent vegetation. Stock change attribution according to fire was achieved by spatial overlay of LANDFIRE-mapped burn areas on the stock change rasters. The fire-attributed stock changes account only for carbon contained in live and dead pools associated with the post-fire (e.g. 2012) vegetation type, and have no memory of the previous vegetation type, i.e. they do not account for potential post-fire carbon persisting in unburned fuels or in killed trees. Elsewhere, fires re-occurred during the 2010-2012 period. In these locations, it was not possible to quantify stock change associated with each fire occurrence, because stock change attribution to fire was based on a stock difference between 2010 and 2012.

2B.4 – Stock Change Attribution: Thinning, Harvest, and Clearcut (IPCC 3D1)

Tree harvests transfer a fraction of tree carbon from live biomass to wood product pools. In the process, some carbon is lost to the atmosphere while a fraction persists for a time in solid form. Harvests and other vegetation management activities generate stock changes that are difficult to quantify using remotely-sensed data, since such activities are episodic, affect different tree size/age class cohorts, generate varied proportions of residues and products, and because vegetation recovers at varying rates between data acquisition years.

LANDFIRE disturbance and state timber harvest geodata for 2010-2012 was used to locate areas where Thinning, Clearcut, Harvest, Mastication or Other Mechanical activities occurred. Thinning is a forestry practice that reduces the number of trees per unit land area in order to improve growing conditions for remaining trees. Clearcuts remove essentially all trees in order to harvest wood and to produce exposed sites for re-planting or for natural regeneration. LANDFIRE defines Harvest as a general term for a variety of practices that involve cutting and gathering forest trees and assigns the term to locations where there is insufficient information to classify activities as either Clearcut or Thinning (Saah, et al., 2016). Mastication and Other Mechanical methods are among a variety of techniques applied by land managers to reduce vegetation fuel loads and wildfire hazard in selected areas. LANDFIRE defines Mastication as the mowing or chipping of vegetation, while Other Mechanical represents a variety of vegetation fuels management techniques such as felling and piling, lop and scatter, and chaining.

Stock change estimates were retrieved for areas mapped as having been clearcut, harvested, thinned, or subjected to mastication or other mechanical treatment during the 2010-2012 period. For purposes of this analysis, Mastication and Other Mechanical were assumed to generate no off-site wood products. Stock changes associated with Mastication and Other Mechanical are therefore included in the Results section (**Table 3**) for informational purposes, but are not components of wood product quantification. The estimated stock changes in the AGL pool for Thinning, Clearcut and Harvest areas represent the amount of tree biomass removed from the live pool and destined for processing into wood products. The amount of wood product produced from the biomass removed from these areas was estimated using California-specific coefficients based on Stewart and Nakamura (2012) and Saah et al. (2012). From these, it was estimated that approximately 76% of removed AGL carbon persists in solid form two years after production. To estimate the net stock change associated with Thinning, Harvest and Clearcut, the estimated amount of persistent wood product carbon was deducted from the associated harvest AGL gross stock change. The estimated net stock change of harvest represents carbon losses to the atmosphere associated with the fate of residues on-site, at mills, and with discards.

2C – Data Sources

2C.1 – Forests and Other Lands

LANDFIRE geospatial vegetation data for 2010 (version LF 1.2.0) and 2012 (version LF 1.3.0) used in the analysis include the raster products Existing Vegetation Type (EVT), Existing Vegetation Cover (EVC), Existing Vegetation Height (EVH), and disturbances from 2010 through 2012 (DISTYEAR). All were obtained from the LANDFIRE data distribution site (LANDFIRE, 2018). Supplemental harvest geodata was obtained from the state Forest Practice GIS database (CALFIRE, 2017). Regression equations used to estimate biomass densities (Mg ha-1) for tree-dominated lands from LANDFIRE vegetation attributes EVT, EVC and EVH were developed by researchers at the University of California at Berkeley and the National Park Service (Battles, et al., 2013) (Gonzalez, et al., 2015).

Biomass densities (Mg ha-1) for land classified by LANDFIRE as shrub-dominated were compiled from the LANDFIRE reference database (LFRDB) and from published literature (Battles, et al., 2013) (Gonzalez, et al., 2015).

For land classified by LANDFIRE as dominated by grasses and herbaceous vegetation, NPP raster data (MODIS satellite product MOD17A3, available from the USGS Land Processes Distributed Active Archive Center) was used to approximate biomass densities (Battles, et al., 2013) (Gonzalez, et al., 2015).

Default biomass densities for Croplands and Settlements were based on compilations from literature and from spatial analysis (Saah, et al., 2016).

2C.2 – Fire, Thinning, Harvest, Clearcut

Supplemented by state harvest geodata, the LANDFIRE raster product DISTYEAR was used to locate and select fire and harvest areas in the 2010-2012 period in order to attribute and tabulate stock changes according to fire or harvest (**Figure 7**). Estimates for carbon persisting as wood product were based on coefficients developed by Stewart and Nakamura (2012) and by Saah et al. (2012).

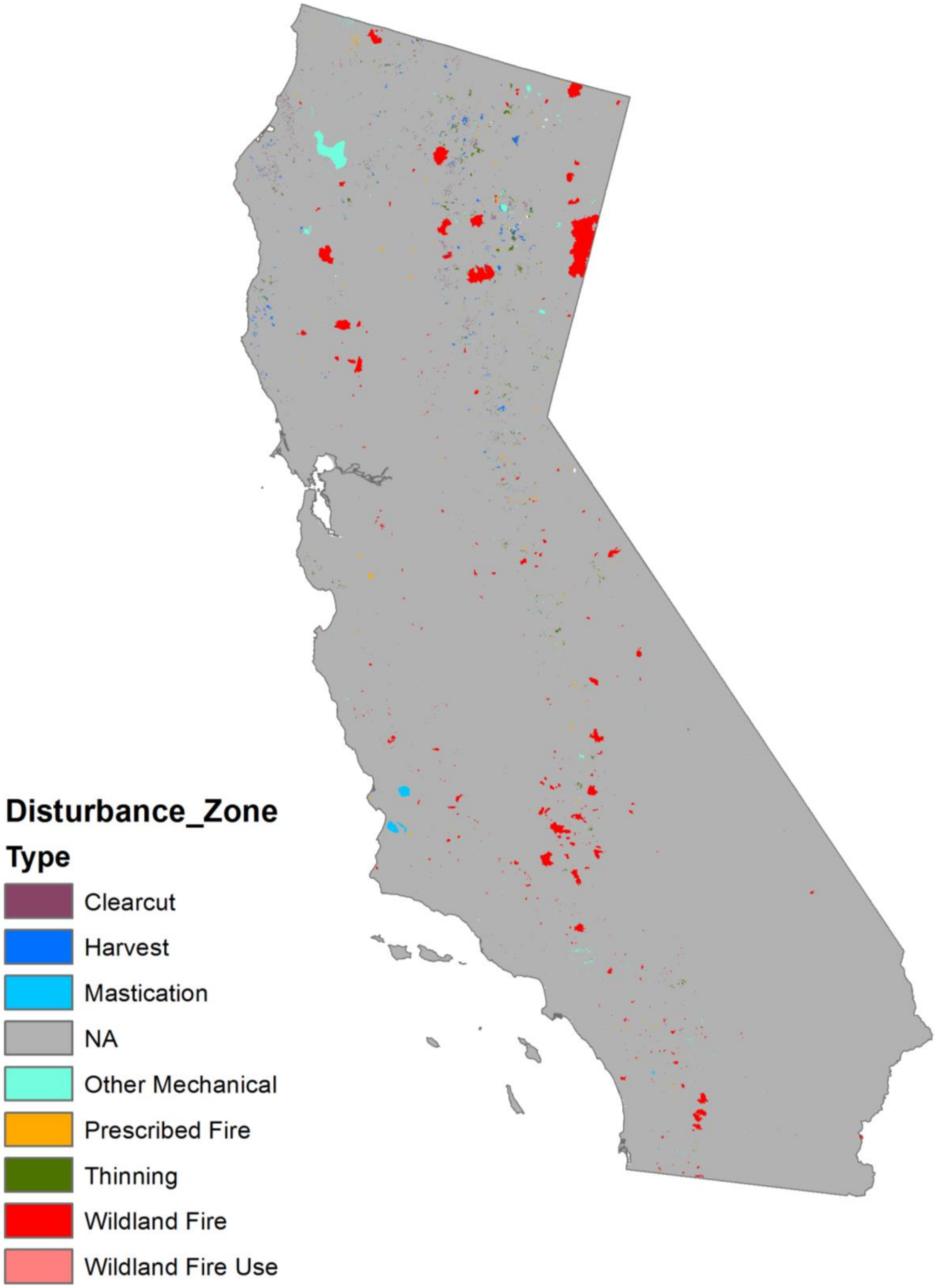

Figure 7. Disturbances by type during 2010 – 2012.

2D – Results

As in prior analyses, the Forest Land category contained the vast majority of statewide land carbon stock, arrayed in mountain regions of the state (not shown). Areas that were tree-dominated in both 2010 and 2012 contributed to a net change of +11.5 MMT C in the AGL pool for the category Forest Land remaining Forest Land (IPCC 3B1a, **Table 3**), representing an annualized rate of approximately +5.7 MMT C yr^{-1}. This rate is a factor of 3 greater than in 2001-2010 and is due to comparatively less disturbance. Overall, Total carbon stocks (live and dead pools, not including soils) increased in lands that remained forested over the period. Elsewhere, stock decline exhibited in land that changed from forest cover to grassland (IPCC 3B3bi, **Table 3**) is associated with losses due to fire (**Table 5**).

For the 2010-2012 period, land that changed from forest cover to developed (category IPCC 3B5bi) exhibited stock declines of 6.9 MMT C in the AGL pool and 16.6 in the Total pool. The declines are an order of magnitude greater than stock declines reported for this category in the 2001-2010 period (ARB 2017). Inspection of the stock-change rasters revealed spatial networks of stock-loss, corresponding to local roads (not shown). Further examination revealed that mapped local roads were a new feature of the LANDFIRE EVT product for 2012. Taken together, local roads present in the 2012 EVT and not in the 2010 EVT products created artifact changes in land type and stock-loss at those locations from 2010 to 2012. Spatial analysis estimated that over 5.7 MMT C of the AGL and 13.5 MMT C of the Total stock-loss for this category are artifacts of the (pre-existing yet) newly mapped roads. If applied to the values reported above, the adjusted change in AGL and Total carbon for this category would be approximately 1.1 and 3.1 MMT C, respectively. The revised estimate of change in forest AGL due to conversion over two years (0.6 MMT C) is slightly below a range (0.87-1.85 MMT C) derived from a recent analysis (Christensen, et al., 2017). Because the quantities of forest stock involved are small relative to overall forest stocks, the artifact portion of the forest stock-changes for this category have not been applied to modify either the LANDFIRE raster datasets or the values reported in Forest Land remaining Forest Land (IPCC 3B1a).

For the 2012 – 2014 period, Forest Land that remained Forest Land exhibited a net gain in AGL carbon that was nearly half the magnitude for 2010 – 2012, approximately 5 MMT (**Table 3b**). Elsewhere, carbon losses are associated with Forest Land that changed to land dominated by grasses, driven largely by fire. Also for the 2012-2014 period, carbon gains are associated with grasslands that became Forest Land during the period. These changes were observed in locations within regions of the southern Cascades and central and southern coasts, where areas classified by LANDFIRE as grassland in 2012 were classified in 2014 as woodlands.

2D.1 – Uncertainty

Uncertainties associated with measurement, sampling, regression, and model selection influence regional-scale estimates of forest biomass and carbon stocks. Sampling errors (SE) represent the uncertainty associated with sampling areas (plots) that are small relative to total forest area. Uncertainties are associated with regression models (allometric equations) that are the basis for estimating tree wood volume and biomass (bole, bark, stems, roots, foliage) from measurements of trunk diameter and tree height. Moreover, multiple regression models exist for given tree species, and model selection can contribute to uncertainties in carbon estimates ranging between ± 20 to 40 percent (Melson, et al., 2011). These sources of uncertainty, together with land cover classification uncertainty associated with LANDFIRE, result in an overall uncertainty of approximately ±20% (95%

confidence interval) for AGL carbon stocks and change across natural lands statewide (Battles et al. 2013, Gonzalez et al. 2015). Uncertainty estimates for dead carbon pools are not yet developed.

Table 3a. 2010 – 2012 change in land carbon stocks ecosystem budget sign convention: gains (+), losses (-). Note categories To Be Determined (TBD).

IPCC Land Category	Category Code	IPCC Category	10^6 Metric Tons Carbon (MMT C)	
			Above-Ground Live (AGL)	Total[1] (Live & Dead)
3B1 Forest Land[2]	3B1a	Forest Land remaining Forest Land	11.53	14.85
	3B1bi	Cropland Converted to Forest Land	TBD	TBD
	3B1bii	Grassland Converted to Forest Land	0.00	0.00
	3B1biii	Wetlands Converted to Forest Land	NA	NA
	3B1biv	Settlements Converted to Forest Land	NA	NA
	3B1bv	Other Land Converted to Forest Land	NA	NA
		subtotal	**11.53**	**14.85**
3B2 Cropland	3B2a	Cropland remaining Cropland	TBD	TBD
	3B2bi	Forest Land Converted to Cropland	-0.49	-2.56
	3B2bii	Grassland Converted to Cropland	-0.05	-0.11
	3B2biii	Wetlands Converted to Cropland	NA	NA
	3B2biv	Settlements Converted to Cropland	NA	NA
	3B2bv	Other Land Converted to Cropland	-0.004	0.02
		subtotal	**-0.55**	**-2.64**
3B3 Grassland	3B3a	Grassland remaining Grassland	-0.30	-1.54
	3B3bi	Forest Land Converted to Grassland	-3.67	-10.87
	3B3bii	Cropland Converted to Grassland	TBD	TBD
	3B3biii	Wetlands Converted to Grassland	NA	NA
	3B3biv	Settlements Converted to Grassland	NA	NA
	3B3bv	Other Land Converted to Grassland	NA	NA
		subtotal	**-3.97**	**-12.41**
3B4 Wetlands	3B4ai	Peatlands remaining Peatlands	NA	NA
	3B4aii	Flooded Land remaining Flooded Land	0.00	0.00
	3B4bi	Land Converted for Peat Extraction	NA	NA
	3B4bii	Land Converted to Flooded Land	NA	NA
	3B4biii	Land Converted to Other Wetlands	0.00	NA
		subtotal	**0.00**	**0.00**
3B5 Settlements	3B5a	Settlements remaining Settlements	TBD	TBD
	3B5bi	Forest Land Converted to Settlements	footnote [3]	footnote [3]
	3B5bii	Cropland Converted to Settlements	TBD	TBD
	3B5biii	Grassland Converted to Settlements	-0.02	-0.09
	3B5biv	Wetlands Converted to Settlements	NA	NA
	3B5bv	Other Land Converted to Settlements	-0.00	0.00
		subtotal	**-0.02**	**-0.09**
3B6 Other Land[4]	3B6a	Other Land remaining Other Land	0.00	0.00
	3B6bi	Forest Land Converted to Other Land	0.23	0.94
	3B6bii	Cropland Converted to Other Land	TBD	TBD
	3B6biii	Grassland Converted to Other Land	-0.00	-0.00
	3B6biv	Wetlands Converted to Other Land	NA	NA
	3B6bv	Settlements Converted to Other Land	NA	NA
		subtotal	**0.23**	**0.94**
		sum MMT C[5]	**7.22**	**0.65**

1 Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

2 IPCC definition of Forest Land includes land dominated by shrubs. Category 3B1a AGL stock change includes 0.01303 fractional stock increment associated with tree growth in lands dominated by trees in both 2010 and 2012, from FIA data (growth not detected by satellite).

3 See discussion in Results section.

4 IPCC definition of Other Land includes sparsely vegetated, barren, rock/ice, and lands that do not fall within the other 5 categories.

5 Does not account for carbon persisting in wood products

Table 4a. 2012 – 2014 change in land carbon stocks ecosystem budget sign convention: gains (+), losses (-). Note categories To Be Determined (TBD).

IPCC Land Category	Category Code	IPCC Category	10^6 Metric Tons Carbon (MMT C)	
			Above-Ground Live (AGL)	Total[1] (Live & Dead)
3B1 Forest Land[2]	3B1a	Forest Land remaining Forest Land	4.96	3.63
	3B1bi	Cropland Converted to Forest Land	TBD	TBD
	3B1bii	Grassland Converted to Forest Land	3.18	27.85
	3B1biii	Wetlands Converted to Forest Land	NA	NA
	3B1biv	Settlements Converted to Forest Land	NA	NA
	3B1bv	Other Land Converted to Forest Land	0.00	0.00
		subtotal	**8.15**	**31.49**
3B2 Cropland	3B2a	Cropland remaining Cropland	TBD	TBD
	3B2bi	Forest Land Converted to Cropland	NA	NA
	3B2bii	Grassland Converted to Cropland	NA	NA
	3B2biii	Wetlands Converted to Cropland	NA	NA
	3B2biv	Settlements Converted to Cropland	NA	NA
	3B2bv	Other Land Converted to Cropland		
		subtotal	**NA**	**NA**
3B3 Grassland	3B3a	Grassland remaining Grassland	0.00	0.00
	3B3bi	Forest Land Converted to Grassland	-6.05	-15.87
	3B3bii	Cropland Converted to Grassland	TBD	TBD
	3B3biii	Wetlands Converted to Grassland	NA	NA
	3B3biv	Settlements Converted to Grassland	NA	NA
	3B3bv	Other Land Converted to Grassland	NA	NA
		subtotal	**-6.05**	**-15.86**
3B4 Wetlands	3B4ai	Peatlands remaining Peatlands	NA	NA
	3B4aii	Flooded Land remaining Flooded Land	0.00	0.00
	3B4bi	Land Converted for Peat Extraction	NA	NA
	3B4bii	Land Converted to Flooded Land	NA	NA
	3B4biii	Land Converted to Other Wetlands	0.00	NA
		subtotal	**0.00**	**0.00**
	3B5a	Settlements remaining Settlements	TBD	TBD

3B5 Settlements	3B5bi	Forest Land Converted to Settlements	NA	NA
	3B5bii	Cropland Converted to Settlements	TBD	TBD
	3B5biii	Grassland Converted to Settlements	NA	NA
	3B5biv	Wetlands Converted to Settlements	NA	NA
	3B5bv	Other Land Converted to Settlements	NA	NA
		subtotal	**NA**	**NA**
3B6 Other Land[4]	3B6a	Other Land remaining Other Land	0.00	0.00
	3B6bi	Forest Land Converted to Other Land	NA	NA
	3B6bii	Cropland Converted to Other Land	TBD	TBD
	3B6biii	Grassland Converted to Other Land	NA	NA
	3B6biv	Wetlands Converted to Other Land	NA	NA
	3B6bv	Settlements Converted to Other Land	NA	NA
		subtotal	**NA**	**NA**
		sum MMT C[5]	**2.10**	**15.63**

[1] Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

[2] IPCC definition of Forest Land includes land dominated by shrubs. Category 3B1a AGL stock change includes 0.01303 fractional stock increment associated with tree growth in lands dominated by trees in both 2010 and 2012, from FIA data (growth not detected by satellite).

[3] See discussion in Results section.

[4] IPCC definition of Other Land includes sparsely vegetated, barren, rock/ice, and lands that do not fall within the other 5 categories.

[5] Does not account for carbon persisting in wood products

In contrast to the 2001-2010 period, wildfire activity in 2010-2012 represented a reduced contribution to disturbance-related stock changes. Of the eight LANDFIRE disturbance types evaluated, wildfires affected 1.5 times more area than all other disturbance types combined (**Table 5**), approximately half the rate exhibited for the pyrogenic 2001-2010 period. The total wildfire area in the state mapped by LANDFIRE for 2010-2012 was approximately 1% greater than an area total derived from a state geodatabase (4,660 km^2) (FRAP, 2017). The difference in area is attributed largely to differences in minimum fire area mapping thresholds of the two geodatabases. Spatial analysis attributed approximately 9 MMT C of stock loss from the Total carbon pool to wildfires, representing approximately half of the overall stock change (**Table 5**), less than in 2001-2010, when losses attributed to wildfires represented 80% of overall stock change. Prescribed fire and WFU represented order of magnitude smaller stock losses. Greater wildfire activity in the 2012-2014 period (1,936,568 acres) than in 2010-2012 (1,161,962 acres) contributed to a concomitant increase in carbon stock loss.

For the 2010 – 2012 period, the total area affected by Thinning, Clearcut, Harvest, Mastication and Other Mechanical activities was almost 60% of the magnitude of the area affected by wildfire, and stock declines (not accounting for post-harvest carbon persisting in wood products) were less than half the magnitude of the loss represented by wildfire. Of the -1.4 MMT C gross stock change in the AGL pool attributed to Thinning, Clearcut and Harvest (**Table 6**), approximately 1.04 MMT of the removed carbon persisted in solid form over the period. Taken together, accounting for post-harvest persistent carbon evaluated to a net stock change for harvest activities of -0.3 MMT C for the AGL pool (**Table 6**). Meanwhile, stock change associated with Mastication and Other Mechanical was approximately one-fourth the magnitude of the other three harvest-related activities combined. As of this writing, CARB staff has assessed that harvest activities may be under-represented in LANDFIRE's disturbance geodata for the 2012-2014 period. Staff are examining supplemental geodata to locate harvest activities and to improve stock change attribution for this analysis period. Draft estimates of stock change attributed to harvest activities reported here are based on 2010 – 2012 stock changes prorated (or scaled) to harvest acreages for 2012, 2013 and 2014 as reported in the 2017 Forest and Range Assessment.

Table 5. State-wide 2010 – 2012 stock change attribution by LANDFIRE disturbance category in the total[1] carbon pool.

Note: Quantities reported here are subsumed within the stock changes reported in **Table 3** and are not additive.

Attribution	10^6 Metric Tons Carbon (MMTC)[1]	km^2	acres
Wildfire	-9.04	4,702.3	1,161,962.3
Thinning[2]	-0.52	653.3	161,440.1
Clearcut[2]	-2.36	382.0	94,396.1
Harvest[2]	-0.38	445.3	110,038.1
Other mechanical	-0.39	999.5	354,398.5
Prescribed fire (Rx fire)	-0.32	327.4	246,977.6
Wildland Fire Use (WFU)	0.00	5.7	1,409.3
Mastication	-0.45	243.8	60,238.1

[1] Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

[2] Stock-loss estimate does not include carbon persisting as wood product.

Table 4b. State-wide 2012 – 2014 stock change attribution by LANDFIRE disturbance category in the total[1] carbon pool.

Note: Quantities reported here are subsumed with the stock changes reported in **Table 3b** and are not additive.

Attribution	10^6 Metric Tons Carbon (MMTC)[1]	km^2	acres
Wildfire	-19.7	7,837	1,936,568
Thinning[2]	TBD	TBD	TBD
Clearcut[2]	TBD	TBD	TBD
Harvest[2]	-6.49[3]	1,922	475,000[3]
Other mechanical	TBD	TBD	TBD
Prescribed fire (Rx fire)	-0.06	365	90,233
Wildland Fire Use (WFU)	NA	NA	NA
Mastication	TBD	TBD	TBD

[1] Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

[2] Stock-loss estimate does not include carbon persisting as wood product.

[3] SDraft estimates, based on sum of harvested acres 20012-2014 (2017 Forest and Range Assessment).

Table 6a. 2010-2012 stock change attribution by IPCC category.

Note: Quantities reported here are subsumed within the stock changes reported in **Table 3** and are not additive.

IPCC Category Code	Category Description	10^6 Metric Tons Carbon (MMT C)	
3C1	Biomass Burning[2] Forest Land[3] (3C1a), Grassland (3C1c) and Other Land[4] (3C1d)	Above-Ground Live (AGL)	Total[1] (Live & Dead)
		-3.5	-9.4
3D1	Harvest, Thinning and Clearcut		
	Gross stock change	-1.4	-5.0
	Net stock change[5]	-0.3	-1.2

[1] Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

[2] Includes Wildfire, Rx Fire and WFU.

[3] IPCC definition of Forest Land includes land dominated by shrubs.

[4] IPCC definition of Other Land includes sparsely vegetated, barren, rock/ice, and lands that do not fall within the other 5 categories.

[5] Accounts for 1.04 MMT post-harvest C persisting as wood product.

Table 5b. 2012 – 2014 stock change attribution by IPCC category.

Note: Quantities reported here are subsumed within the stock changes reported in **Table 3b** and are not additive.

IPCC Category Code	Category Description	10^6 Metric Tons Carbon (MMT C)	
3C1	Biomass Burning[2] Forest Land[3] (3C1a), Grassland (3C1c) and Other Land[4] (3C1d)	Above-Ground Live (AGL)	Total[1] (Live & Dead)
		-8.3	-19.7
3D1	Harvest, Thinning and Clearcut		
	Gross stock change[5]	-1.77	-6.49
	Net stock change[6]	-0.43	-5.15

[1] Includes Above-Ground Live (AGL) and Below-Ground Live (tree, understory, shrub, grass/herbaceous) Standing Dead, Down Dead, Litter - Not including soil.

[2] Includes Wildfire, Rx Fire and WFU.

[3] IPCC definition of Forest Land includes land dominated by shrubs.

[4] IPCC definition of Other Land includes sparsely vegetated, barren, rock/ice, and lands that do not fall within the other 5 categories.

[3] Draft estimate, based on harvest acres reported for 2012-2014 (2017 Forest and Range Assessment).

[6] Accounts for 1.35 MMT post-harvest C persisting as wood product.

Assessing stock changes associated with harvest activities behooves an evaluation between reported harvest data and LANDFIRE-based harvest estimates adjusted for land ownership type. Taking into account variation in biomass removal with respect to activity and ownership type (FRAP, 2014), Saah et al. (2016) derived harvest volumes from AGL stock change estimates associated with the Thinning, Clearcut and Harvest categories. Using methods developed by Saah and coworkers (2016) AGL stock changes in 2010-2012 associated with harvest activities translated to a harvest volume of approximately 2,522 million board-feet (mbf), representing 79% of the 2010-2012 harvest volume reported by the state Board of Equalization (BoE) timber yield tax program. The ostensive harvest volume underestimate may be attributed to limitations from having the LANDFIRE Harvest category serve to represent a variety of silvicultural activities which embody different stock change outcomes (e.g. group selection, variable retention, seed tree removal, and seed tree step), harvests undetected by LANDFIRE, and uncertainties associated with conversions between biomass densities and wood volumes.

2E – Further Development

2E.1 – Forests and Other Lands: LANDFIRE Products

LANDFIRE geospatial products are evolving as the consortium expands its resource management capacity beyond wildfires. LANDFIRE is co-funded by two federal agencies (US Department of Agriculture and US Department of the Interior) and has constituents among analysts and researchers in federal and state agencies, academia, and non-governmental organizations. With each update, LANDFIRE endeavors to respond to requests for a variety of improvements. LANDFIRE vegetation mapping also abides by guidelines in the federal National Vegetation Classification System (NVCS). As a result, LANDFIRE has become a central clearinghouse of national vegetation mapping data. Consequently, continual modification of the Existing Vegetation Type (EVT) product is likely as user needs and standards change. The major source of uncertainty in ARB's land carbon quantification method for forests and other lands is EVT classification (Battles, et al., 2013) (Gonzalez, et al., 2015). Given that LANDFIRE can assign generalized vegetation classes with greater accuracy (NatureServe, 2012) new regression equations for estimating carbon densities as functions of height class, cover class and subclass (e.g., closed-canopy, evergreen forest, sparse canopy mixed forests, open canopy deciduous forest, etc.) may afford greater consistency and reduce uncertainty (Saah, et al., 2016). Continuous improvement in classification and mapping consistency will help reduce errors in mapping transitions between land categories. Moreover, the increasing volume of FIA data affords opportunities for updating inputs to the LANDFIRE-C tool, and for improving uncertainty estimates for live and dead carbon pools.

2E.2 – Stock Change Attribution: Fire

By default, the stock change estimates attributed to wildfire assume complete transfer (oxidation) of carbon to the atmosphere. Fires also emit varying amounts of CH_4 and N_2O, depending on combustion conditions. However, not all ecosystem carbon is immediately emitted by fire: post-fire land carbon stocks in the form of residual unburned dead fuels and killed trees represent carbon pools of varying persistence. Accounting for these post-fire pools (and for other gases) could serve to better represent the timing and magnitudes of losses associated with wildfire (Hurteau & Brooks, 2011).

2E.3 – Advances in Methods

The approach to land carbon quantification described in the Methodology combines temporal geospatial data (LANDFIRE products) with ground-based tabular data. Airborne or space-based active sensor technologies such as Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) provide information on the three-dimensional structure of forests and other vegetation, and have been used in combination with ground-based data to generate high fidelity geospatially explicit estimates of above-ground biomass over large areas (Chen, et al., 2012) (Gonzalez, et al., 2010) (Zhang, et al., 2014). Other efforts to interpret processes linking land carbon, disturbance and climate integrate remotely sensed and ground-based data (Kennedy, et al., 2017) with process models (Liu, et al., 2011) (Liu, et al., 2008) (Golinkoff, 2010) (Nemani, et al., 2002) (Potter, et al.,

1993) (Running & Hunt Jr., 1993). Advances in remote sensing and analysis tools are rapid and will afford for future improvements in ARB land carbon quantification and monitoring at varieties of spatial and temporal scales.

3 – Cropland Woody Biomass

3A – Background

Growth from orchard trees removes CO_2 from the atmosphere. The rate of CO_2 uptake by the land from the atmosphere is largely governed by type of crop in production, crop age (maturity) and planting density (Arneth, et al., 2017). Lands used to grow crops may also undergo land use change resulting in a shift among carbon pools. For instance, urban development on existing orchard lands removes the established trees and its associated above and belowground carbon. Conversely, conversion of annual crops to woody perennials could store carbon for many decades as above and belowground carbon without frequent disruption to the soil. Differences in agriculture practices, particularly the use of tillage can lead to increased oxidation of soil organic carbon (SOC) in the form of CO_2 (West & Marland, 2002). Tracking changes of land use practices over time via remote sensing coupled with land cover datasets can inform new tools aimed at quantifying carbon stocks of different crop types and allow a statewide GHG inventory to be created (Sobrino & Raissouni, 2000) (Kroodsma & Field, 2006).

Situated between the Sierra Nevada Mountains to the east and coastal range to the west and extending approximately 60 miles across and 450 miles long, California's Central Valley contains the majority of the State's agricultural land (**Figure 8**). The Central Valley is home to various types of annual crops including alfalfa, rice and wheat. However, perennial crop orchards consisting of almonds, walnuts and pistachios is increasing (USDA, 2012). California's coastal valleys, which include the Salinas and Napa Valleys, experience a cooler climate (average daily maximum July temperature 22.9 -28.1 °C), more suitable for vineyards compared to the warmer Central Valley. Here, the average daily maximum July temperature is 34.6 °C (USDA, 2010) (PRISM, 2017).

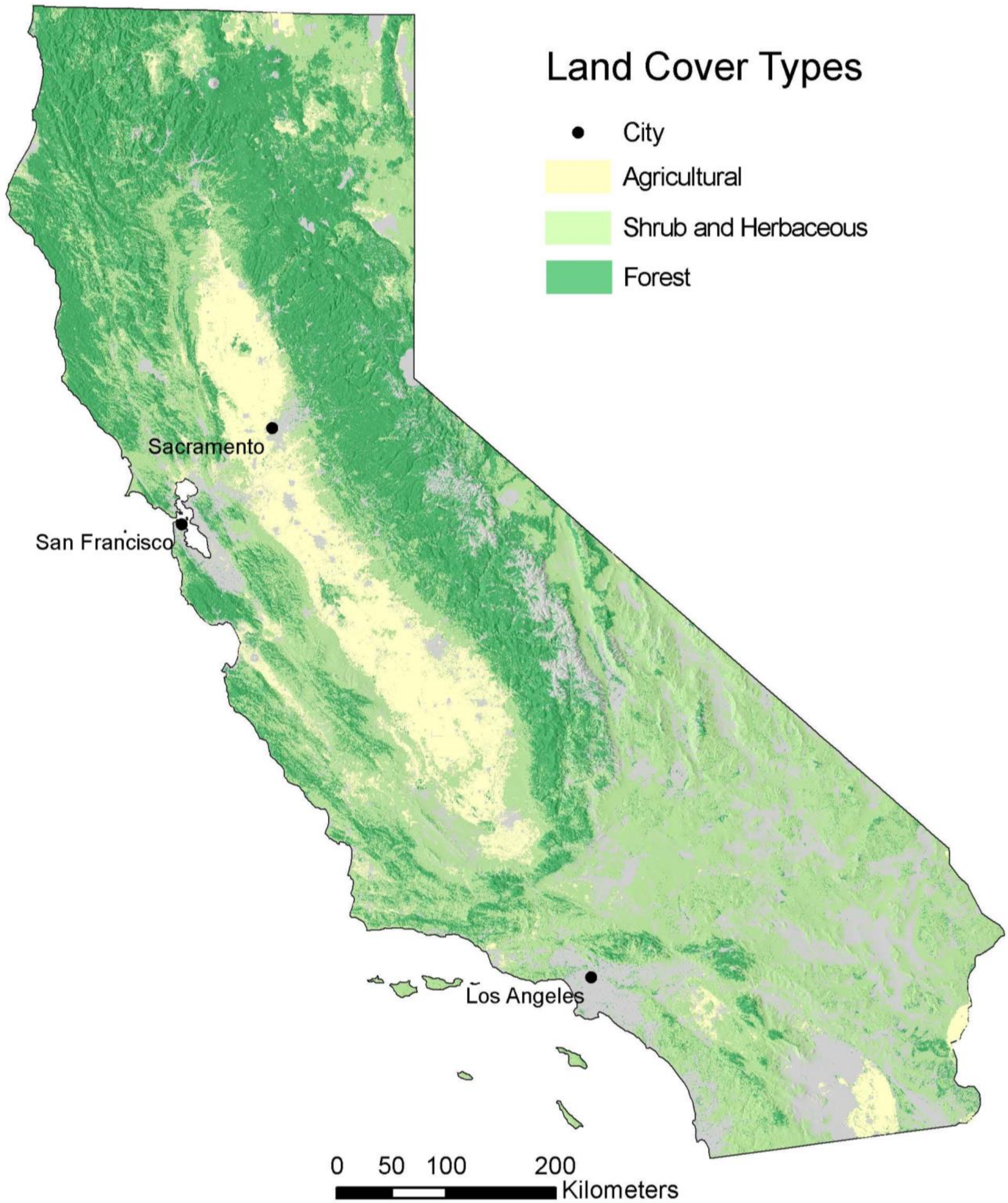

Figure 8. Broad vegetation land cover types of California with agriculture lands highlighted in yellow, shrugs and herbaceous plants in light green, and forest in dark green (USDA, 2010) (LANDFIRE, 2010).

Cultivated lands play a significant role in the US carbon cycle and how they are managed determines the amount and length of time carbon is stored (Burke, et al., 1989) (Houghton, et al., 1999) (Conant, et al., 2017) (Lal, 2004). Carbon on these lands are quantified with newly developed computer models by processing large amounts of remote sensing data using machine learning algorithms that provide an in-depth landscape view of the carbon cycle (Zomer, et al., 2016) (Schimel, et al., 2014) (Vos, et al., 2017). As of 2007 the United States contains 408 million acres of cropland, 18% of the Country's land area (USDA, 2018a). United States cropland area has fluctuated during the 20th century. From 1945 to 2002 cropland area declined 2% and has remain relatively steady at 442 million acres, while urban land area had quadrupled to 60 million acres (Lubowski, et al., 2006). Market forces, farm programs and technologies that affect supply often drive changes in cropland type and area (USDA, 2018c).

Despite the relatively level trend in cropland area over the past century, California orchards and vineyards have increased 30% from 1980 to 2000, largely displacing annual crops and consequently adding more woody carbon to the landscape (Kroodsma & Field, 2006). Conversion of crop types lead to differing carbon sequestration rates. Kroodsma and Field (2006) found that annual crops that were replaced by vineyards sequestered 68 g C m^{-2} yr^{-1}, where annual crops that were converted to orchards sequestered 85 g C m^{-2} yr^{-1}. This creates a shift in how carbon is stored on the landscape with a greater portion being stored in the aboveground live (AGL) pool. Farming practices involving orchard trees are inherently less disruptive to the soil by decreasing tillage thereby not exposing SOC to atmospheric oxygen and promoting heterotrophic respiration. The commercial lifespan of an orchard represents the length of time for which carbon is accumulated and stored in the form of live biomass. Depending on the species, orchard trees remain economically viable and are kept in production for many decades. Nut trees, such as almonds, walnuts and pistachios have a commercial lifespan of about 25, 35, 60 years, respectively (Marvinney, et al., 2014).

CARB staff developed a method called the Diameter Estimated Method for Even-aged Trees Examined Remotely (DEMETER) to fill the cropland carbon accounting gap for California. The DEMETER's model processes spatial cropland data provided by the USDA Cropscape program and CARB staff calibrated it against the National Agriculture and Statistics Service census inventory database (USDA, 2012). DEMETER meets the IPCC tier 3 level standards by providing species-specific biomass estimates for a specific region (IPCC, 2006e), while additionally incorporating several datasets from federal, state and private sources.

3B – Methodology

CARB staff evaluated various remote sensing platforms and cropland inventory data to develop an above and below ground carbon inventory for croplands that can be refreshed on an annual basis. CARB staff extracted tree diameter information from ground-based and aerial imagery to inform allometric equations provided by the USDA for estimating tree biomass. Since biomass accumulates with orchard age, CARB staff randomly sampled cloud free imagery from Landsat 1-5 MSS/ TM, 7 ETM+, 8 OLI time series from 1972 to 2017 to develop an age distribution for each orchard type.

Photo interpretation of the Landsat time series was conducted to record disturbance (tree planting) of the orchard. CARB staff then derived regression equations by species to estimate carbon values based on crop type and age class to produce a map of above and belowground carbon. CARB staff summarized data products by year and by orchard type with a Monte Carlo analysis to test the sensitivity of the DEMETERs model (**Figure 9**).

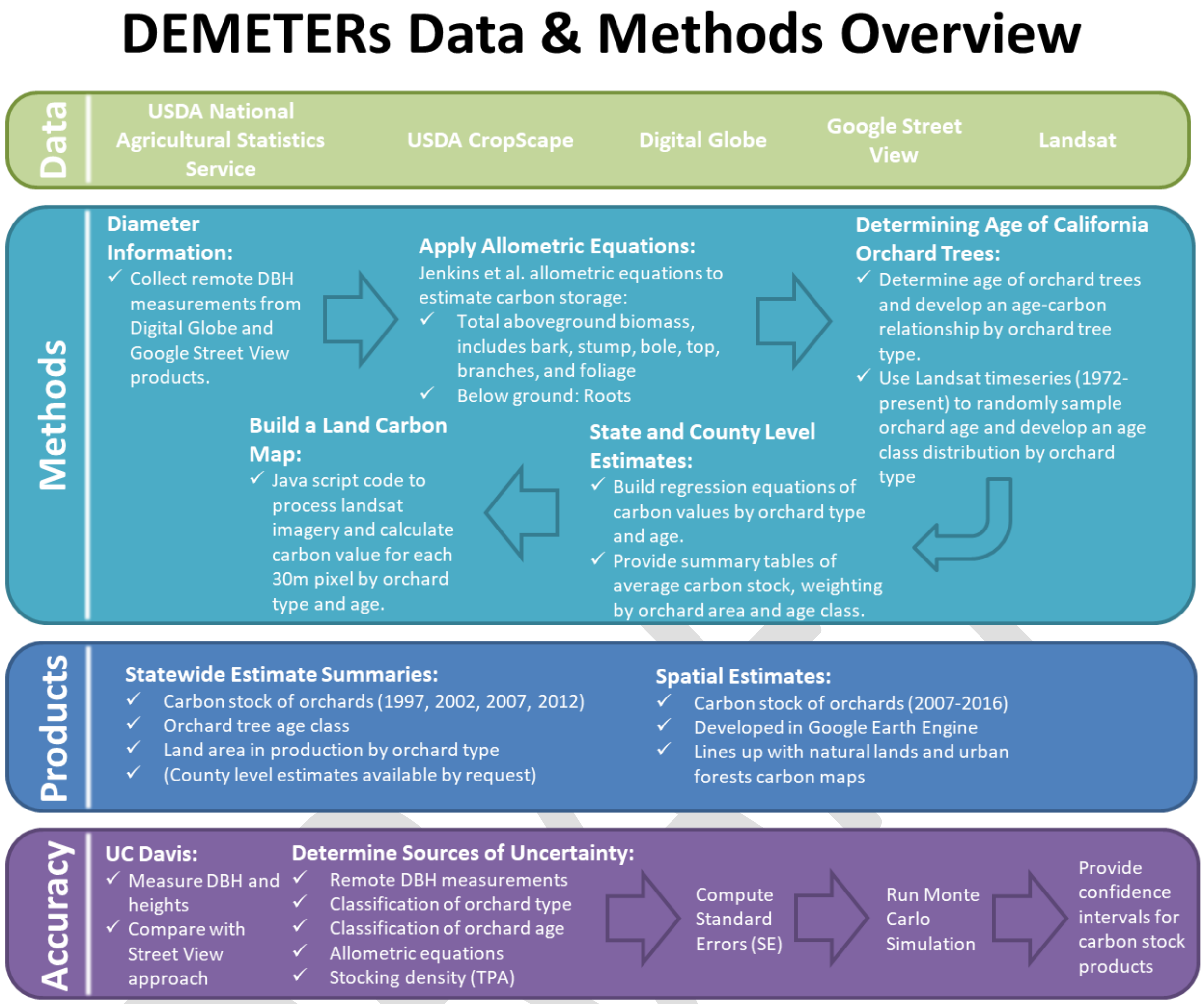

Figure 9. Overview of data, methods, products, and accuracy assessment from the DEMETER model. Data sources include tabulated crop information from NASS (USDA-NASS 2012) land cover classification, high and moderate resolution imagery from Digital Globe, Landsat, and Google Street View ground-based imagery.

CARB staff used Cropscape Cropland Data Layer (CDL) to delineate the analysis area into different orchard and vineyard types, thereby quantifying the spatial range of almond, walnut, pistachio, orange and vineyard crop types. Cropscape CDL classifies crop types onto a 30 m grid. Data used in CDL classification include Landsat TM 5, ETM+ 7, and National Land Cover Database (NLCD) derived products such as the National Elevation Dataset (NED), percent canopy cover, and percent impervious products (Boryan, et al., 2011) (Han, et al., 2012). A supervised decision tree classification was used to derive the CDL dataset (Boryan, et al., 2011) (Johnson & Mueller, 2010).

The National Agriculture and Statistics Service (NASS) collects, maintains and provides crop information for the entire United States relevant to the production, supply, consumption and costs through two inventory programs known as "census" and "survey". The census dataset is collected every 5 years and is the more detailed and comprehensive of the two datasets. The survey dataset is collected annually with information provided by the farm operators with a total sample size of 65,000 to 81,000 nationwide (USDA, 2012). From NASS, CARB staff extracted crop acreage data for the five most prevalent perennial crops in California: grapes, almonds, walnuts, pistachios and oranges.

Together these five perennial crops make up 2.6 million acres or 84% of all perennial plants found on croplands in California (**Table 7**) (USDA, 2012). The 44 other perennial crops listed in NASS (i.e. cherries, lemons, plums, etc.) occupied approximately 16% of the total perennial cropland area. CARB staff did not use the annual survey dataset in the analysis as the two datasets are not directly comparable and the survey data is the more robust of the two (USDA, 2012).

Table 7. NASS 2012 dataset showing land are of bearing and non-bearing of the top 5 woody perennial crops in California

Crop	Area (ha)	Area (%)
Grapes	380,477	30.0
Almonds	378,707	29.8
Walnuts	133,187	10.5
Pistachios	92,369	7.3
Oranges	78,140	6.2
Other	207,407	16.3
Total	**1,270,286**	**100**

To estimate above and belowground biomass of an individual tree, foresters often use diameter at breast height (DBH) within an allometric equation (Ketterings, et al., 2001) (Smith & Wood, 2006) (Gonzalez, et al., 2015). When estimating live biomass remotely CARB staff needed to determine a tree's DBH without being present in the field, requiring CARB staff to take advantage of high resolution imagery (< 1 m). Such data was provided by WorldView in Google Earth Pro and coupled with ground base photography available from Google Street View that were acquired the same year. The sub-meter WorldView imagery is used to determine the height of the tree by measuring the length of the tree's shadow on flat ground starting from the base (or tree's center) to the furthest edge of the shadow cast by the tree (**Figure 10**). The sun's altitude angle is determined by selecting a nearby utility pole and is assumed to be positioned at a right angle with respect to the ground, while the azimuth of the shadow cast by the utility pole is measured in Google Earth (**Figure 10**).

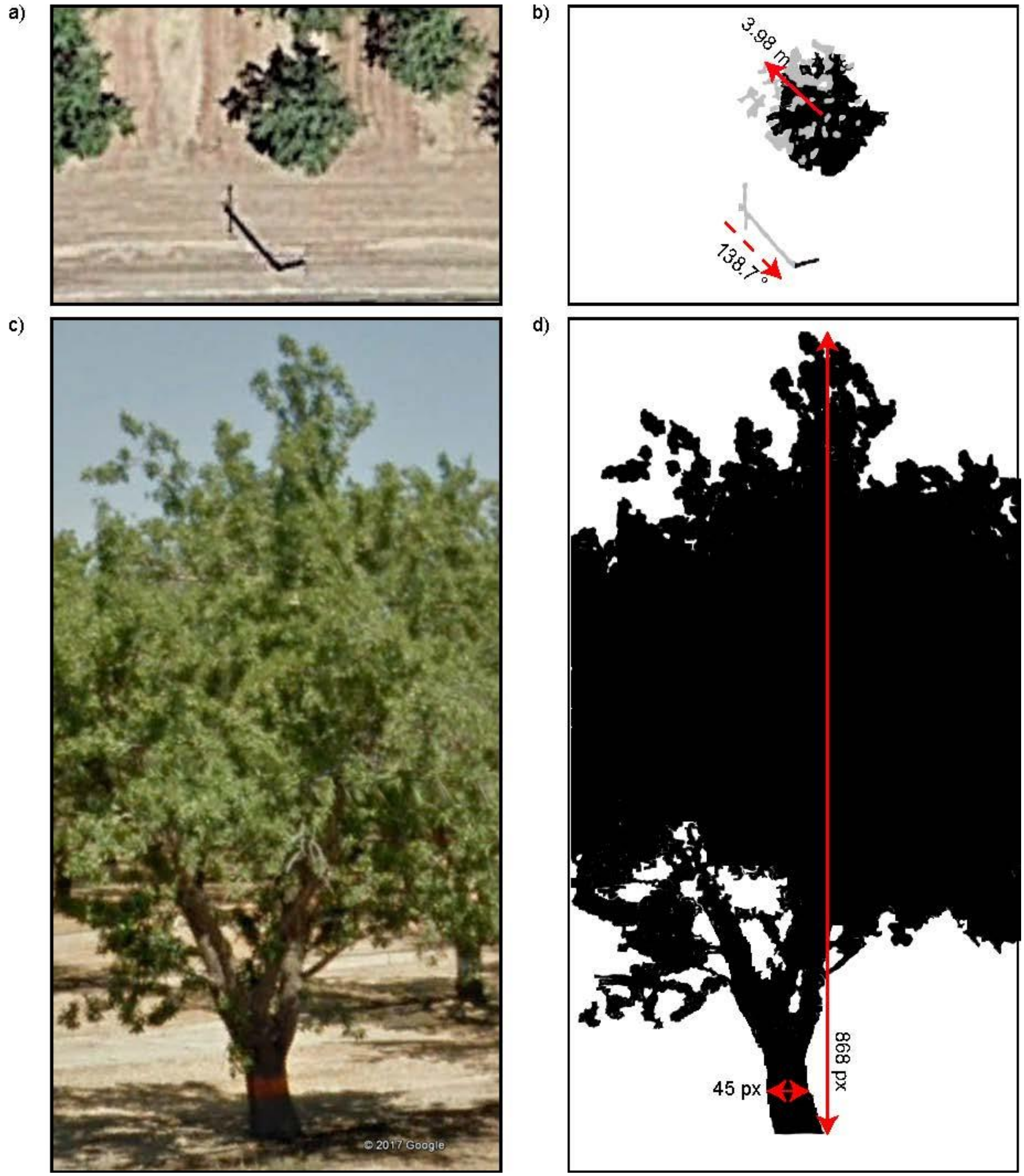

Figure 10. a) World View image of an almond tree and utility pole, **b)** Masked tree canopy (black) and tree canopy shadow cast at a length of 3.98 m (gray). Below is the utility pole (black) and shadow cast at 138.7 degrees form north (gray), **c)** Google Street view image of the same almond tree measured in figures 11 a & b, **d)** Masked almond tree from figure c measuring the height (868 px) and DBH (45 px).

A nearby utility pole instead of the tree is used to measure the sun's azimuth due to its straight and often perpendicular stance relative to the ground and absence of foliage, resulting in casting a distinct shadow that is easily measured. With the azimuth angle, location and photo acquisition date, the sun's altitude can be determined with a sun angle calculator (US Navy, 2011). The height of the tree (H_{tree}) is determine by measuring the shadow length (L_{shadow}) and multiplying by the tangent of the Sun's altitude (θ) (**Equation 1**).

$$H_{tree} = L_{shadow}\mathrm{TAN}(\theta) \qquad (1)$$

To determine a tree's DBH (D_{tree}) remotely, Google Street View is used to measure ratio between DBH and height ($\frac{D_{pixels}}{H_{pixels}}$) (**Figure 10b**) and then multiplied by the height of the tree (H_{tree}) (**Equation 2**). To ensure the same tree is selected on Google Street View as the aerial imagery, trees near the roadway are selected and counted form a cross street that is observed with both sets of data.

$$D_{tree} = \frac{D_{pixels}}{H_{pixels}} x\, H_{tree} \qquad (2)$$

To estimate tree biomass, CARB staff used the DBH measurements with the USDA's component ratio method (Woudenberg, et al., 2010) that is comprised of species-specific allometric equations capturing the top, bole, foliage, stump and roots. **Equation 3** estimates the aboveground biomass ($B_{aboveground}$) in kg stored by knowing the tree's DBH (D_{tree}) in cm for the four common orchard types (almonds, walnuts, pistachios and oranges) in California.

$$B_{aboveground} = \left(e^{-2.48+2.4835\ln(D_{tree})}\right) \qquad (3)$$

To estimate the belowground biomass ($B_{belowground}$) in kg stored in the trees roots **Equation 4** is used by knowing the tree's DBH (D_{tree}) in cm.

$$B_{belowground} = \left(e^{-2.48+2.4835\ln(D_{tree})}\right) \qquad (4)$$

Carbon storage was derived by multiplying the carbon fraction (0.47g carbon (g biomass)$^{-1}$ (McGroddy, et al., 2004)) by the above and belowground biomass estimate.

The USDA's allometric equations provide biomass storage estimates by DBH size, but not by tree age, which is needed for generating a carbon density map of perennial crops. To estimate the carbon storage by tree age CARB staff measured and aged the trees at the University of California Davis' Wolfskill Experimental Orchards located west of the main campus in Davis, CA. The experimental orchard lands consists of hundreds of hectares with many common nut and fruit trees such as peach, cherry, almond, prune, pistachios, walnut, apricot and avocado while spanning various age classes and DBH sizes. To measure DBH of individual trees CARB staff used a tree diameter tape (commonly used in forestry applications) and an Opti-Logic hypsometer for measuring tree heights. Tree age was provided by UC staff and also determined through photo interpretation from imagery available on Google Earth Pro and the Landsat imagery time series. Orchard trees were sampled and measured in groups of three to record DBH and heights measurements and then averaged to minimize bias in the trees position within the orchard that may result in differences in growing conditions.

To scale up the carbon storage estimates from the level of individual trees to orchard lands CARB staff sampled WorldView satellite imagery in Google Earth Pro and counted the number of trees per hectare that were present for each orchard type across the Central Valley of California. This was done by randomly selecting orchards of different age classes from the Cropscape CDL database and then measuring out fixed 1 hectare rectangular plots and counting the number of trees present (**Figure 11**).

Figure 11. Sampling of tree per hectare. The sampling unit is 1 hectare (100 m x 100 m) outlined in black. Trees were counted within the fixed sample unit to estimate orchard tree density by type and age.

In developing a perennial cropland map, CARB staff used Google Earth Engine (https://earthengine.google.com/) to process a time series of Landsat imagery (1972-2018) in order to derive age-class estimates of orchard trees statewide. To run the model CARB staff utilized several Landsat datasets from satellites 1-5, 7, and 8. Google Earth Engine did not provide NDVI rasters derived for the Landsat 1-3 and consequently CARB staff calculated NDVI using bands 5 (red) and 6 (NIR) with the "LANDSAT/LM01/C01/T2", "LANDSAT/LM02/C01/T2" and "LANDSAT/LM03/C01/T2" with cloud free collections (Huang et al. 2010). NDVI values were provided by Google Earth Engine (Huang et al. 2010) from 1983 to 2011 using the "LANDSAT/LT4_L1T_8DAY_NDVI" and "LANDSAT/LT5_L1T_8DAY_NDVI" derived from Landsat 4 and 5. For the year 2012 CARB staff used NDVI estimates provided from Landsat 7 (Huang et al. 2010) with the "LANDSAT/LE7_L1T_8DAY_NDVI" collection. For year 2013 and after CARB staff used

Landsat 8 NDVI estimates using the Google Earth Engine collection from 2013 to 2016 “LANDSAT/LC8_L1T_8DAY_NDVI” and “LANDSAT/LC08/C01/T1_SR” collection for years 2017 and 2018 for estimating NDVI. All imagery underwent level L1T processing with orthorectification (Chander, et al., 2009). With the Landsat NDVI collection, CARB staff calculated the median pixel value for each year to reduce the number of images for analysis (**Figure 12**). The imagery was then masked to the extent of the orchard as defined by Cropscape 2010, allowing CARB staff to estimate the year in which the orchards trees had been planted (**Figure 13**).

To be able to estimate tree age of all orchard lands in California, CARB staff identified supervised classification training sites through photo interpretation of Landsat and Google Earth imagery, capturing different orchard types and ages. These training sites contained unique pixel information that was used to develop age class signatures to inform a random forest machine learning algorithm and produce an age class map of tree orchards. With the orchard age class and the Cropscape CDL crop classification layers CARB staff produced an orchard carbon density layer spanning the state of California. Knowing the orchard type and age for each 30 m pixel CARB staff derived a carbon estimate from an exponential regression equation that CARB staff derived from field plot and Street View imagery, depicting the relationship between carbon storage, orchard type and age.

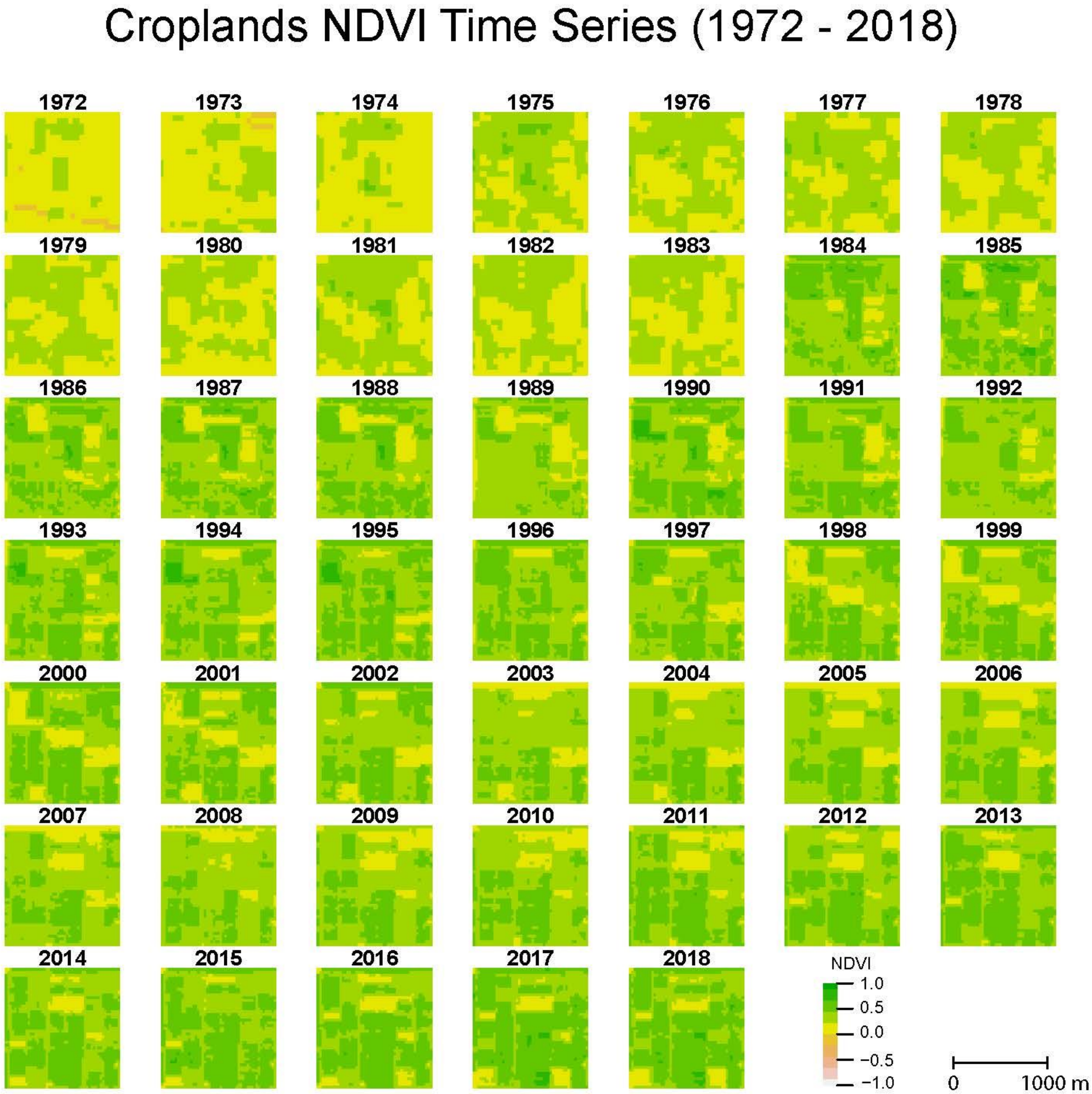

Figure 12. NDVI time series (1972 – 2018) of a small representative region 60km south-east of Fresno, CA of California perennial crops. Extent of example time series above is (36.42888, -119.23805, 36.41755, -119.22466).

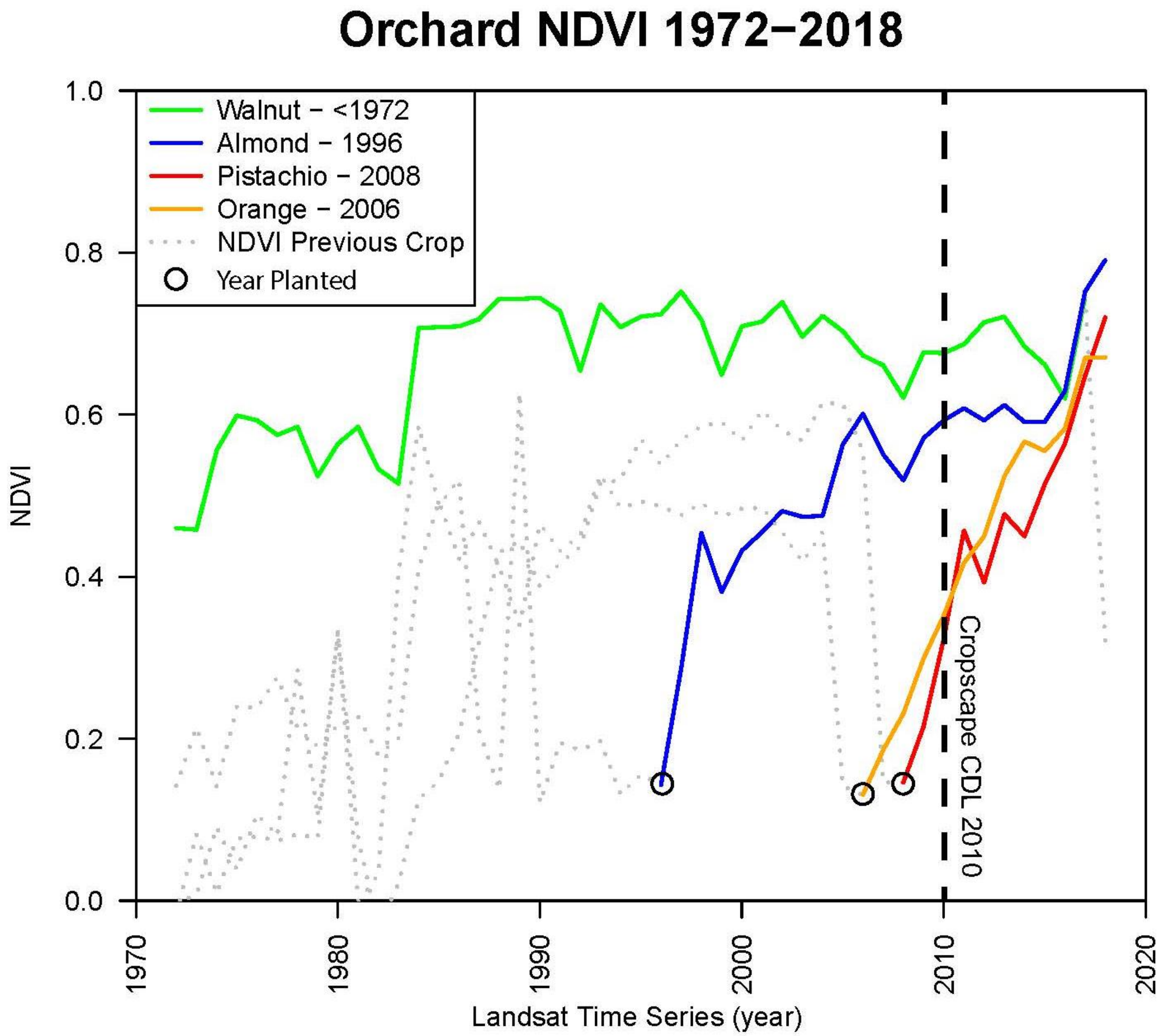

Figure 13. Median NDVI time series for the months of June – August from 1972 to 2018. NDVI values of selected orchards are presented for each orchard type, Walnut (38.627418°, -121.566367°), almond (38.945792, -122.020383), pistachio (36.900523, -119.878285) and orange (36.42349, -119.24844) . The shift in NDVI from low to high indicates growth in orchard crops.

Estimates of uncertainty in the above and belowground carbon of perennial croplands were estimated using a Monte Carlo analysis incorporating several sources of error: (1) estimate of tree height, (2) estimate of tree diameter, (3) estimate of orchard tree density, (4) statistical uncertainty in allomteric equations, (5) variation in correlation between age vs DBH, (6) statistical uncertainty in the carbon fraction, (7) spatial uncertainty in area estimates by orchard type. For the first three sources CARB staff developed error estimating **Equations 5 – 7** for tree height ($\widehat{H}$), tree diameter ($\widehat{D}$), and tree density($\widehat{T}$):

$$\widehat{H} = H_{shadow} + X_{height} SE_{height} \quad (5)$$

Where, $H_{shadow}$is the length of the tree's shadow (m), X_{height} is a random number from a normal distribution with a mean = 0 and a standard deviation = 1 and SE_{height} is the standard error of the height.

$$\widehat{D} = D_{tree} + X_{dbh}SE_{dbh} \quad (6)$$

Where, D_{tree} is the diameter (cm) of a tree. X_{dbh} is a random number from a normal distribution with a mean = 0 and a standard deviation = 1 and SE_{dbh} is the standard error of dbh.

$$\widehat{T} = T_{tph} + X_{tph}SE_{tph} \quad (7)$$

Where, T_{tph} is the number of trees per hectare. X_{tph} is a random number from a normal distribution with a mean = 0 and a standard deviation = 1 and SE_{tph} is the standard error of tree per hectare.

Individual tree aboveground ($\hat{B}_{aboveground}$) and belowground ($\hat{B}_{belowground}$) biomass estimates (kg) were calculated with standard errors provided by the USDA (Jenkins) and are shown in **Equations 8 and 9**:

$$\hat{B}_{aboveground} = \left(e^{-2.48+2.4835\ln(\widehat{D})}\right) + X_{aboveground}SE_{aboveground} \quad (8)$$

$$\hat{B}_{belowground} = \left(e^{-1.691+0.816\ln(\widehat{D})}\right) + X_{belowground}SE_{belowground} \quad (9)$$

The estimates of aboveground and belowground biomass were added together for a combined biomass estimate for each tree that was sampled. A power regression analysis was conducted comparing age vs biomass from individually sampled trees for each orchard to scale up individual tree estimates to statewide estimates of biomass by orchard type and age class (**Equation 10** and **Table 8**).

$$\hat{B}_{age} = b_0 y^{b_1} + X_{age}SE_{age} \quad (10)$$

Where, $\hat{B}_{age}$ is the biomass estimate (kg) for a given tree age and y is the age of the tree. X_{age} is a random number from a normal distribution with a mean = 0 and a standard deviation = 1 and SE_{age} is the standard error of the age.

Table 8. The coefficients and standard error by orchard type for equation 10.

Orchard Type	b_0	b_1	SE_{age}
Almond	13.72	1.38	0.048
Walnut	12.56	1.49	0.058
Pistachio	2.81	1.74	0.067
Orange	2.52	1.37	0.046

$$\hat{C}_{orchard\ type} = \sum_{i=1}^{age\ classes} (f_c + X_{fc}SE_{fc})(\hat{B}_{age})(A_{area} + X_{area}SE_{area})$$

(11)

Where, $\hat{C}_{orchard\ type}$ is the California statewide carbon storage for a given orchard type. f_c, is the carbon fraction, X_{fc} is a random number from a normal distribution with a mean = 0 and a standard deviation = 1 and SE_{fc} is the standard error of the carbon fraction (McGroddy, et al., 2004). A_{area} is the land area for a given orchard type (USDA, 2012).

3C – Results

Orchard trees were found to exponentially grow and accumulate carbon in the bole, branches, leaves, and roots. Among the four orchard species CARB staff found walnut trees to store the most carbon with the oldest trees reaching 1662 kg per tree, while finding individual orange trees to store the least carbon and slowest growth rates (**Figure 14**). At 38 years of age walnuts, almond, pistachio and orange store 1333, 976, 740, 172 kg respectively. CARB staff noticed walnut trees to have the steepest curve accumulating the most carbon while orange trees accumulating the least carbon over time.

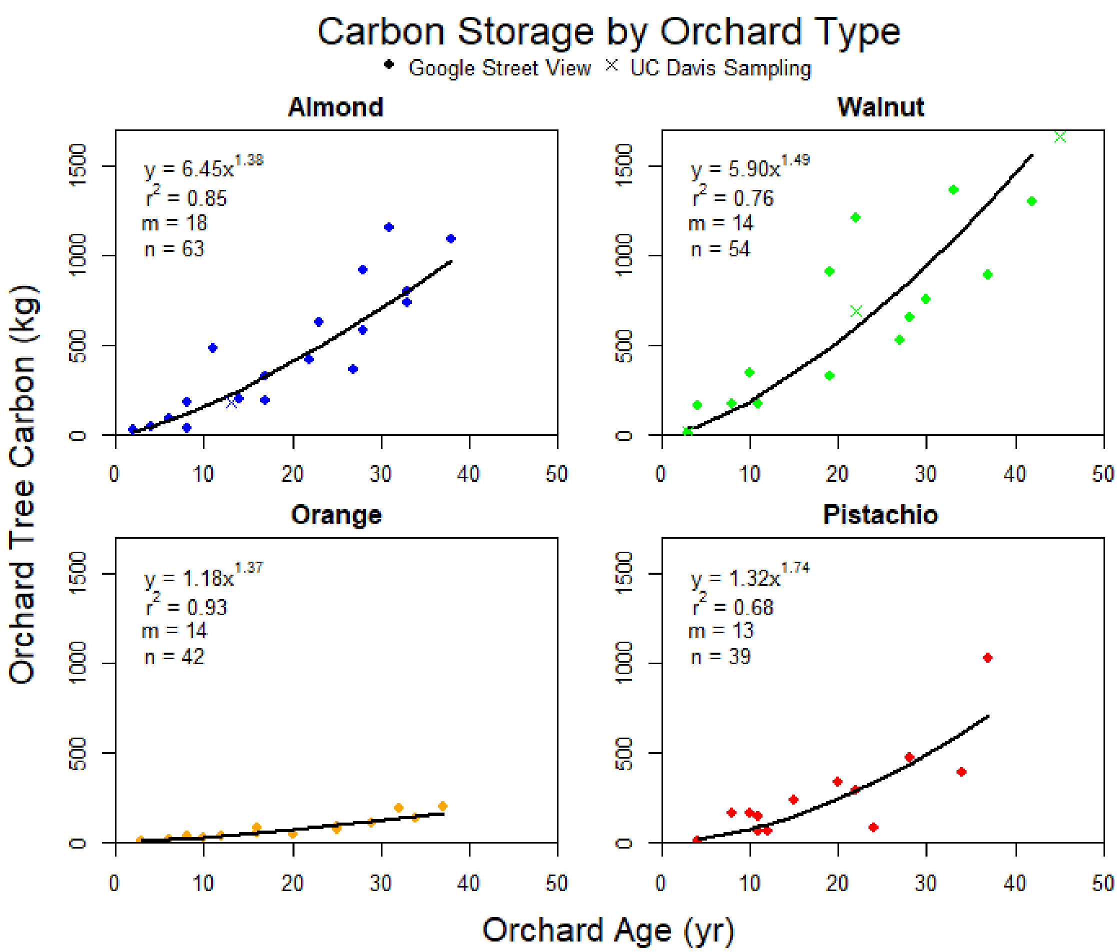

Figure 14. A comparison of carbon accumulation by age for four orchard types (almond, walnut, orange, and pistachio). Where r^2 is the least-squares goodness-of-fit, m is the number orchards sampled and n is the sample size of individual trees.

Tree densities (trees ha^{-1}) for all orchard types were found to decline with age. The highest densities observed were of young recently planted orange trees, while the lowest tree density found were among the oldest walnut tree orchards. Tree density among orange orchards also declined the most quickly compared to other orchard types with densities dropping from 418 to 214 trees per ha over 38 years (**Figure 15**). Walnuts declined from about 170 to 70 trees per ha during the same period of time. Almond and pistachio orchard densities were more similar and declined from 268 to 142 trees ha^{-1} and 356 to 213 trees ha^{-1} respectively.

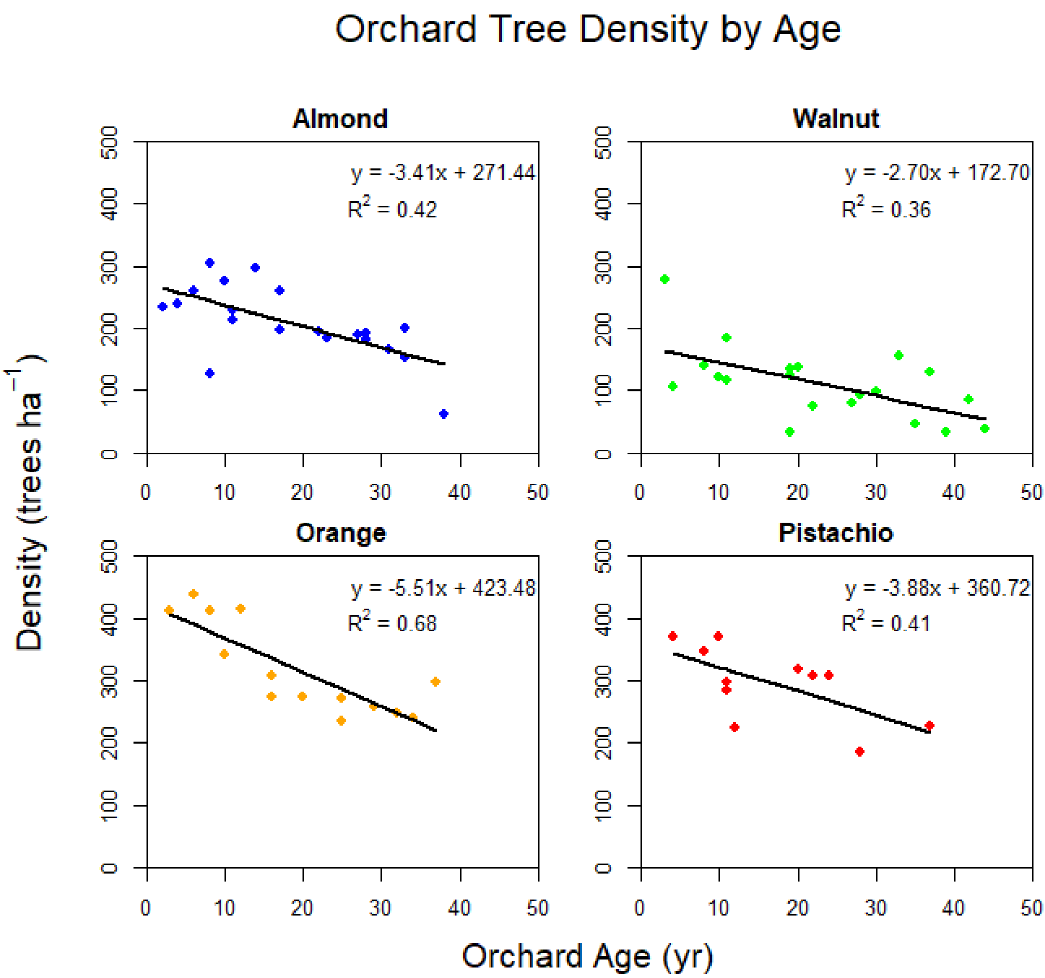

Figure 15. Orchard tree density by age for almond, walnut, oranges and pistachio. All orchard species show a decline in trees per hectare with increase in age.

The average above and belowground carbon storage for all California perennial croplands in 1997 was 29.7 ± 3.1 Tg and by 2012 the carbon grew to 42.7 ± 3.7 Tg. Statewide, almonds orchards were found to store the most carbon with 19.2 ± 4.0 Tg with an increase in land area going into almond production (2,299 to 3,787 km^2) from 1997 to 2012. Walnut orchards were second in terms of statewide carbon storage (14.8 ± 3.9 Tg in 2012) while only occupying approximately a third of the land area as almonds. Pistachio, orange and grape orchards stored the least amount of carbon in California with each having less than 4 Tg (**Figure 16** and **Table 9**).

Table 9. Above and belowground carbon storage for grapes, almond, walnut, pistachio, and orange orchards in California from 1997 – 2012.

	1997			2002			2007			2012		
	Carbon Tg	**95% CI Tg**	**Area km²**	**Carbon Tg**	**95% CI Tg**	**Area km²**	**Carbon Tg**	**95% CI Tg**	**Area km²**	**Carbon Tg**	**95% CI Tg**	**Area km²**
Total	29.7	3.1	8039	34.8	3.8	9101	35.6	3.7	9254	42.7	3.7	10629
Grapes	3.4	0.4	3400	3.6	0.5	3605	3.5	0.4	3514	3.8	0.4	3805
Almond	11.6	2.9	2299	14.3	3.6	2818	16.2	4.0	3198	19.2	4.0	3787
Walnut	11.2	3.6	1014	13.0	4.3	1173	11.9	3.9	1070	14.8	3.9	1332
Pistachio	1.4	0.4	390	1.7	0.5	492	2.2	0.6	613	3.3	0.6	924
Orange	2.1	0.5	935	2.2	0.5	1013	1.9	0.5	859	1.7	0.5	781

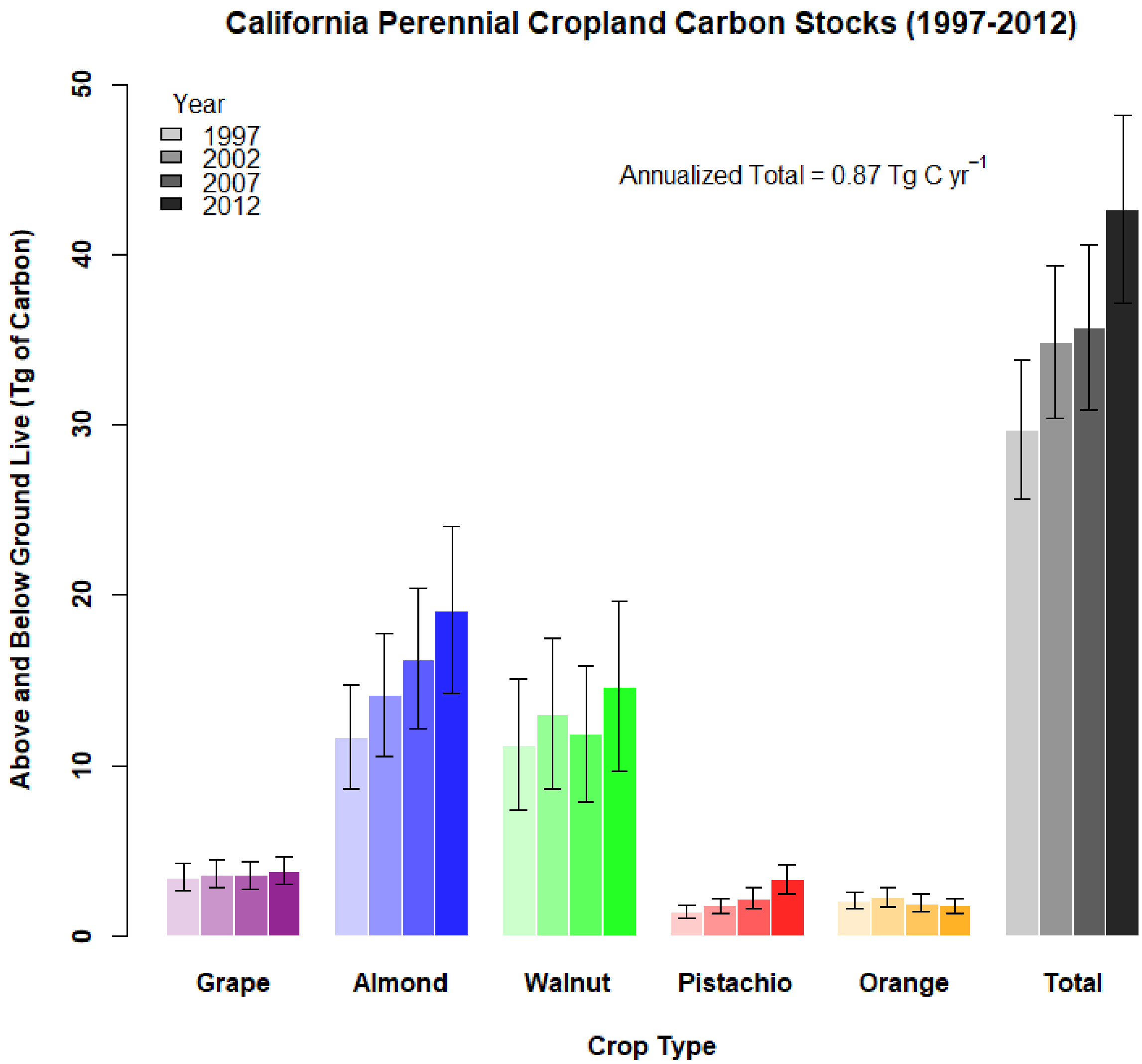

Figure 16. Statewide totals of above and below ground carbon every 5 years from (1997-2012). Almond and walnuts were found to store the most carbon while orange and pistachios had the least. The total carbon among orchards and vineyards has grown from about 29.7 Tg C in 1997 to 42.7 Tg CO2e in 2012.

Estimates of orchard age and carbon density values for almond, walnut, orange and pistachio were computed and mapped in California for the year 2010. As an orchard matures the tree canopy begins to fill in with dark green foliage while newly planted orchards consist of little foliage with bare ground that is tan in color (Figure 17**a**). Generally, trees from a given orchard were found to be of even-age, however CARB staff did observe canopy gaps within individual orchards resulting from dead trees that had been replanted. The Cropscape CDL provided spatial information of orchard types (Figure 17**b**) and were used to mask the Landsat time series for determining orchard age class (Figure 17**c**). Carbon densities estimates varied based on orchard type, tree density and age (Figure 17**d**).

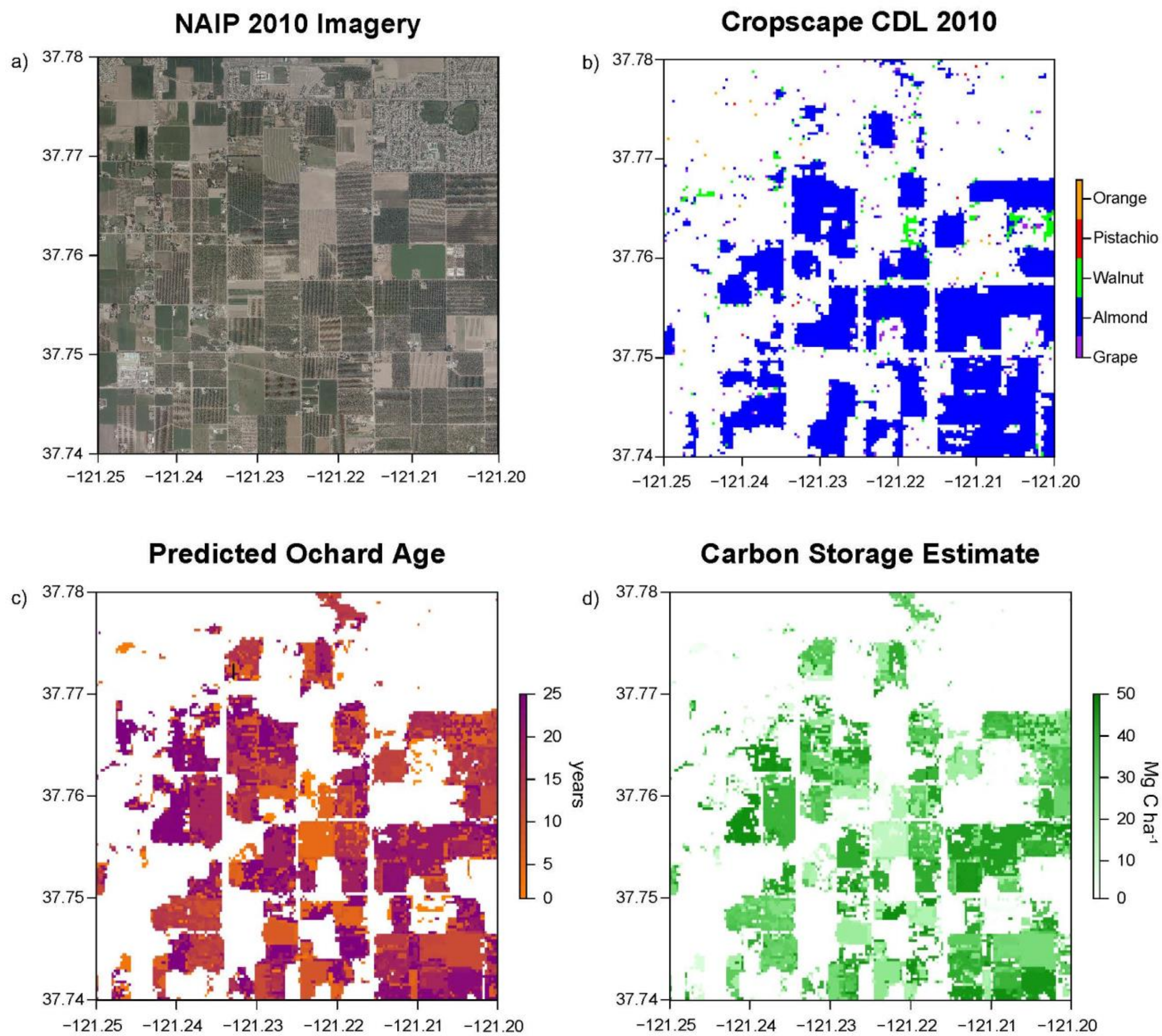

Figure 17. Orchard carbon density a) NAIP (1 m) imagery foliage density in dark green a result of orchard age and tree density. b) Cropscape 2010 (30 m) classification with dark green classified as almond and light green for developed (roads). C) Orchard age (years) (30 m) derived from Landsat imagery time series. D) Orchard carbon density map (Mg C ha-1) (30 m) resulting from orchard type and age.

By graphing a one-to-one line (n=45) comparing ground truth orchard age with the random forest classification age CARB staff found the slope to be 0.90 with an R^2 of 0.87 (**Figure 18**). Overall CARB staff found there to be a slight bias at under predicting the true age of the perennial crop. By looking at perennial crop age by land area were found California to be diverse with broad distribution spanning a wide range of age classes among all crop types (**Figure 19**).

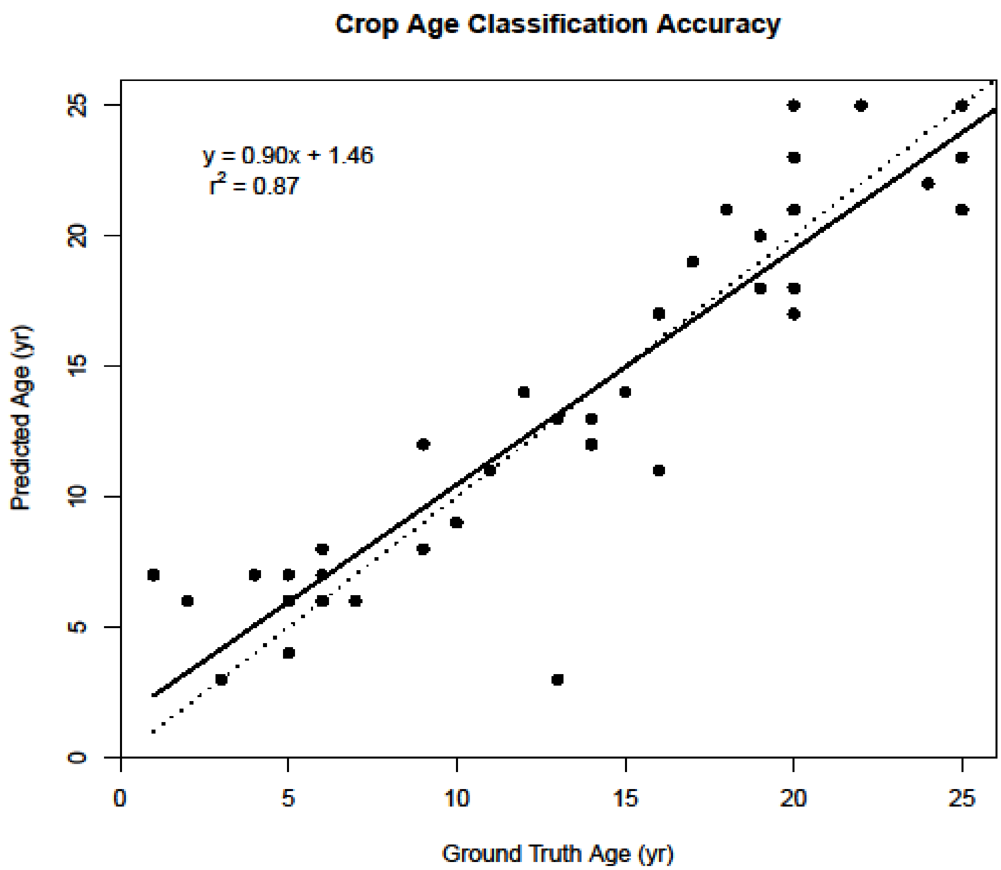

Figure 18. The relationship between ground truth and random forest estimates of perennial crop age. The solid line is the linear regression fit of random sampled age estimates (n = 45) with a slope of 0.90. The dotted line is 1:1 line with a slope of 1 and an intercept of 0. Comparison of the two lines show a slight over prediction of age in young orchard lands with a slight under prediction of age in older orchard lands.

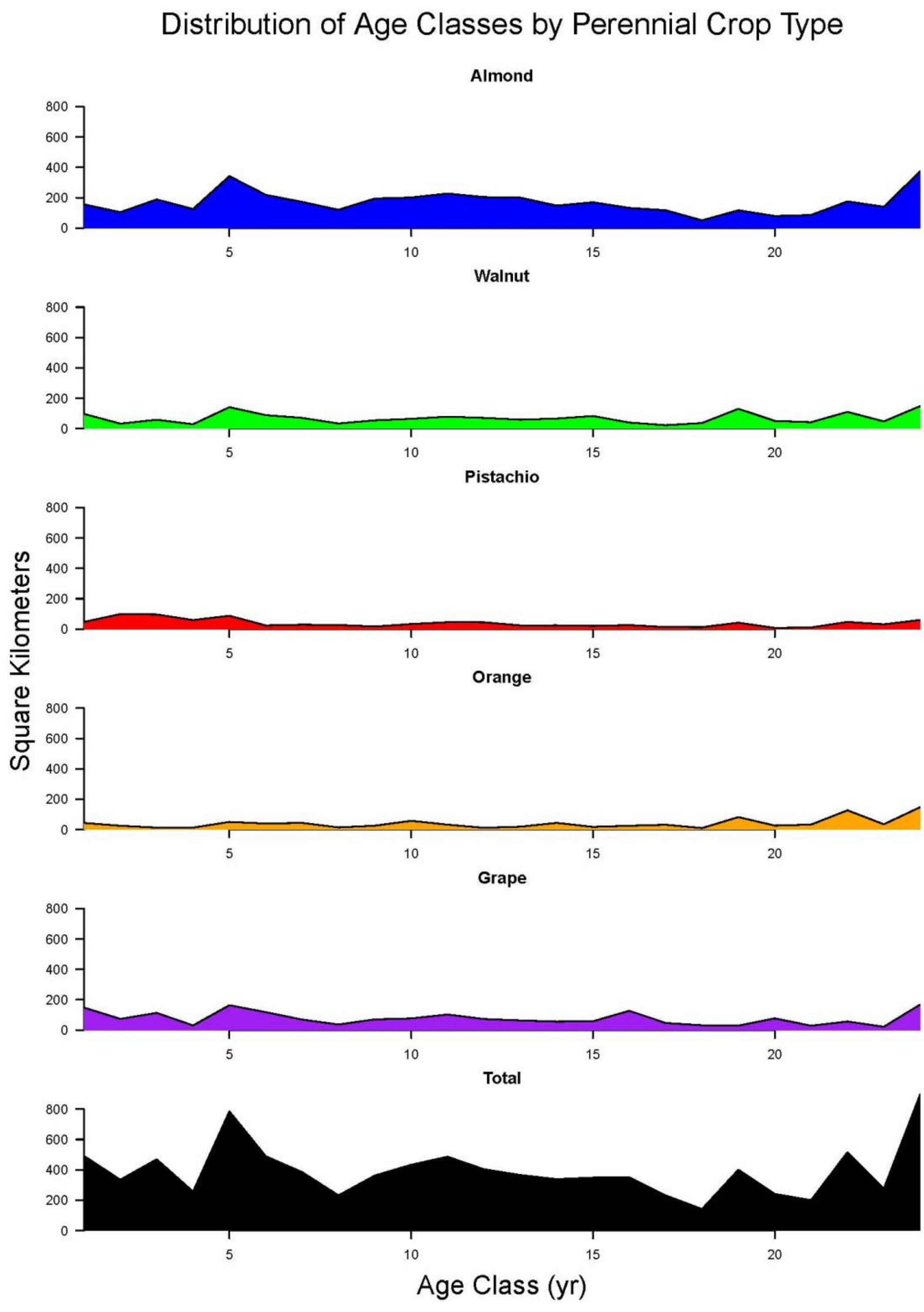

Figure 19. Distribution of age classes by land area for perennial crop types that include almond, walnut, pistachio, orange and grape. Note for grapes that Cropscape CDL land area is about half compared to what is reported by NASS Census data for California (**Table 7**). Orchards 24 years and older were grouped together due to Landsat data availability.

3D – Uncertainty

Despite there not being a directly comparable analysis of orchard land carbon storage statewide for California, our estimates of uncertainty were found to have the same order of magnitude as other publications studying natural and working land carbon pools (Gonzalez, et al., 2015) (Baccini, et al., 2012). While we did account for planting density and periodic orchard thinning over time, CARB staff were unable to capture the loss in biomass resulting from pruning. While DEMETER was able to track the age of vineyards, an allometric equation or age dependent biomass estimate was not available from the scientific literature to spatially track carbon. As a result, the growth or biomass accumulation for grapes with age could not be estimated and a non-age specific carbon density value of 10.0 Mg C ha^{-1} measuring only the woody components (cordons, trunk and roots) of the crop were used (Morande, et al., 2017). According to Kroodsma and Field's (2006) 21-year (1980-2000) analysis, California's agriculture lands sequestered a total of 14.5 Tg C statewide and when annualized this amounts to 0.69 Tg C yr^{-1}. The statewide DEMETER model found carbon sequestered on agriculture lands to be 13.05 Tg C (1997-2012) or 0.87 Tg C yr^{-1}. While the results are similar to Kroodsma and Field's (2006) estimates of California agriculture carbon storage, they do span different time periods and only overlap by a few years, making them difficult to directly compare.

Data quality and usability from other sources was strongly considered when building DEMETER in order to provide estimates of uncertainty for predicting carbon storage and annualized sequestration estimates. The NASS dataset has the most extensive survey and detailed information regarding acreage by crop type for the contiguous 48 states of the U.S.A. down to the county level. While this information is not provided in a spatial format directly, Cropscape CDL (https://nassgeodata.gmu.edu/CropScape/) provides a 30-m map of crop types built upon data from NASS, NLCD and Landsat, to create a carbon map for California's agriculture lands on an annual basis (Han, et al., 2012). We found Cropscape CDL's crop classification to have over 20% error, often making it a challenge to build a carbon map (particularly for vineyards) at a 30-m scale. For instance, significant sized regions of some crops such as vineyards in Sonoma County were unclassified or misclassified as natural lands. This reduced our confidence and ability in predicting carbon storage at fine scales (sub-county) while exceeding the NASS database resolution. More comprehensive remote sensing based land cover classification products for California agriculture lands are becoming available and may alleviate some of these challenges while serving to better inform CARB's retrospective NWL inventory. New crop cover maps are being created for California and may substitute the Cropscape CDL classification products (LandIQ, 2018).

3E – Discussion

CARB's DEMETER tool is intended to be used as a carbon accounting method for agriculture lands that can be refreshed annually and provide estimates of carbon stocks in California. The carbon storage map layers produced from DEMETER will be juxtaposed with CARB's other carbon mapping tools that span of land cover types such as forests, shrubs, grasslands and wildlands (Gonzalez, et al., 2015). The Municipal Estimated Tree Rate of Productivity on Lands in the State (METROPOLIS) tool developed by Bjorkman et al. (2015) and McPherson et al. (2017) is used to quantify and track carbon in the settlements IPCC land use category.

Other research has estimated carbon in orchard tree biomass that include almonds, walnuts and pistachios using life cycle assessment (LCA) models. Kendall (2012) devised the Time Adjust Warming Potential (TAWP) approach with an LCA that uses relative cumulative radiative forcing (CRF) and captures the difference in the emission or removal of GHGs at a particular point in time to that of an emission of CO_2 today. Marvinney et al. (2014) applied the TAWP method to run a business-as-usual scenario that included total carbon storage time (orchard lifespan) and found the average storage density to be 187.4, 981.3, 356.4 kg CO_2e ha^{-1} for almond, walnut and pistachio respectively. When considering the LCA with chemical inputs, mechanized operations and soil processes for orchard lands, Marvinney (2014) found the mean annual greenhouse gas (GHG) footprints to be 4260, 3480, 4050 kg CO_2e ha^{-1} for almond, walnut and pistachio respectively. While the DEMETER approach leverages remote sensing data to measure land use change, age class and crop type to estimate carbon storage, it does not look at the LCA. However, the State's anthropogenic GHG inventory maintained by the California Air Resources Board (CARB) does track many aspects of the LCA through quantification of GHG emissions resulting from fertilizer use and mechanized operation. CARB's GHG inventory also includes soil carbon fluxes that are modeled separately from the DEMETER model.

The observed decline in tree density with orchard age across all major orchard types likely resulted from mortality of individual trees over several decades. Replanting or replacing dead tree with young seedlings was observed from the World-View imagery and was most prevalent in younger orchards where older orchards consisted of gaps and lower number of trees per area. In the case of young orange orchards the densities were found to be quiet high (438 tree ha^{-1}) and are likely due to the tree's relatively small size throughout its life when compared to the nut trees CARB staff studied. While the 30m analysis did capture some intra-variation in orchard age class, CARB staff found the majority of the orchards to be of even-age. The maximum age, CARB staff found for a walnut orchard in 2010 was 38 years old, which was eventually harvested in 2018. Almond trees typically have a commercial lifespan of 25-30 years (Almond Board 2016) with walnuts and pistachio reaching 35 and 60 years respectively (Marvinney, et al., 2014).

Future climate change in California with rising temperatures and increasing drought has been predicted under many future climates scenarios and may reduce the extent where orchard trees can be commercially grown. According to Lobell et al. (2006) California crop yields of almonds, walnuts, avocados and table grapes are expected to decline through 2050 and while opportunities for expansion to cooler regions are possible, they are likely to be limited by non-climatic constraints. Given the rather long lifespan of orchards and vineyards (30-60 years), consideration of climate change should be a factor in selecting crop varieties and locations to plant in order ensure commercial viability and vigor. Many fruit and nut trees require locations that experience a winter chill to be commercially viable, which is likely to change with rising minimum daily temperatures. Under all global climate models (GCM) and emission scenarios, Luedeling et al. (2009) found that the lack of winter chill (chilling hours) in California would affect the ability to produce nuts on 50-75 percent of orchards by 2050 and 90-100 percent by 2100. While sterile orchard trees may continue to accumulate carbon, there may be little incentive for land owner to grow or keep the crops if temperatures continue to rise and the looming threat of drought becomes more frequent.

4 – Urban Forest

4A – Background

At 5 percent (21,538 km^2), urban forest make up a relatively small portion of California while co-located with 95 percent of the State's population providing unique greenhouse gas (GHG) and ecological benefits that promote human health. Urban forest reduce greenhouse gas (GHG) by sequestering and storing atmospheric CO_2 and reduce energy consumption by casting shade on residential and commercial buildings. In addition to sequestering atmospheric CO_2, urban trees also remove several common types of air pollution (O_3, PM_{10}, NO_2, SO_2 and CO) through dry deposition and rainfall interception (Nowak, et al., 2006). Having trees within the urban landscape provides other benefits to residents, many of whom who plant urban trees to increase their property value and aesthetics and to minimize heat effects and reduce exposure to UV rays and noise pollution (Bjorkman, et al., 2015). Although modest compared to wildlands, the combined total effects and close proximity of urban trees to people provide a unique net GHG and human health benefit.

To understand the composition and structure of urban trees in California, CARB staff started by looking at several field inventories. In general, all available urban forest inventories tend to be fragmented at the local level and not refreshed on a regular basis making it difficult to track changes in growth, planting and removal of trees. There are some existing urban forestry studies that capture the major urban centers of California and include Los Angeles, San Jose, Sacramento and parts of Sonoma County (McPherson, et al., 2013). Municipal street tree data record individual towns and cities, but vary in the level detail and information that is collected. The USDA Forest Service's Urban FIA program collects and maintains tree inventory data across the country including several cities in California. While the urban FIA inventory plots are more sparsely distributed than many of the municipal datasets, the sampling design is well equipped to provide statewide estimates on urban trees capturing information of smaller towns and communities. With a combination of all three types of inventories (UFORE, Municipal and Urban FIA) estimates of captured and stored CO_2e can be determined.

Priority areas for urban forests improvement projects have been evaluated by the State of California (CalFire) and the federal government (USDA Forest Service). CalFire's Fire Resource Assessment Program (FRAP) studies urban forest conditions and identifies areas for tree planting and maintenance based on the threat to property and is described in the California's Forest and Rangelands Assessment (2010). The FRAP assessment utilized the National Land Cover Dataset (NLCD) to map tree canopy and prioritize tree planting needs. The USDA Forest Service published a report entitled "Urban and Community Forests of the Pacific Region" (Nowak & Greenfield, 2010) that provides information and identifies areas for urban tree planting and maintenance based on population density, tree canopy and carbon storage. The Forest Service also relies on the NLCD land cover map to estimate tree canopy cover along with census data for demographic information.

CARB's approach to estimating CO_2e storage utilizes field inventory data following the Bjorkman et al. (2015) method to establish a 2010 baseline coupled with remote sensing to track changes in CO_2e storage over time. Bjorkman et al. (2015) found the CO_2e stored in California urban trees to be 102,995,988 metric tons in 2010. Since many of the urban forest inventories measure a large number of trees only once, CARB staff doesn't have a way to track the growth of the individual tree through repeated measurements. What is more is that field inventories take time and relying solely on them would create a lag and constrain the ability in maintaining a current up-to-date inventory. Consequently, CARB relies on remote sensing imagery from the USDA's National Agriculture Imagery Program (NAIP) to measure and record changes in canopy cover of urban areas for the entire state of California. Combining field tree inventories and biennial NAIP imagery, CARB staff track CO_2e

storage of California urban trees with the CARB staff derived method called “Municipal Estimated Tree Rate Of Productivity on Lands in the State (METROPOLIS).”

4B – Methodology

CARB’s METROPOLIS estimates of CO_2e storage (1995-2016) utilize several data sources and previously developed methods that span three major field inventories, urban forest growth models and high resolution remote sensing. Data used includes NAIP imagery and three field inventory plots: urban forest effects model (UFORE), urban forest inventory and analysis (FIA) and municipal (**Figure 20**). To estimate biomass and establish a CO_2e storage baseline, allometric equations found in forest growth models developed by the US Forest Service (iTree) are used. To track changes in the growth and losses of CO_2e spatially and temporally, remote sensing image analysis is completed to observe statewide changes in urban forest over time. To gauge the level of uncertainty of the method, CARB staff performed a Monte Carlo analysis to quantify sources of error in the estimates of CO_2e.

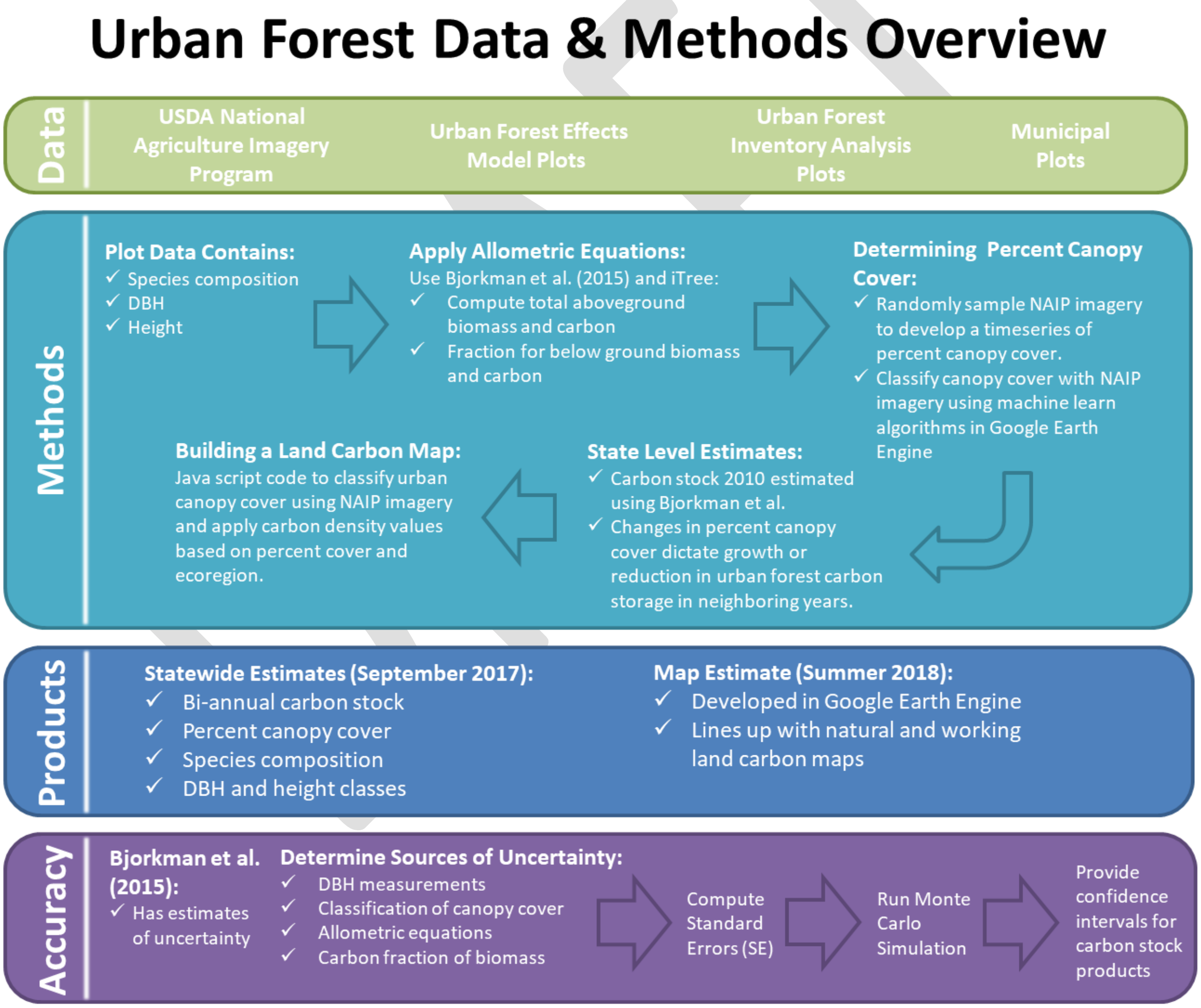

Figure 20. Overview of data, methods, products and accuracy of the METROPOLIS method in quantify carbon storage of urban forests.

The urban forest field data are drawn from three major datasets, which include the Urban Forest Effects Model (UFORE), the US Forest Service's Forest Inventory and Analysis (FIA) and Municipal Inventories. All three inventory types were collected using different protocols and at different times (Nowak, et al., 2006) (Bjorkman, et al., 2015). The UFORE protocol consists of 703 randomly located circular plots that are 0.04 ha in size capturing 1,913 trees within the urban boundary (Nowak, et al., 2008) (McPherson, et al., 2013) (**Table 10**). The UFORE plots are located in the cities of Los Angeles, Sacramento and Santa Barbara. The FIA dataset consist of 682 plots and 1,890 trees throughout 35 California counties with a plot size of 0.067 ha and a subplot of 0.0168 ha (Nowak, et al., 2008) (Bjorkman, et al., 2015). The municipal inventory consisted of 49 street tree inventories consisting of 908,304 trees from across California. All three urban tree inventories are important for determining the species composition, diameter at breast height (DBH) and height of trees.

Table 10. Taken from Bjorkman et al. (2015). The number of urban plots and trees sampled by climate zone in California. Three inventory types exists (FIA, UFORE and Municipal) that have different sampling protocols.

		Inland Empire	Inland Valleys	Interior West	North Cal Coast	South Cal Coast	Southwest Desert	Totals
FIA	# of plots	154	158	8	136	202	24	682
	# of treed plots	79	96	NA	85	109	14	383
	# of trees	335	436	NA	581	500	38	1,890
UFORE	# of plots	150	276	NA	NA	277	NA	703
	# of treed plots	92	163	NA	NA	153	NA	408
	# of trees	341	626	NA	NA	946	NA	1,913
Municipal Inventories	# of city inventories	17	8	NA	8	15	1	49
	# of trees	273,351	261,371	NA	147,659	215,624	10,299	908,304

Estimating a tree's biomass involves identifying the species and being able to measure the diameter of the main stem at breast height or 1.3 m above the ground. Each species will accumulate biomass differently and will have different wood densities relative to the diameter of the main stem. An allometric equation is often a species specific equation that estimates the total biomass of the main stem plus the branches and roots of the tree. In general, many tree species are found to exponentially grow biomass with increasing diameter and age, but the rate of growth and biomass acquired do vary by species. All trees found in the field inventories were processed using allometric equations within i-Tree Streets (http://www.itreetools.org/index.php) to estimate biomass and calculate CO_2e storage (**Figure 21**). Bjorkman et al. (2015) method and analysis establish a CO2e 2010 baseline estimate of all urban tree in California.

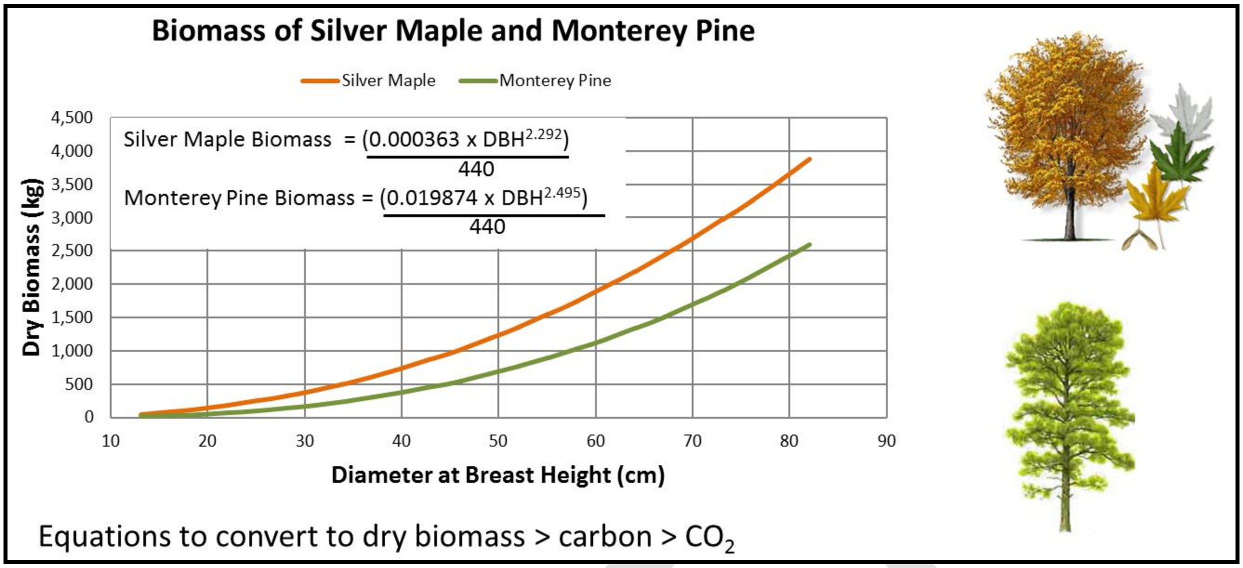

Figure 21. An example of how two species accumulate biomass differently with respect to growth in DBH. The orange line (Silver Maple) and green line (Monterey Pine) depicts the dry biomass accumulation with respect to the DBH. iTree has over hundred allometric equations that were used for different urban tree species each have a different dry biomass accumulation rate.

Tracking urban tree canopy cover with remote sensing is used to record growth and loss of urban trees. NAIP imagery is a 1 m product that is comprised of four bands (blue, green, red and near infrared). The near infrared band is particularly useful when studying live vegetation and often appears in contrast with the rest of the urban environment. Visible light is largely absorbed by most tree canopies particularly blue and red light where chlorophyll a & b are used for photosynthesis while reflecting mainly green light. CARB staff use near infrared light outside of the visible spectrum, which is highly reflective among live vegetation from other urban cover types such as bare ground, water and buildings (**Figure 22a**). Difference in the spectral reflectance can also vary by tree type (**Figure 22b**), canopy density and tree health.

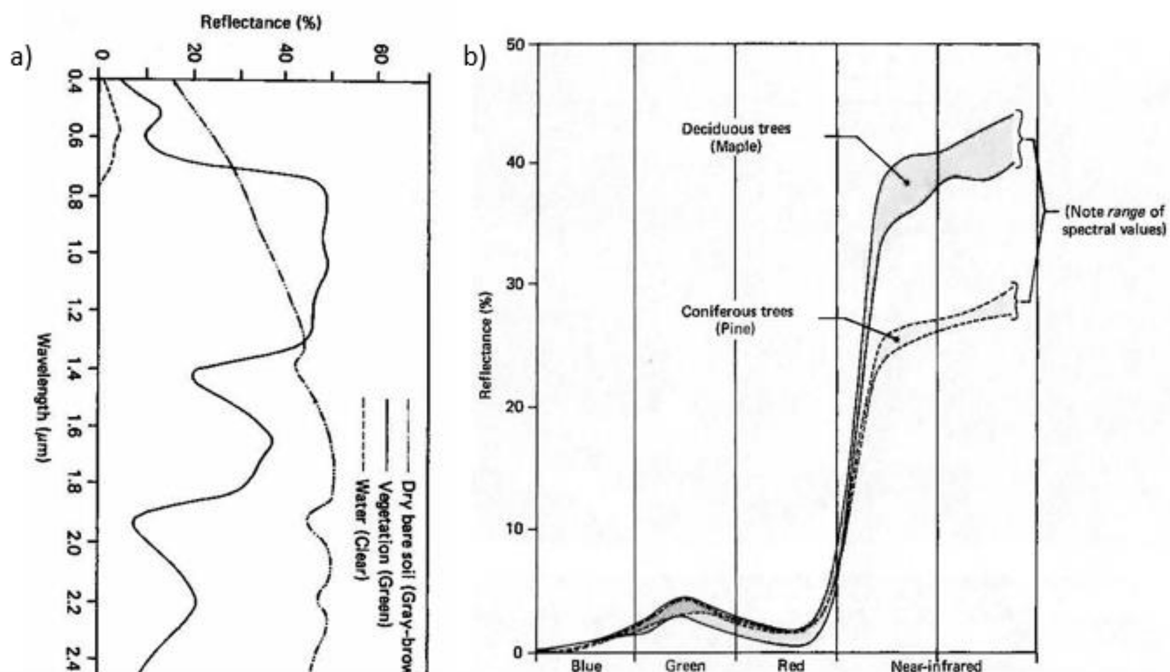

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Figure 22. a) Generalized spectral reflectance for deciduous and coniferous trees. Live vegetation is more reflective in the near infrared region than the visible (blue, green and red) part of the electromagnetic spectrum (Taken from Lillesand et al. 2003). **b)** A comparison of spectral reflectance of three major land cover type (dry bare soil, vegetation and water).

With the spectral information captured by the NAIP imagery the urban tree canopy can be delineated from the rest of the landscape and the area quantified. By having the computer display the green band as near infrared CARB staff can see the urban tree canopy clearly depicted from the rest of the urban landscape (**Figure 23**). To track changes in urban tree canopy cover, NAIP imagery spanning from 2005 to 2018 is compiled into a time series and then processed and analyzed.

Figure 23. NAIP false color image (bands: NIR, Red and Green) is used to identify the urban forest canopy from the rest of the urban landscape.

Prior to mapping the urban tree canopy using a computer based machine learning algorithm, CARB staff employed a photogrammetric sampling approach to establish a best estimate of the State's total urban tree canopy cover. The photogrammetric approach takes a 1 m NAIP imagery time series (2005 – 2016) and randomly samples 2,500 points state-wide within the urban boundary according to the U.S. Census (2010) to determine the fraction of urban tree canopy cover (**Figure 24**). For each time step an estimate of percent canopy cover, standard error and confidence intervals were computed. Plots that did not intercept the urban tree canopy largely consisted of building, roads, lakes, streams, turf grass, etc.

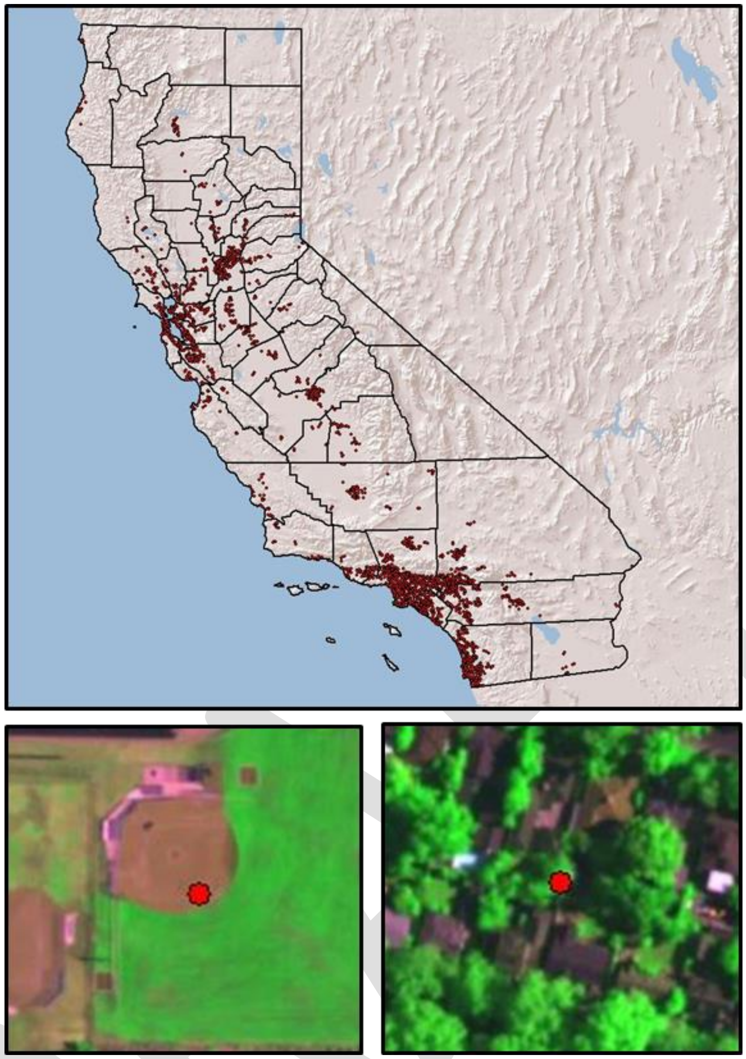


Figure 24. a) The map of California depicts a simple random sample locations (n = 2,500) used to track urban tree canopy cover through time (1995 – 2016). **b)** A point that intercepts bare ground of a baseball field. **c)** A second point that intercepts the urban tree canopy.

To estimate the proportion of urban area that contained tree canopy cover ($\hat{p}$), CARB staff recorded the total of number of points that had intercept an individual tree's crown (x) and divide it by the total number of random sample points (n) (**Equation 12**). The proportion of urban tree cover was estimated for Digital Orthophoto Quarter Quads (DOQQ) and NAIP imagery for the years 1995, 2005, 2009, 2010, 2012, 2014 and 2016.

$$\hat{p} = \frac{x}{n} \tag{12}$$

To quantify the uncertainty in the proportion estimate of urban tree canopy cover CARB staff calculated confidence intervals using an α = 0.05 and a critical value (z-score) = 1.96 (**Equation 13**).

$$\hat{p} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \tag{13}$$

To track California net (growth – loss) CO_2e urban forest storage (C_{Year}), CARB has expanded on the Bjorkman et al. (2015) method by developing METROPOLIS and quantifying the urban tree canopy cover over time. To do this, CARB staff compared the percent canopy cover for a given year ($Canopy_{year}$) relative to the 2010 canopy cover estimate ($Canopy_{2010}$) using the baseline estimate of 103 Tg of CO_2e (C_{2010}) (Bjorkman, et al., 2015) to determine whether net CO_2e storage had increased or decreased from the 2010 baseline (**Equation 14**). CO_2e storage of the urban forest was determined for each year that imagery was available (1995-2016).

$$C_{Year} = C_{2010}\ x\ \frac{Canopy_{year}}{Canopy_{2010}} \tag{14}$$

To provide regional urban forest storage estimates of CO_2e in California CARB staff looked at six climate zones that were used by the Bjorkman et al. (2015) approach. Climate zones provide a "clean" way to parse urban tree inventory along physiographic gradients (i.e. precipitation, temperature and soil), where differences in the urban tree species composition vary among these zones. CARB staff scaled the annualized state-wide estimates of CO_2e (that includes mortality and prunning) to reflect the Bjorkman et. al. (2015) estimates. To estimate annualized carbon sequestration by climate zone ($S_{climate\ zone}$), the ratio of the urban climate zone area ($A_{climate\ zone}$) to the State's urban area ($A_{state\ total}$) was multiplied by the State's total urban estimate of CO2e sequestration per year ($S_{state\ total}$) (**Equation 15**).

$$S_{climate\ zone} = S_{state\ total}\ x\ \frac{A_{cliamte\ zone}}{A_{state\ total}} \tag{15}$$

To determine the uncertainty of the urban forest CO_2e storage estimates CARB staff preformed one-thousand Monte Carlo simulations for each time period CARB staff had DOQQ or NAIP imagery (1995 – 2016). Sources of error include the field plot sampling (McPherson et al., 2016), allometric equations (Pillsbury et al. 1998), proportion of tree canopy and the carbon fraction (McGroddy, et al., 2004). The estimate of CO_2e storage for the baseline year 2010 ($\hat{C}_{2010}$) was calculated by multiplying by the carbon fraction (F_c) by the sum of the biomass of all the plots (B_{plot}) divide by the area of each plot (A_{plot}) (**Equation 16**). The X variable is a random number from a normal distribution with a mean = 0 and a standard deviation = 1. The SE variable is the standard error.

$$\hat{C}_{2010} = (F_c + X_{fc}SE_{fc}) \sum_{i=1}^{plot} \frac{(B_{plot} + X_{plot}SE_{plot})}{A_{plot}} \tag{16}$$

To estimate the uncertainty of carbon storage of urban forests outside the (2010) base year. CARB staff multiply baseline (2010) carbon estimate ($\hat{C}_{2010}$) by the proportion of urban tree canopy cover ratio for a given year ($\hat{p}_{year}$) to the base year ($\hat{p}_{2010}$) and the urban area of a given year (U_{year}) to the base year (U_{2010}) (**Equation 17**).

$$\hat{C}_{year} = \hat{C}_{2010}\ x\ \frac{\hat{p}_{year}+X_{year}SE_{year}}{\hat{p}_{2010}+X_{2010}SE_{2010}}\ x\ \frac{U_{year}}{U_{2010}} \tag{17}$$

Converting to CO_2e is calculated by multiplying the carbon estimate of a given year ($\hat{C}_{year}$) by the ratio between molar mass of carbon dioxide (M_{CO_2}) 44.01 g mol^{-1} and carbon (M_C) 12.01 g mol^{-1} (**Equation 18**).

$$\widehat{CO_2e}_{year} = \hat{C}_{year}\ x\ \frac{M_{CO_2}}{M_C} \tag{18}$$

To produce a carbon density map of the urban forest, CARB staff employed a machine learning approach with a random forest classifier that involves training a subset of the NAIP imagery into two classes, urban tree canopy and non-urban tree canopy (i.e. buildings, roads, and bare ground and water bodies). These training sites were used to inform the random forest machine learning algorithm in Google Earth Engine to predict the extent of the urban tree canopy statewide for the year 2010.

To study California's future urban forest, CARB staff looked at CARB's scoping plan (2017) to consider two scenarios involving low and high management for increasing California's urban forest canopy. The low and high management scenarios aims to increase the current urban forest canopy by 20% and 40% respectively by 2030. CARB staff calculate and present the potential CO_2e storage that could be found under these two scenarios with a growing urban tree canopy cover and compare them to the current trend. The methods for projecting future carbon stocks are the same as the retrospective approach in analyzing changes in canopy cover as a proxy for CO_2e storage.

4C – Results

With a simple random sample CARB staff estimate the urban tree canopy cover in California to be 14.4% in 2010 with a range of 12.1% in 1995 and a high as 15.5% in 2016 (**Table 11**). Overall the urban tree canopy has increased 3.4% from 1995 to 2016. The 2030 percent canopy cover values are the State's target for increasing and improving California urban forest under the low and high scenario (**Figure 25**).

Table 11. Urban tree canopy cover (UTC) for California by year (1995 – 2016) extracted from DOQQ and NAIP imagery.

	Year						
	1995	**2005**	**2009**	**2010**	**2012**	**2014**	**2016**
Mean CA UTC	12.1	13.1	13.7	14.4	14.6	14.6	15.5
Lower CI	10.8	11.8	12.4	13.0	13.3	13.2	14.1
Upper CI	13.4	14.4	15.1	15.8	16.0	16.0	16.9

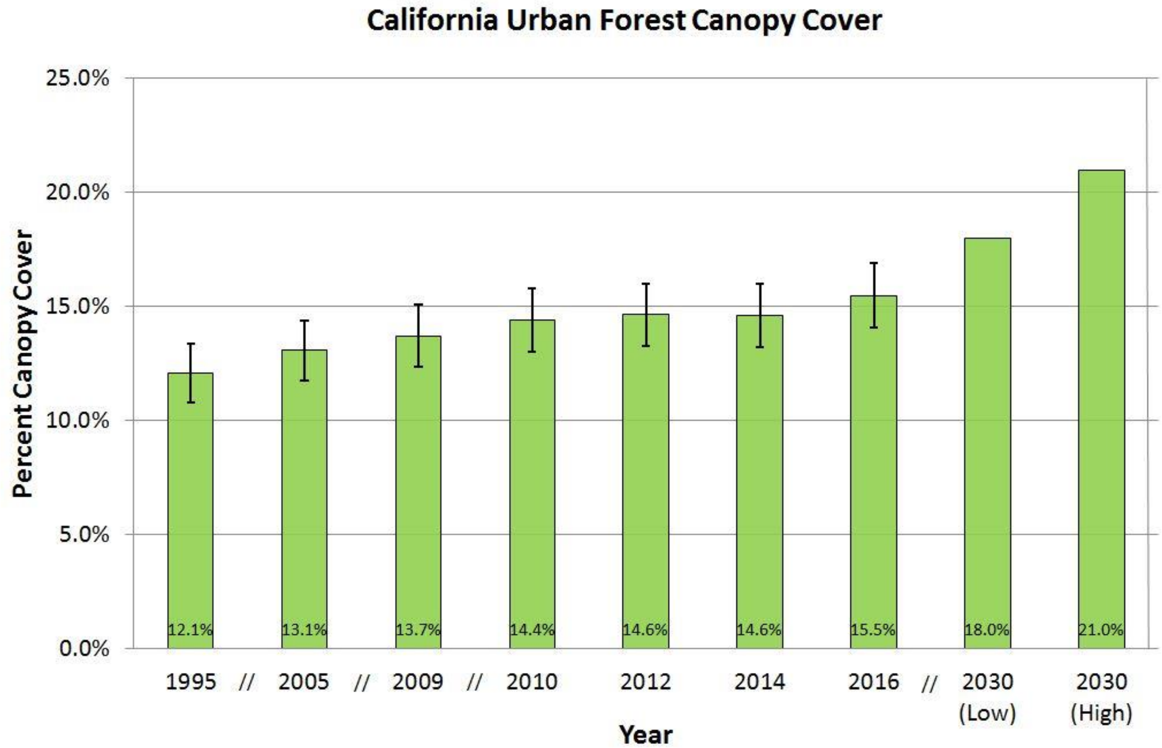


Figure 25. California urban forest canopy cover by year with error bars represent confidence intervals (α = 0.05). Changes in percent urban tree canopy cover was estimated from DOQQ (1990-1999), aerial imagery from the USDA NAIP (2005, 2009, 2010, 2012, 2014 and 2016). The point sample size, n = 2,500 for each year.

When calculating California's urban forest CO_2e storage, CARB staff found a net increase of 69 to 109 Tg over a 21-year period (1995 to 2016) (**Table 12**). This increase coincides with an urban expansion into crop and natural lands. To control for the increase CO_2e storage due to the growing urban footprint, CARB staff found the urban tree canopy cover to have also increase within the US Census (1990) urban footprint. This suggests an increase in urban forest CO_2e storage without urban expansion due to increase canopy cover (**Figure 26** and **Figure 27**). After 2010 NAIP imagery was flew more regularly allowing for biennial estimates of carbon storage.

Table 12. California urban forest CO_2e storage by year from 1995 to 2016 with two 2030 future scenarios. The first row shows stored CO_2e within the 1990 urban footprint. The second row presents CO_2e with a growing urban footprint as defined by the U.S. Census. The 2030 low and high estimates assumes a year 2010 urban footprint (*).

	Year								
	1995	**2005**	**2009**	**2010**	**2012**	**2014**	**2016**	**2030 (Low)**	**2030 (High)**
Tg CO_2e Stored (1990 Urban Footprint)	68.6	74.2	77.8	81.6	83.0	82.8	87.8	102.0	119.1
Tg CO_2e (with urban growth)	68.6	88.1	92.4	101.3	103.0	102.7	108.9	126.6*	147.7*
95% CI (Tg CO_2e)	7.3	8.9	9.1	9.7	9.7	9.7	10.0	-	-
Urban Area (km^2)	17333	20581	20581	21509	21509	21508	21508	21508	21508

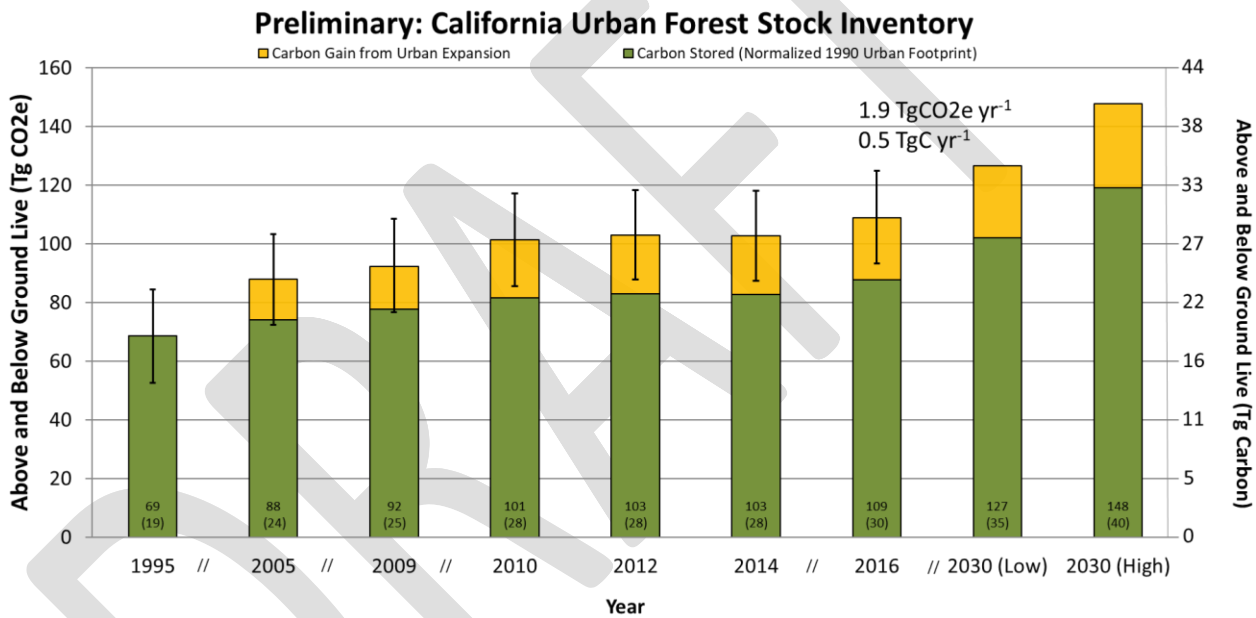


Figure 26. Above, shows California urban forest carbon inventory by year from 1995 to 2016. Error bar confidence intervals ($\alpha = 0.05$) were estimated through a Monte Carlo simulation evaluating error from four major sources (percent canopy cover, field sampling, allometric equations, and carbon fraction of biomass). California urban land area has increased from 17,333 to 21,509 km^2 from 1990 to 2010 (US Census). The Bjorkman et al. (2015) method was used to estimate CO2e for urban forest lands with data from urban FIA, UFORE and municipal tree inventories. Change in percent urban tree canopy cover was estimated from DOQQ (1990-1999), aerial imagery from the USDA NAIP (2005, 2009, 2010, 2012, 2014 and 2016).

CARB staff processed the urban FIA dataset with iTree to see how CO_2e storage was allocated by tree species across the California urban forest. Of the 185 species recorded, CARB staff found the top 3 urban trees to be native to California and include coast live oak (*Quercus agrifolia*) (15%), coast redwood (*Sequoia sempervirens*) (9%), and Monterey pine (*Pinus radiata*) (5%). Canary island pine (*Pinus canariensis*) (3%) and bluegum eucalyptus (*Eucalyptus globulus*) (3%) were found to share the greatest CO_2e storage among non-native urban tree in California (**Figure 26**).

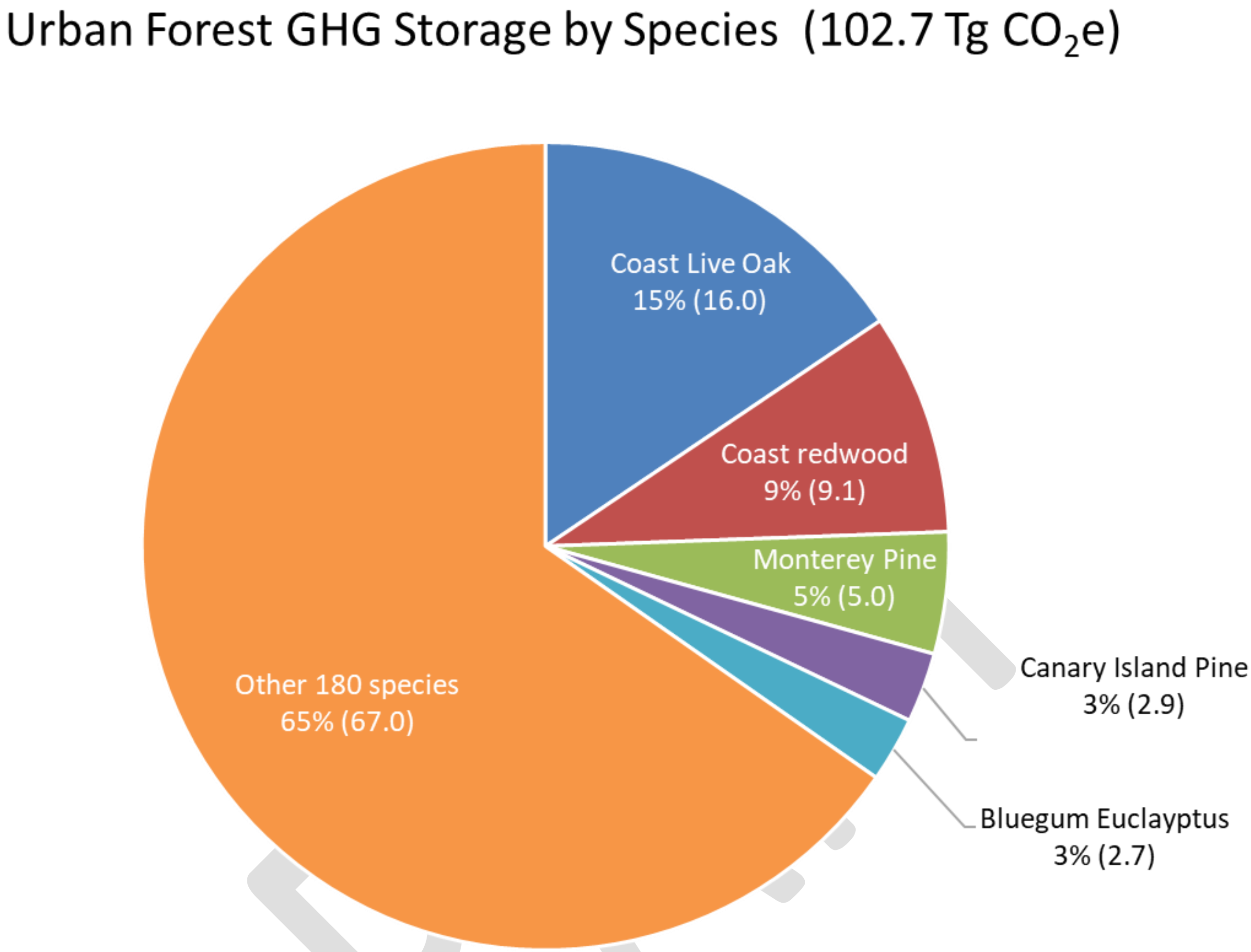


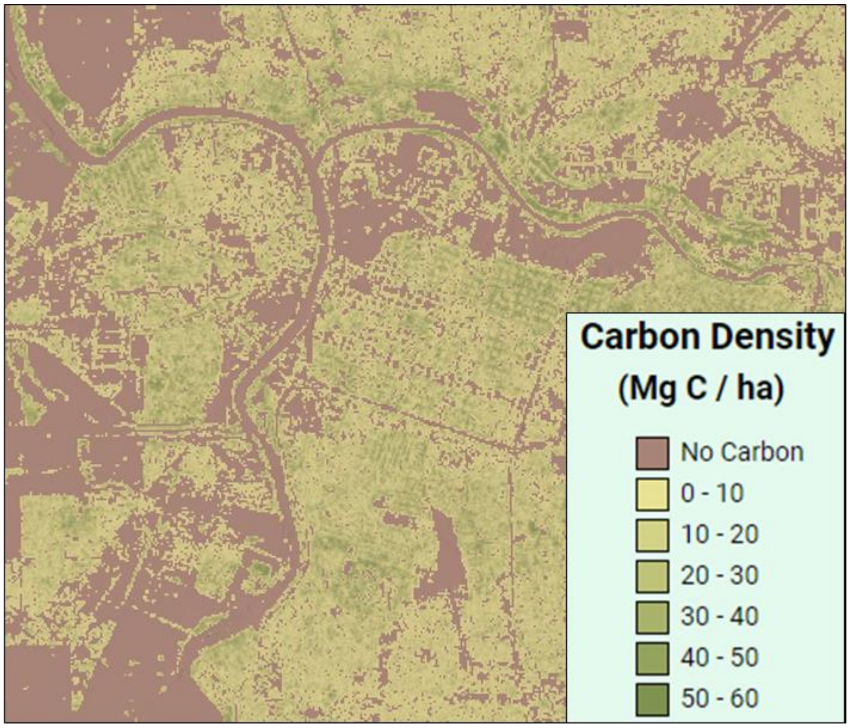
Figure 27. A 2010 distribution of CO2e storage among 185 tree species in California's urban forest.

Sequestering of carbon dioxide (CO2e yr-1) occur at different rates across the six climate zones of California urban forest. The northern California coast sequester the most per unit of land with 1.92 MT CO2e yr-1 ha-1, where the south west desert was found to have a lower sequestration density of 0.20 MT CO2e yr-1 ha-1. Rate of sequestration density varied greatly across California (**Table 13**). Estimate urban forest carbon density for 2010 were mapped onto a 30 m grid. CARB staff found higher densities of carbon along protected areas, city parks and older residential neighborhoods. Younger neighborhood showed lower carbon densities (**Figure 28**).

Table 13. Urban forest CO_2e storage and sequestration density for 6 California climate zones (Inland Empire, Inland Valleys, Interior West, Northern California Coast, Southern California Coast and Southwest Desert). The zones are based largely on the Sunset National Garden Book's 45 climate zones (Brenzel, 1997).

		Climate Zones						
		UA State Total	**Inland Empire**	**Inland Valleys**	**Interior West**	**N. CA Coast**	**S. CA Coast**	**SW Desert**
Bjorkman et al. 2015	*Urban Tree Canopy (ha)*	320,048	46,932	108,045	5,089	84,484	69,837	5,662
	CO_2 stored (metric tons)	102,995,988	11,504,190	35,544,868	1,389,054	33,768,935	19,823,727	965,214
	CO_2 sequestered (metric tons yr^{-1})	7,225,191	785,169	2,171,692	92,592	2,745,568	1,340,972	89,198
	Urban Land Area (km^2)	21,280	4,712	6,189	361	3,806	5,030	1,183
CARB METROPOLIS – Mortality Corrected	*(Tg CO2e yr^{-1})*	1.9	0.2	0.6	0.0	0.7	0.4	0.0
	(MT CO2e yr^{-1})	1,919,694	208,615	577,007	24,601	729,482	356,289	23,699
	(MT CO2e yr^{-1} ha^{-1})	**0.90**	**0.44**	**0.93**	**0.68**	**1.92**	**0.71**	**0.20**

a)



b)

Figure 28. a) Sacramento 2010 urban forest carbon density derived from machined learning urban tree canopy cover. **b)** Satellite image of Sacramento's urban forest.

4D – Uncertainty

The uncertainty associated with the annual urban forest carbon estimates is approximately +/- 10% each year. This uncertainty stems from the errors that could occur in the field sampling, allometric equations, proportion of canopy cover and the carbon fraction. These errors are typical when performing field based and remotely sensed measurements and must be aggregated to account for the full level of confidence. As more and newer field and remote sensed data becomes available and better allometry is derived, the confidence in these estimate will increase and the uncertainty will decrease.

4E – Discussion

The METROPOLIS method quantified carbon stocks of urban trees spanning over two decades (1995 – 2016) to see how urban forest carbon could be spatially mapped (2010) using field inventories of individual trees processed with iTree software. The field inventory was collected among different cities spanning several years over. Repeated measurement of the same tree to observe growth or tree mortality could not be extracted from these datasets. As a result, CARB staff estimated tree growth and loss from aerial imagery (NAIP) by capturing changes in canopy cover. The approach allows for tracking changes in CO_2e at 30 m starting in 1995 and biennial after 2010. Since the urban forest field inventory is not refreshed, CARB staff assume during the duration for the aerial imagery (1995-2016) that the species composition of the urban forest has not changed significantly and that the distribution of tree heights and DBH among the urban tree population in California remains relatively constant during this time period. METROPOLIS captures changes in CO_2e with respect to an increase or decrease canopy cover and urban land area. Ideally, to verify the assumptions, CARB staff would have revisited field plot data that could be used to further correct potential biases in the approach.

The urban tree canopy cover image classification is an integral part in being able to spatially track change occurring in urban forests and discover specific areas where urban forest are well stocked versus communities with under planted trees. There are other tree canopy cover classification products that are available that are comparable to the approach. First, Bjorkman et al. 2015 had used an urban tree canopy layer of California provided by a private company called Earth Define (2012). Their product estimated a statewide average tree canopy cover of 15.7 % with an overall accuracy of 82.4% for the year 2012. This approach involves calculating the presence and absence of classified 1 m tree canopy cover pixels over a 30 m grid to estimate percent tree canopy cover. Another approach is the Landsat Tree Cover Continuous Fields, which provides a 30 m grid of canopy cover and an estimate of uncertainty in woody vegetation greater than 5 meters in height (Sexton, et al., 2013). The Landsat Tree Cover Continuous Fields canopy cover product is available for years 2000, 2005 and 2010. CARB is continuing to explore new novel remote sensing approaches to spatially and temporally quantify and track urban forest canopy and CO2e storage of individual trees resulting from tree growth, planting, pruning and removal (**Figure 29**).

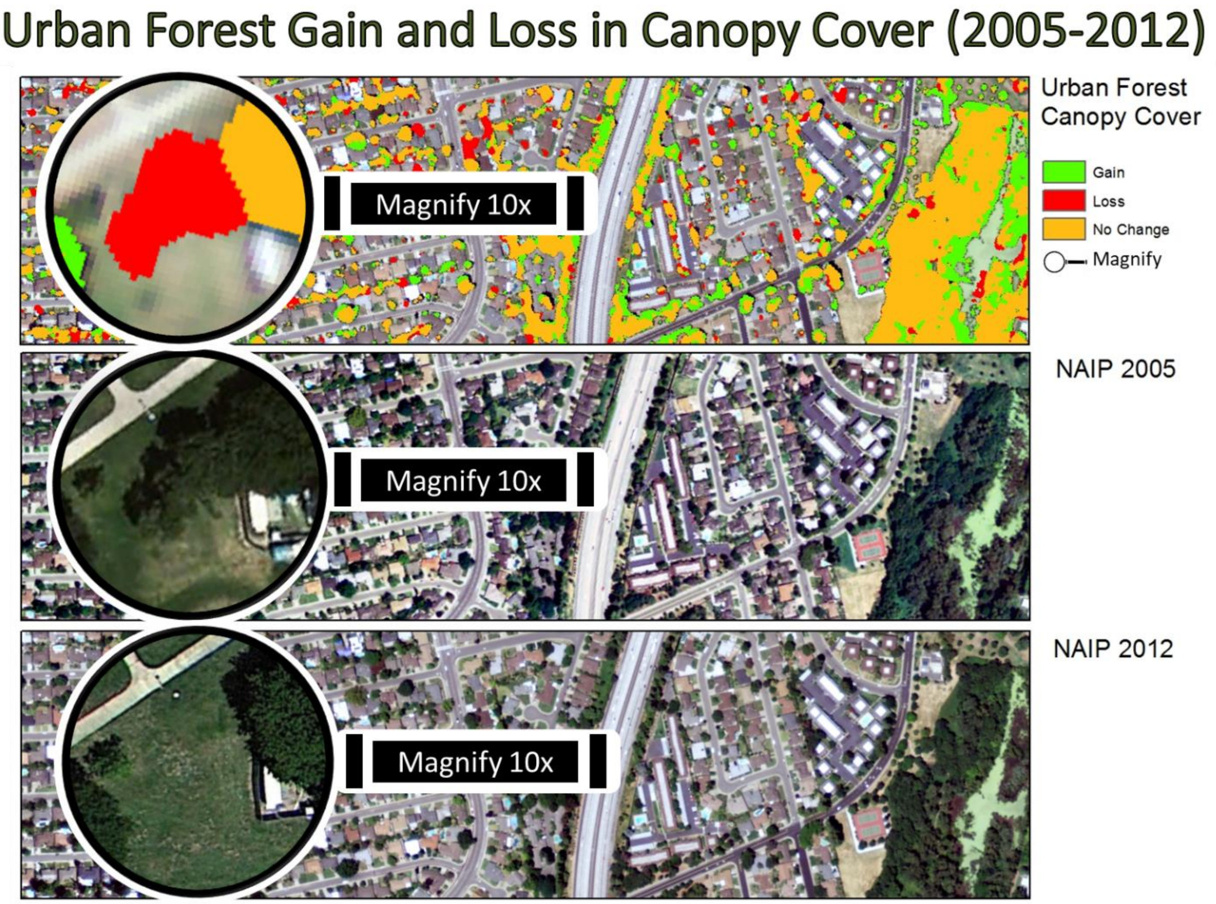


Figure 29. CARB is developing a new machine learning approach to track gains and losses in urban tree canopy cover. The top image shows the extent of the urban tree canopy in 2012 relative 2005. Areas in orange represents the urban tree canopy that remains unchanged, where light green pixel represent growth and red a loss in tree canopy cover between 2005 and 2012.

While urban forest only make up a modest 3% (103 Tg CO_2e) of the natural working lands GHG inventory, the trees' close proximity to people provides a unique opportunity to sequester CO_2 that is publicly visible along with providing many co-benefits (**Figure 30**). Despite the relatively modest GHG storage capacity of urban forest, carbon sequestered on these lands are very stable compared to California's natural forest lands that are experiencing a longer fire season with more intense and larger wild fires. In comparison to wild lands, urban forest are irrigated through the summer and are often well cared for by land owners and professional arborists. Urban lands do continue to expand, but existing urban areas are unlikely to undergo land type conversion enabling many trees to become old and large in both residential and commercial urban communities. Urban forests are potentially less likely to succumb to natural disasters that include wildfire, high winds and flooding as human population take measures to resist natural disasters. Lastly, urban forest carbon is likely to persist well into the future because of how the carbon is allocated, which is fairly well distributed across 185 species. This reduces the probability of a widespread impact from pests, pathogens or diseases, which the same cannot be said for California natural forests that consisting of a handful of dominant forest species making up the bulk of the carbon storage.

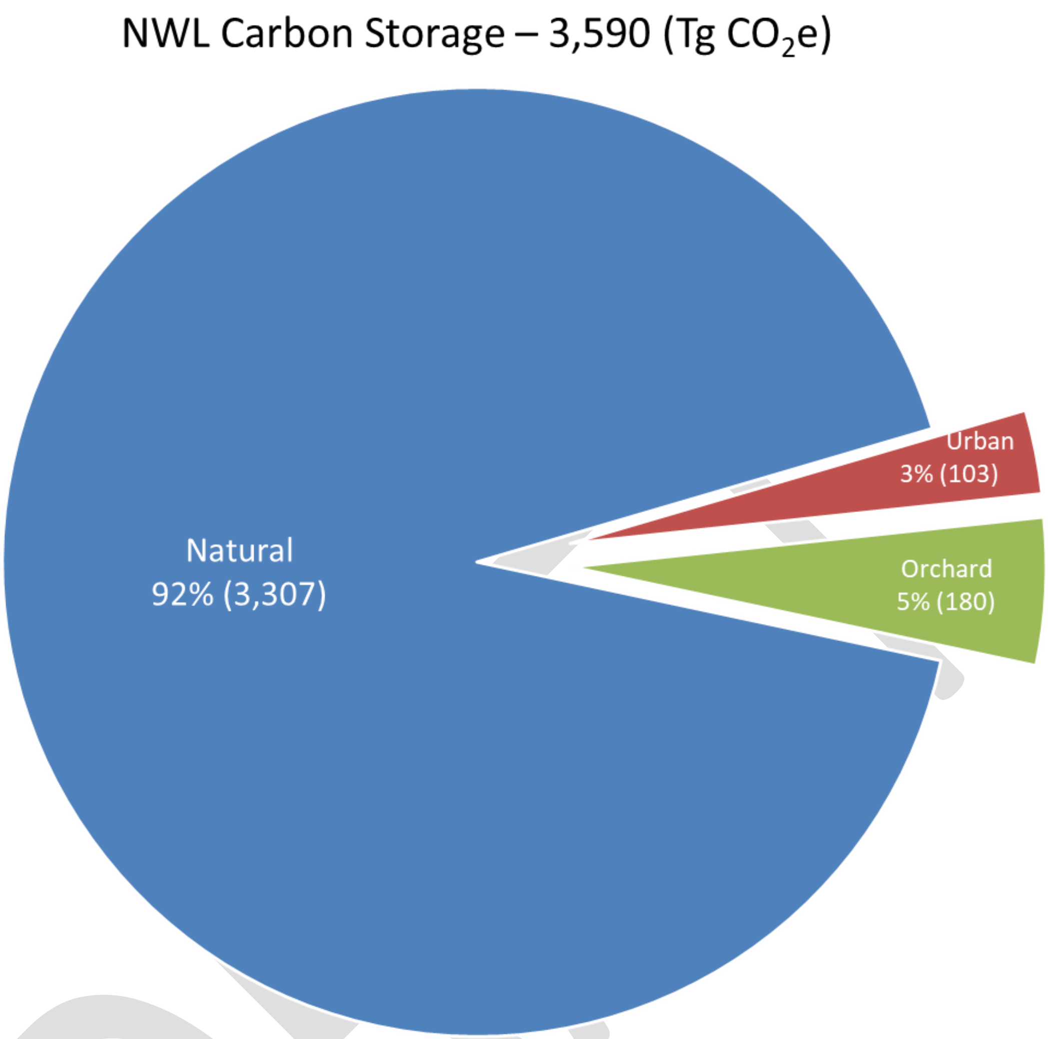


Figure 30. The urban forest carbon storage represents about 3% (103 Tg CO_2e) of the total natural and working lands carbon inventory (3,590 Tg CO_2e).

Urban forests continue to remain a predictable and reliable sink for atmospheric carbon to be stored. The land cover type, tree species diversity and co-benefits make them an obvious, healthy and safe choice to invest GHG reduction resources for promoting carbon storage. While urban lands are typically not under threat of land type conversion, they have and will likely continue to expand, replacing current agricultural and natural lands. Other natural and working lands serve many important functions to California's economy and provide a rich diverse ecology with their own unique carbon story to tell.

5 – Soil Organic Carbon – All Land Cover Types

5A – Background

A combination of IPCC Tier 3, Tier 2, and Tier 1 methodologies were used to develop soil carbon stock change estimates for the inventory time period of 2001 to 2010. The inventory was differentiated by IPCC land-use/land-use change categories (**Table 2**) from managed soils in order to calculate soil carbon stock change due to land cover change and management. The Tier 3 approach employed the process-based biogeochemical model DeNitrification-DeComposition (DNDC) (Li, et al., 1992) (Li, 2000) with California-specific activities data. The Tier 2 approach utilized the United Nations Intergovernmental Panel on Climate Change's (UN IPCC) 2006 IPCC Stock Difference Method, the SoilGrids soil organic carbon (SOC) raster dataset (ISRIC, 2018), and IPCC provided emission/stock change factors (IPCC, 2006a). Tier 1 used the emission factors provided in the IPCC methodology. All land cover was mapped using the LANDFIRE existing vegetation dataset crosswalked to the IPCC defined land use/cover categories (Battles, et al., 2013).

The DNDC model was used to estimate soil carbon stocks and stock change for all croplands, excluding cultivated, high organic matter containing soils (histosols) located on the Sacramento-San Joaquin Delta (hereafter referred to as the Delta). This includes croplands that remained croplands during the inventory period, croplands that were converted to other land types, and other land types that were converted to croplands (**Table 14**). For those lands that underwent conversion to/from cropland during the inventory period, DNDC was only used to model soil carbon stocks and stock change for the period during which those lands were classified as croplands. For the period before/after conversion the soil carbon stocks and stock change were calculated using the Tier 2 IPCC stock-difference approach. Similarly, soil carbon stocks and stock change for all other land use/land use change categories were calculated using the Tier 2 IPCC stock-difference approach. Emissions from the microbial oxidation of drained organic soils on the Delta were calculated using Tier 1 emission factors provided in the 2006 IPCC Greenhouse Gas Inventory Methodology (IPCC, 2006a).

Table 14. Land use/land use change categories for which soil carbon stocks and stock change were modeled at Tier 3 using the DNDC model.

IPCC Land Category	Category Code	IPCC Category
3B2 Cropland	3B2a	Cropland Remaining Cropland
3B2 Cropland	3B2bi	Forest Land Converted to Cropland
3B2 Cropland	3B2bii	Grassland Converted to Cropland
3B2 Cropland	3B2biv	Settlements Converted to Cropland
3B2 Cropland	3B2bv	Other Land Converted to Cropland
3B1 Forest Land	3B1bi	Cropland Converted to Forest Land
3B3 Grassland	3B3bii	Cropland Converted to Grassland
3B5 Settlements	3B5bii	Cropland Converted to Settlements
3B6 Other Land	3B6bii	Cropland Converted to Other Land

5B – Croplands – Tier 3

5B.1 – Background

The DNDC model (Li, et al., 1992) (Li, 2000) is a process-based computer simulation model of carbon and nitrogen biogeochemistry. It was developed to quantify carbon sequestration and greenhouse gas emissions in agroecosystems. Soil carbon stock and change on croplands were estimated using the DNDC model to the standard IPCC depth of 30 cm (IPCC 2006). The model was calibrated to California-specific cropland soil properties, management practices, and climate (Deng, et al., 2018b).

DNDC is driven by inputs for climate, soil, vegetation, and management practices. The core of DNDC consists of microbe-mediated biogeochemical processes common in terrestrial soils. The processes simulated by DNDC include decomposition, nitrification, denitrification, fermentation, and methanogenesis. DNDC simulates the rates of these processes by tracking various microbe groups' responses to environmental conditions, such as: temperature, soil moisture content, pH, redox potential (E_h), and substrate concentration gradient. Redox potential (E_h) is a key process in DNDC. Daily soil E_h following soil saturation was calculated using the Nernst Equation, which is a thermodynamic equation that calculates E_h based on concentrations of paired oxidative and reductive forms of dominant oxidants in the soil. Daily E_h was then used to determine the anaerobic microbial activity under a given set of soil conditions using standard Michaelis-Menten-type kinetics.

Figure 31 provides a functional overview of DNDC and how climate, soil, vegetation, and management practices influence E_h, dissolved organic carbon (DOC), substrate concentrations, and greenhouse gas (GHG) emissions in the model architecture. A full description of the DNDC scientific basis and processes, including all equations involved, is available at the DNDC hosting site at the University of New Hampshire (UNH, 2012).

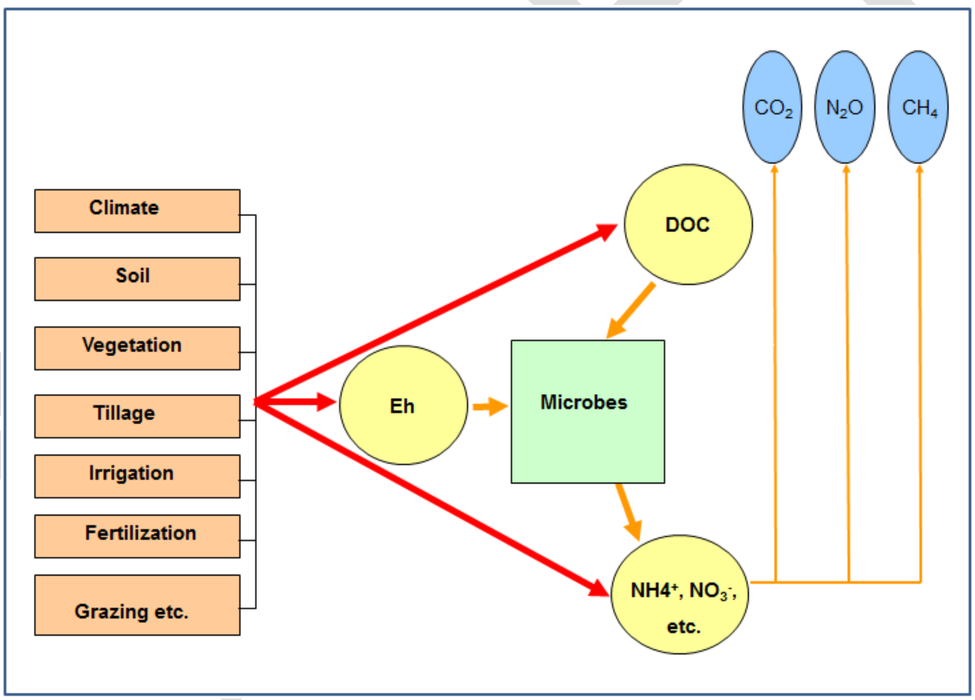


Figure 31. DNDC functional overview.

5B.2 – Methodology

Simulation of soil carbon fluxes to a 30 cm depth on croplands was performed by linking DNDC with both the California-specific database containing temporal and spatial information on weather, crop, soil, and farming management practices in California and annual DayMET weather data. Acreages per county per crop were obtained from the National Agricultural Statistics Service (USDA, 1999-2010a). For each reported year, model runs involved a simulated two year spin-up to initialize and equilibrate carbon to match reference field data. Model output from the third simulated year was used for reporting.

To harmonize the DNDC outputs with the rest of the inventory, first the discrepancies in cropland acreage had to be reconciled. The methodology by which acreage is reported to NASS inherently over-estimates total acreage because acreage is reported in terms of the acres of a crop type cultivated in a calendar year. This produces an over estimate because fields that support a crop rotation, which is a common agricultural practice, are accounted for more than once in the county cropland total. This is one source of discrepancy between the NASS tabular data and LANDFIRE geospatial data that was addressed in this iteration of the soil carbon inventory. NASS data was scaled to match the LANDFIRE geospatial dataset used to map land cover and land cover change for most of the NWL inventories (urban forest and woody cropland biomass excluded). To produce a more accurate depiction of the proportion of annual crops to perennial crops in the final inventory, the acreage of perennial crops (e.g. orchards and vineyards) were held constant per county. Annual crops were proportionally scaled back so that the total crop acreage in a county would match the LANDFIRE dataset and more accurately reflect the ratio of annual to perennial crops in each county. Finally, each crop was cross walked to a corresponding IPCC crop type for use in calculating SOC stock change before/and land cover conversion (**Table 15**). Please refer to the *Noncropland Mineral Soils – Tier 2* section for more detail.

Table 15. Crosswalk of NASS crop types and IPCC crop types.

NASS Crop Type	IPCC Crop Type	NASS Crop Type	IPCC Crop Type
Almonds	Tree	*Melons, Cantaloupe*	Long Term Cultivated
Apples	Tree	*Melons, Honeydew*	Long Term Cultivated
Apricots	Tree	*Melons, Watermelon*	Long Term Cultivated
Artichokes	Long Term Cultivated	*Mint, Peppermint Oil*	Long Term Cultivated
Asparagus	Long Term Cultivated	*Nectarines*	Tree
Avocados	Tree	*Oats*	Long Term Cultivated
Barley	Long Term Cultivated	*Olives*	Tree
Beans, Dry Edible	Long Term Cultivated	*Onions, Dry*	Long Term Cultivated
Beans, Snap	Long Term Cultivated	*Oranges*	Tree
Broccoli	Long Term Cultivated	*Peaches*	Tree
Cabbage	Long Term Cultivated	*Pears*	Tree
Carrots	Long Term Cultivated	*Peppers, Bell*	Long Term Cultivated
Cauliflower	Long Term Cultivated	*Peppers, Chile*	Long Term Cultivated
Celery	Long Term Cultivated	*Pistachios*	Tree
Cherries, Sweet	Tree	*Plums*	Tree
Corn, Grain	Long Term Cultivated l	*Potatoes*	Long Term Cultivated
Corn, Silage	Long Term Cultivated	*Prunes*	Tree
Cotton	Long Term Cultivated	*Pumpkins*	Long Term Cultivated
Cucumbers	Long Term Cultivated	*Raspberries*	Long Term Cultivated
Dates	Tree	*Rice*	Rice
Figs	Tree	*Safflower*	Long Term Cultivated
Garlic	Long Term Cultivated	*Spinach*	Long Term Cultivated
Grapefruit	Tree	*Squash*	Long Term Cultivated
Grapes, Raisin Type	Tree	*Strawberries*	Long Term Cultivated
Grapes, Table Type	Tree	*Sugarbeets*	Long Term Cultivated
Grapes, Wine Type	Tree	*Sunflower*	Long Term Cultivated
Hay, Excluding Alfalfa	Long Term Cultivated	*Sweet Corn*	Long Term Cultivated
Hay, Alfalfa	Long Term Cultivated	*Sweet Potatoes*	Long Term Cultivated
Haylage, Excluding Alfalfa	Long Term Cultivated	*Tangerines*	Tree
Haylage, Alfalfa	Long Term Cultivated	*Tomatoes*	Long Term Cultivated
Kiwifruit	Tree	*Tomatoes, Processing*	Long Term Cultivated
Lemons	Tree	*Walnuts, English*	Tree
Lettuce, Head	Long Term Cultivated	*Wheat, Spring*	Long Term Cultivated
Lettuce, Leaf	Long Term Cultivated	*Wheat, Winter*	Long Term Cultivated
Lettuce, Romaine	Long Term Cultivated		

Once the county cropland acreages were adjusted, they were combined with the SOC density (to a 30 cm depth) modeled with DNDC to produce the soil carbon stocks disaggregated by county and crop type. For croplands that remained croplands, this method was applied to the proportionally-adjusted cropland acreages, disaggregated by county, using the DNDC modeled SOC density for January 1, 2001 and December 31, 2010. The resultant calculation of soil carbon stock change was reported under IPCC category 3B2a – Cropland Remaining Cropland.

Areas that were mapped as cropland in 2001 but underwent conversion to another land use/land cover type utilized the same methods as described above to calculate soil carbon stock and stock change for the period of time that the land was classified as cropland. Since LANDFIRE does not provide information on the date of conversion, all conversion was assumed to occur at the end of December 31, 2005 – exactly halfway through the inventory time period. Stock change for the second half of the inventory period, January 1, 2006 – December 31, 2010, was calculated using the Tier 2

IPCC methodology described in the *Noncropland Mineral Soils - Tier 2* section. Stock change for the two halves of the inventory period were summed to report the total stock change from 2001 to 2010 per land use change category.

Lands that were converted to cropland were presumed to have undergone conversion at the same time as croplands that underwent conversion, on December 31, 2005. Stock and stock change on these lands from January 1, 2001 through December 31, 2005 were calculated using the IPCC Tier 2 methodology. Stock change from January 1, 2006 through December 31, 2010 was calculated by first quantifying the difference between the calculated soil carbon density of each raster cell and the average cropland soil carbon density for the county in which the cell was located as modeled by DNDC. This difference was divided by 20, which is the number of years that the IPCC methodology designates for the full effect of land use conversion to take place (IPCC, 2006b). This 20 year annualized difference was summed for each year after conversion, in this case 5 years, to quantify stock difference. Again, stock change for the two halves of the inventory period were summed to report the total stock change from 2001 to 2010 per land use change category.

5B.3 – Data Sources

A California-specific database was developed to contain daily meteorological parameters, crop acreage by crop type, soil properties, and management practices. Data were compiled by county and crop type.

Daily meteorological data for minimum and maximum air temperature, precipitation, and solar radiation were obtained from DAYMET (Thornton, et al., 2014). Statewide crop area data were from USDA's NASS QuickStats (USDA, 1999-2010a). County level crop area data were either downloaded from USDA for census years or interpolated between census years.

Soil characteristics data were obtained from USDA's Soil Survey Geographic Database (SSURGO) database (USDA, 1999-2010b). Key soil data included bulk density, clay content, soil organic carbon (SOC) content, and pH. Area-weighted means of soil properties for each county were calculated using a geographic information system (GIS), by overlaying SSURGO map units on to agricultural land-use spatial data from the California Department of Water Resources (CDWR, 2001-2010).

Inputs were developed for four irrigation methods: surface gravity irrigation (flooding), sprinkler, surface drip, and sub-surface drip (Deng, et al., 2018a). Crop irrigation method fractions were developed from data reported by CDWR for years 2000 to 2010. The baseline irrigation method and irrigation water depth for each crop were first determined from the "Cost and Return Studies" of the University of California at Davis (UC Davis, 2001-2010). The baseline irrigation depth was then varied using the ratios of 1.58, 1.27, 1.06, and 1.0 for surface gravity irrigation, sprinkler irrigation, surface drip, and subsurface drip, respectively, consistent with the reported water use efficiencies of the four irrigation methods of 60%, 75%, 90%, and 95% for flooding, sprinkler irrigation, surface drip, and subsurface drip, respectively (Brouwer, et al., 1989). The final irrigation depth was further adjusted for each county-based on the ratio of the county's annual mean air temperature to the state-mean air temperature so that more irrigation water would be applied for counties with a higher air temperature.

5C – Non-Cropland Mineral Soils – Tier 2

5C.1 – Background

Soil carbon stock change on non-crop lands was calculated using the 2006 IPCC Tier 2 methodology. These land types include Forest Land (IPCC category 3B1), Grasslands (IPCC category 3B3), Wetlands

(IPCC category 3B4), Settlements (IPCC category 3B5), and Other Lands (IPCC category 3B6). All stocks are reported to a 30 cm depth as designated by IPCC (IPCC, 2006b).

5C.2 – Methodology

This section provides the equations and methods used to estimate the carbon stocks and stock change for the soil stratum on all non-crop land types on mineral soil. The annual change in soil carbon stock was calculated on a per pixel basis using raster algebra in ArcGIS. Once the annualized change in soil organic carbon (SOC) stock was calculated for each pixel using the following series of equations, the carbon stock change values were summed by land cover/land cover change category to yield statewide carbon stock and change results for the 2001 to 2010 inventory period and multiplied by 10 to represent total change over the ten year inventory period. **Equations 20 through 22** were used to quantify the annual stock change for the soil carbon pool on mineral soils (IPCC, 2006b).

Equation 20: Annual Change in Carbon Stocks in Soils

$$\Delta \boldsymbol{C_{SOILS}} = \Delta \boldsymbol{C_{MINERAL}} - \boldsymbol{L_{ORGANIC}} + \Delta \boldsymbol{C_{INORGANIC}}$$

Where:

$\Delta C_{SOILS} = Annual\ change\ in\ carbon\ stocks\ in\ soils\ (tonnes\ C\ year^{-1})$
$\Delta C_{MINERAL} = Annual\ change\ in\ organic\ carbon\ stock\ in\ mineral\ soils\ (tonnes\ C\ year^{-1})$
$L_{ORGANIC} = Annual\ loss\ of\ carbon\ from\ drained\ organic\ soils\ (tonnes\ C\ year^{-1})$
$\Delta C_{INORGANIC} = Annual\ Change\ in\ inorganic\ carbon\ stocks\ from\ soils\ (tonnes\ C\ year^{-1})\ (assumed\ to\ be\ 0\ unless\ using\ a\ Tier\ 3\ approach)$

When calculating soil carbon stock change using the Tier 2 methodology, the $\Delta C_{INORGANIC}$ variable in **Equation 20** is assumed to be zero (IPCC, 2006b). The $L_{ORGANIC}$ variable will be discussed in the *Drained Organic Soils – Tier 1* section below. The annual change in organic carbon stock in mineral soils ($\Delta C_{MINERAL}$) was calculated using **Equation 21**.

Equation 21: Change in Soil Carbon Stock of Mineral Soils

$$\Delta C_{MINERAL} = \frac{(SOC_0 - SOC_{(0-T)})}{D}$$

Where:

$SOC_0 = Soil\ organic\ carbon\ stock\ in\ the\ last\ year\ of\ an\ inventory\ time\ period\ (tonnes\ C)$

$SOC_{(0-T)} = Soil\ organic\ carbon\ stock\ at\ the\ beginning\ of\ the\ inventory\ time\ period\ (tonnes\ C)$

$D = Time\ dependence\ of\ stock\ change\ factors, which\ is\ the\ default\ time\ period\ for\ transition\ between\ equilibrium\ SOC\ values\ (year)$

$The\ default\ value\ for\ D\ is\ 20\ years, which\ was\ used\ in\ this\ version\ of\ the\ inventory$

Equation 22: Reference Carbon Stock

$$SOC_0 = \sum (SOC_{REF} \cdot F_{LU} \cdot F_{MG} \cdot F_I \cdot A)$$

Where:

$SOC_0 = Soil\ organic\ carbon\ stock\ at\ the\ end\ of\ the\ inventory\ period\ (tonnes\ C\ ha^{-1})$

$SOC_{REF} = The\ reference\ soil\ carbon\ stock\ (tonnes\ C\ ha^{-1})$

$F_{LU} = Stock\ change\ factor\ for\ land-use\ systems\ for\ a\ particular\ land\ use\ (dimensionless)$

$F_{MG} = Stock\ change\ factor\ for\ management\ regime\ (dimensionless)$

$F_I = Stock\ change\ factor\ for\ input\ of\ organic\ matter\ (dimensionless)$

$A = Land\ area\ of\ the\ stratum\ being\ estimated\ (ha)$

5C.3 – Data Sources

Initial soil carbon stocks (SOC_{REF} in **Equation 22**) were retrieved from the global SoilsGrids geospatial dataset (ISRIC, 2018). The SoilGrids global dataset was clipped to the extent of California using GIS, and overlaid upon the 2001 LANDFIRE Existing Vegetation Type (EVT) raster dataset to map initial soil carbon stocks by IPCC land cover/land cover change category. EVT assignments to IPCC land categories are described in ARB contract final report 10-778 (Battles, et al., 2013).

The IPCC default stock change factors (**Table 16**) were the foundation for the stock change factors developed for use in this inventory. When creating a Tier 1 inventory, the defaults are used to accompany the Tier 1 default SOC densities in order to calculate the soil carbon stock at the beginning and end of the inventory period in **Equation 21** and **Equation 22**. The stock change factors are based on the assumption that varying land use and land management regimes will result in the landscape SOC density equilibrating at some fraction of the theoretical default maximum value, differentiated by climate regime, provided by the IPCC methodology. For example, forest lands are assumed to have stock change factors for land use (F_{LU}), management (F_{MG}), and organic matter inputs (F_I) equal to 1. Meaning that forest lands which have not experienced land use change in the previous 20 years are assumed to contain the maximum SOC density for the climate region in which they are located. California is defined as being located in the temperate (as opposed to boreal or tropical) climate region.

Since the SOC inventory was conducted at Tier 2 and did not use the IPCC provided default SOC densities, the default stock change factors were no longer applicable. In order to calculate SOC stock at the end of the inventory period while using the SoilGrids SOC density raster, new stock change factors were developed for each land use/land use change category using the proportional change of the default factors using **Equation 23**. The resulting factors that were used in the inventory are reported in **Table 17**.

Table 16. IPCC default stock change factors.

Land-Use Category	F_{LU}	F_{MG}	F_I
Cropland – Long Term Cultivated	0.80	1.00	1.00
Cropland – Tree Crops	1.00	1.00	1.00
Cropland – Rice	1.10	1.00	1.00
Forest Land	1.00	1.00	1.00
Grassland	1.00	0.95	1.00
Settlements	0.80	0.80	0.80
Other Lands[1]	NA	NA	NA
Wetlands	1.10	1.00	1.00

[1] At Tier 1, Other Lands are assumed to have a SOC stock = 0, so when land is converted to the Other Land cover type it is assumed to lose 1/20 of it's SOC stock every year during the 20 year transition period until either another land use change occurs or stock = 0.

Equation 23: Stock Change Factors Developed for the Tier 2 Methodology

$$\boldsymbol{F_{DEV}} = \frac{F_2}{F_1}$$

Where:

F_{DEV} = Stock change factor developed for the Tier 2 Methodology (dimensionless)
F_1 = Stock change factor for land − use systems for a particular land use at the beginning of the inventory period (dimensionless)
F_2 = Stock change factor for land − use systems for a particular land use at the end of the inventory period (dimensionless)

Table 17. Stock change factors developed for use in the Tier 2 California soil carbon inventory.

IPCC Category Code	IPCC Category Name	F_{LU}	F_{MG}	F_I
3B1bi	Long Term Cultivated Cropland Converted to Forest Land	1.25	1.00	1.00
3B1bi	Tree Cropland Converted to Forest Land	1.00	1.00	1.00
3B1bi	Rice Cropland Converted to Forest Land	0.91	1.00	1.00
3B1bii	Grassland Converted to Forest Land	1.00	1.05	1.00
3B1biii	Wetlands Converted to Forest Land	0.91	1.00	0.91
3B1bv	Other Land Converted to Forest Land	4.88	1.00	1.00
3B2a	Cropland Remaining Cropland	NA	NA	NA
3B2bi	Forest Land Converted to Long Term Cultivated Cropland	0.80	1.00	1.00
3B2bi	Forest Land Converted to Tree Cropland	1.00	1.00	1.00
3B2bi	Forest Land Converted to Rice Cropland	1.10	1.00	1.00
3B2bii	Grassland Converted to Long Term Cultivated Cropland	0.80	1.05	1.00
3B2bii	Grassland Converted to Tree Cropland	1.00	1.05	1.00
3B2bii	Grassland Converted to Rice Cropland	1.10	1.05	1.00
3B2biii	Wetlands Converted to Cropland	NA	NA	NA
3B2biv	Settlements Converted to Cropland	NA	NA	NA
3B2bv	Other Land Converted to Cropland	3.91	1.00	1.00
3B3a	Grassland Remaining Grassland	1.00	0.95	1.00
3B3bi	Forest Land Converted to Grassland	1.00	0.95	1.00
3B3bii	Long Term Cropland Converted to Grassland	1.25	0.95	1.00
3B3bii	Tree Cropland Converted to Grassland	1.00	0.95	1.00
3B3bii	Rice Cropland Converted to Grassland	0.91	0.95	1.00
3B3biii	Wetlands Converted to Grassland	NA	NA	NA
3B3biv	Settlements Converted to Grassland	NA	NA	NA
3B3bv	Other Land Converted to Grassland	3.40	1.00	1.00
3B4a	Wetlands Remaining Wetlands	NA	NA	NA
3B4b	Cropland Converted to Wetlands	NA	NA	NA
3B4b	Forest Land Converted to Wetlands	1.10	1.00	1.00
3B4b	Grasslands Converted to Wetlands	NA	NA	NA
3B4b	Settlements Converted to Wetlands	NA	NA	NA
3B4b	Other Land Converted to Wetlands	NA	NA	NA
3B5a	Settlements Remaining Settlements	1.00	1.00	1.00
3B5bi	Forest Land Converted to Settlements	0.80	0.80	0.80
3B5bii	Long Term Cultivated Cropland Converted to Settlements	1.00	0.80	0.80
3B5bii	Tree Cropland Converted to Settlements	0.80	0.80	0.80
3B5bii	Rice Cropland Converted to Settlements	0.73	0.80	0.80
3B5biii	Grasslands Converted to Settlements	0.80	0.84	0.80
3B5biv	Wetlands Converted to Settlements	NA	NA	NA
3B5bv	Other Land Converted to Settlements	0.94	0.94	0.94
3B6a	Other Land Remaining Other Land	1.00	1.00	1.00
3B6bi	Forest Land Converted to Other Land	0.20	1.00	1.00
3B6bii	Cropland Converted to Other Land	0.26	1.00	1.00
3B6biii	Grassland Converted to Other Land	0.29	1.00	1.00
3B6biv	Wetlands Converted to Other Land	NA	NA	NA
3B6bv	Settlements Converted to Other Land	1.00	1.00	1.00

Other Lands were a unique case that required additional stock change factor development because the IPCC provided stock change factors assumed that Other Lands had a stock = 0 tonnes C/ha (IPCC 2006) whereas all other lands (Forest Land, Grassland, Wetlands, Cropland, and Settlements) were assumed to have SOC > 0. At Tier 2 there were no lands with an SOC stock = 0 in the SoilGrids geospatial dataset, including Other Lands, and so land use stock change factors were developed for conversion from and to the Other Land category. The stock change factors for land use (the F_{LU} variable in **Equation 22**) were developed based on the principle put forth in the IPCC methodology that land use/land cover changes the SOC stock as a percentage of the regional maximum. Undisturbed land types, such as forests, are assumed to be at the maximum stock and more disturbed and/or degraded landscapes are assigned a fraction of the maximum stock. This factor was developed using the average SOC stock density for the land cover type at the end of the inventory period divided by the average SOC stock density for the land cover types the beginning of the inventory period. The average densities used for these calculations only included lands that did not undergo detected land cover change in the inventory period in order to All factors developed using this method are listed in **Table 18.** Conversion of Other Lands to Settlements and vice versa were calculated using the factors provided by IPCC. Other Lands remaining Other Lands (IPCC category 3B6a) were assumed to have no stock loss or gain, as per the IPCC methodology.

Table 18. Stock change factors for the land use category developed using the average statewide SOC density of each land type.

IPCC Category Code	IPCC Category Name	F_{LU}
3B1bv	Other Land Converted to Forest Land	4.88
3B2bv	Other Land Converted to Cropland	3.91
3B3bv	Other Land Converted to Grassland	3.40
3B6bi	Forest Land Converted to Other Land	0.20
3B6bii	Cropland Converted to Other Land	0.26
3B6biii	Grassland Converted to Other Land	0.29

5D – Drained Organic Soils – Tier 1

5D.1 – Background

The Tier 3 DNDC model was not appropriate for modeling cropland soil carbon fluxes on highly organic, or histosol, soils because DNDC is not calibrated to model the biogeochemistry of this soil type. The IPCC methodology treats soil carbon stock change on organic soils is differently than stock change on mineral soils (**Equation 20**). Namely, organic soils, or histosols, are assumed to be purely emissive and stock change is calculated using only emission factors that are differentiated by climate and land use.

In California, histosol soils are only found in the Sacramento-San Joaquin Delta (USDA, 1999-2010b) (**Figure 32**). To create a conservative estimate of emissions from organic soils, the Level 4 Delta Ecoregion as defined by the United States Geological Survey (USGS, 2016) was used to define the extent of organic soils in California.

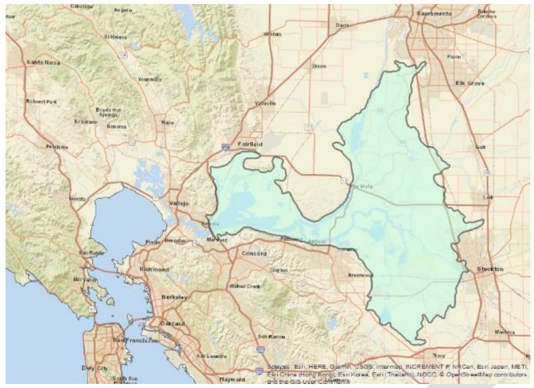


Figure 32. The Sacramento-San Joaquin Delta Ecoregion.

Prior to Euro-American settlement, the Delta was a 540 square mile tidal marsh characterized by deep peat soils (termed organic soils or histosols) slowly formed over millennia (Galloway, 1999). Peat is made of partially decayed organic matter that accumulates under waterlogged, and thus anaerobic, conditions. Since the late 1800s, drainage canals and levees have served to convert the Delta marshes into agricultural fields and orchards.

Drainage exposes peat to oxygen and triggers rapid microbial oxidation. This results in the continual release of large amounts of previously sequestered carbon to the atmosphere as CO_2. Peat oxidation is the principal cause of land subsidence in the Delta. Microbial oxidation of the Delta's drained, organic soils has resulted in severely subsided islands that are up to 25 feet below mean sea level (USGS, 2017). Subsidence driven by microbial oxidation continues at a rate of 1 to 3 inches per year, which translates to approximately 1.25 MMT of carbon lost annually from Deltaic soils.

5D.2 – Methodology

The 2001 - 2010 iteration of the soil carbon inventory calculates soil carbon stock change on histosol soils using the Tier 1 inventory approach. The carbon stock losses were quantified using **Equation 24**, which defines the calculation methods required to compute the $L_{ORGANIC}$ variable from **Equation 19**.

Equation 24: Annual Carbon Loss from Drained Organic Soils

$$L_{ORGANIC} = \sum (A * EF)_c$$

Where:

$L_{ORGANIC} = Annual\ carbon\ loss\ from\ drained\ organic\ soils\ (tonnes\ C\ year^{-1})$
$A = Land\ area\ of\ drained\ organic\ soils\ in\ climate\ type\ c\ (ha)$
$EF = Emission\ factor\ for\ climate\ type\ c\ \ (tonnes\ C\ ha^{-1}\ year^{-1})$

5D.3 – Data Sources

The acreage of each land use category located in the Delta Ecoregion was mapped using the LANDFIRE geospatial product published for 2001 – 2010 (LANDFIRE, 2018). Emission factors were provided in the IPCC methodology and disaggregated by land use type (Table 19).

Table 19. Drained organic soil emission factors by land-use type.

Land Cover Category	Emission Factor (tonnes C ha^{-1} $year^{-1}$)	Reference
Cropland	10	IPCC AFOLU Chapter 5
Forest Land	0.68	IPCC AFOLU Chapter 4
Grassland	2.5	IPCC AFOLU Chapter 6
Settlements	10	IPCC AFOLU Chapter 8
*Other Land**	2.5	IPCC AFOLU Chapter 6

*This iteration deviated slightly from the IPCC methodology with regards to treatment of Other Lands. The Tier 1 default SOC density for Other Lands is assumed to be 0 tonnes C ha-1 (IPCC, 2006i). Under this assumption, such soils would also not emit microbially oxidized CO2 from the SOC pool because that same SOC pool is assumed to be nonexistent and hence Other Lands are assumed to emit no CO2 from microbial oxidation on drained organic soils. After examining the areas mapped in the Delta that were mapped as Other Land, it was found that such lands were quite similar to those mapped as Grasslands in the area. In order to avoid a large under count of emissions, SOC losses from drained organic soils classified as Other Lands were assumed to emit at the same rate as Grasslands.

5E – Wetlands

5E.1 – Background

Wetlands are a unique land-cover type that experience inundation for all or part of the year. During inundation, the soil becomes anaerobic and microbes begin respiring via methanogenesis, which produces methane. Methane is a high global warming potential greenhouse gas (WP_{100} = 25). In addition to methane production, the anaerobic conditions caused by inundation also inhibit microbial decay of organic material. This process accumulates soil organic carbon in wetlands, and wetlands contain an outsized proportion of global soil organic carbon.

5E.2 – Methodology

CARB staff quantified soil organic carbon stock change and methane emissions from wetlands using IPCC Tier 1 methods, the California Aquatic Resources Inventory (CARI) geospatial dataset (SFEI, 2016), and the Habitat Restoration Tracker (SFEI, 2015) for the year 2016. The Tier 1 equations and methods used to calculate the emissions and removals from wetland soils are well documented in the 2013 IPCC Wetland Supplement (IPCC, 2013), hence readers are referred to the Wetlands Supplement for equations, but the assumptions used during the analysis will be detailed here. Tier 1 methods are emission factor based, meaning that emissions are calculated by multiplying the IPCC-supplied emission factor by the land area in each wetland category.

IPCC identifies 7 wetland types: 1) peatlands, 2) flooded lands, 3) drained organic soils, 4) rewetted organic soils, 5) coastal wetlands, 6) inland wetland mineral soils, and 7) constructed wetlands for wastewater treatment (IPCC, 2006) (IPCC, 2013). CARB staff identified that three of these seven types exist in California: 1) rewetted organic soils, 2) coastal wetlands, and 3) inland wetland mineral soils. The remaining four wetland categories either did not exist in California during the 2016 analysis year or existed in such small acreages as to be negligible (< 500 acres Statewide).

Net gains or losses of carbon resulting from the balance between CO_2 and CH_4 emissions and removals for rewetted organic soils was calculated using **Equations W – T**.

CARB staff calculated that wetlands in California emitted just under 1 MMT CO_2e during 2016 (**Table 20**).

Table 20. 2016 wetland emissions. Positive numbers indicate carbon stock increase in the soil and negative numbers indicate carbon loss via methane emissions and/or microbial oxidation.

IPCC Wetland Category	**CH_4 Emissions[1]** (MMT CO_2e)	**SOC C Stock Δ[2]** (MMT CO_2e)	**Net Emissions[3]** (MMT CO_2e)
Coastal Wetlands	0.00	-0.19	-0.19
Inland Wetland Mineral Soils	0.47	0.17	0.64
Rewetted Organic Soil	0.35	0.13	0.49
Total			**-0.94**

5D.3 – Data Sources

According to staff analysis, the 2001 mapping of wetlands was well matched with other datasets, including the National Wetlands Inventory and California Aquatic Resources Inventory. The 2010 mapping converted 99.98% of the wetland acreage mapped in 2001 to other land-use types, including wetland reserves such as the Suisun Marsh Reserve. To avoid enormous soil carbon losses from a clear geospatial modeling artifact, areas mapped as wetlands in 2001 were assumed to remain wetlands in 2010. Future iterations of the soil carbon inventory will attempt to address this issue, and all sections that were impacted by this mapping artifact are labeled To Be Determined (TBD). For further discussion see the "Future Refinements" section.

5F – Results

There were five key categories that generated 88% of total soil carbon losses: 3B2a – Cropland Remaining Cropland (-14 MMT C), 3B2bi – Forest Land Converted to Cropland (-7.1048 MMT C), 3B2bii – Grassland Converted to Cropland (-4.0521 MMT C), 3B6bi – Forest Land Converted to Other Land (-7.0 MMT C), and 3B3a – Grassland Remaining Grassland (-4.7 MMT C). The sole category that exhibited significant soil carbon gains was 3B1bv – Other Land Converted to Forest Land (13 MMT C). Other Land Converted to Forest Land comprised >99% of soil carbon gains for the State. Over the ten year inventory period of 2001 to 2010, an estimated net total (the sum of all stock gains and losses) of 25 MMT C was lost from California soils (**Table 21**). This trend is primarily driven by management practices on the Deltaic drained organic soils and land-use change.

The primary driver behind the large soil carbon losses form IPCC Category 3B2a – Cropland Remaining Croplands is the highly emissive nature of drained organic soils cultivated for crop production. Once such soils are drained, the organic matter that once accumulated under anaerobic conditions is exposed to the atmosphere and undergoes microbial oxidation, resulting in CO_2 emissions. Approximately 125,000 hectares of Cropland Remaining Cropland (LANDFIRE, 2018) were cultivated on drained organic soil for the inventory period; this amounts to just over 3% of the total acreage in this category, yet accounts for 88% of the total category soil carbon losses and 30% of total losses across all land-use categories for the inventory period. In relation to all other categories, 3B2a accounts for 9% of the total acreage but 48% of net SOC stock change (**Table 22**).

Soil carbon losses associated with land-use conversion from Forest Land to Other Land are hinged on the IPCC assumption that Other Land soils have a relatively low carbon density as compared to forest lands, and that lands in this conversion category will quickly loose soil carbon over the 20 year transition period (IPCC, 2006b). Since this inventory period is 10 years and transition was assumed to occur after 5 years, one-quarter of the original soil carbon stock for this land use category was calculated as lost to the atmosphere. The reverse is true for Other Land Converted to Forest Land (IPCC category 3B1bv), which would accumulate soil carbon stocks from the minimum stock density to maximum stock density for the climate regime over a 20 year transition period. This relative change is driven by the stock change factors F_{MG} and F_{LU} in **Equation 23**.

Soil carbon stock losses on Grasslands that Remained Grasslands were derived from the IPCC stock factor for management regime (F_{MG} in **Equation 23**) for slightly degraded grasslands. The slightly degraded F_{MG} factor was chosen because the vast majority of California's grasslands are dominated by invasive annual grasses that decrease the soil carbon stock as compared to California grasslands dominated by native species [REFERENCES] (Barry, et al., 2006) . This factor determined that California's grassland soils were slightly emissive. All remaining categories accounted for 81% of the State's land area but only 17% of total fluxes (**Table 22**).

Table 21. 2001 – 2010 change in soil carbon stocks. Ecosystem budget sign convention: gains (+) to SOC stock, losses (-) from SOC stock to the atmosphere. Note categories To Be Determined (TBD) and Not Applicable (NA).

IPCC Land Category	**Category Code**	**IPCC Category**	$\Delta C_{MINERAL}$	$L_{ORGANIC}$	ΔC_{SOILS}
			MMT C		
3B1 Forest Land	3B1a	Forest Land Remaining Forest Land	0.0000	-0.0098	-0.0098
	3B1bi	Cropland Converted to Forest Land	0.0020	-0.0001	0.0021
	3B1bii	Grassland Converted to Forest Land	0.0039	< -0.0000	0.0039
	3B1biii	Wetlands Converted to Forest Land	TBD	TBD	TBD
	3B1biv	Settlements Converted to Forest Land	NA	NA	NA
	3B1bv	Other Land Converted to Forest Land	12.5929	< -0.0000	12.5929
	Subtotal		**-12.5748**	**-0.0099**	**12.5847**
3B2 Cropland	3B2a	Cropland Remaining Cropland	-1.7232	-12.4521	-14.1753
	3B2bi	Forest Land Converted to Cropland	-7.0504	-0.0544	-7.1048
	3B2bii	Grassland Converted to Cropland	-4.0178	-0.0343	-4.0521
	3B2biii	Wetlands Converted to Cropland	TBD	TBD	TBD
	3B2biv	Settlements Converted to Cropland	NA	NA	NA
	3B2bv	Other Land Converted to Cropland	-0.4899	< -0.0000	-0.4899
	Subtotal		**-13.2813**	**-12.5408**	**-25.8221**
3B3 Grassland	3B3a	Grassland Remaining Grassland	-4.6764	-0.0608	-4.7372
	3B3bi	Forest Land Converted to Grassland	-1.5625	-0.0012	-1.5637
	3B3bii	Cropland Converted to Grassland	0.0001	< -0.0000	0.0001

	3B3biii	Wetlands Converted to Grassland	TBD	TBD	TBD
	3B3biv	Settlements Converted to Grassland	NA	NA	NA
	3B3bv	Other Land Converted to Grassland	0.0482	< -0.0000	0.0482
	Subtotal		**-6.1906**	**-0.0620**	**-6.2526**
3B4 Wetlands	3B4a	Wetlands Remaining Wetlands	TBD	TBD	TBD
	3B4bi	Forest Land Converted to Wetlands	0.0002	NA	0.0002
	3B4bii	Cropland Converted to Wetlands	TBD	TBD	TBD
	3B4biii	Grassland Converted to Wetlands	TBD	TBD	TBD
	3B4biv	Settlements Converted to Wetlands	TBD	TBD	TBD
	3B4bv	Other Land Converted to Wetlands	TBD	TBD	TBD
	Subtotal		**0.0002**	**NA**	**0.0002**
3B5 Settlements	3B5a	Settlements Remaining Settlements	-0.5628	-0.9093	-1.4721
	3B5bi	Forest Land Converted to Settlements	-0.0843	-0.0007	-0.0850
	3B5bii	Cropland Converted to Settlements	-1.0470	-0.0856	-1.1326
	3B5biii	Grassland Converted to Settlements	-0.0768	-0.0005	-0.0773
	3B5biv	Wetlands Converted to Settlements	TBD	TBD	TBD
	3B5v	Other Land Converted to Settlements	-0.0011	NA	-0.0011
	Subtotal		**-1.7721**	**-0.9961**	**-2.7682**
3B6 Other Land	3B6a	Other Land Remaining Other Land	NA	-0.0016	-0.0016
	3B6bi	Forest Land Converted to Other Land	-6.9782	-0.0001	-6.9783
	3B6bii	Cropland Converted to Other Land	-0.1099	-0.0123	-0.1222
	3B6biii	Grassland Converted to Other Land	-0.2764	< -0.0000	-0.2764
	3B6biv	Wetlands Converted to Other Land	TBD	TBD	TBD
	3B6v	Settlements Converted to Other Land	NA	NA	NA
	Subtotal		**-7.3645**	**-0.0140**	**-7.3785**
Total MMT C			**-16.0148**	**-13.6228**	**-29.6376**

Table 22. 2001 – 2010 land-use change percentage of land area and soil carbon flux. Note categories To Be Determined (TBD) and Not Applicable (NA).

IPCC Land Category	**Category Code**	**IPCC Category**	**Area (%)**	**SOC Stock Δ (%)**
3B1 Forest Land	3B1a	Forest Land Remaining Forest Land	61.30	0.02
	3B1bi	Cropland Converted to Forest Land	<0.01	0.03
	3B1bii	Grassland Converted to Forest Land	0.12	0.32
	3B1biii	Wetlands Converted to Forest Land	NA	NA
	3B1biv	Settlements Converted to Forest Land	NA	NA
	3B1bv	Other Land Converted to Forest Land	1.42	18.46
	Subtotal		**62.85**	**18.85**
3B2 Cropland	3B2a	Cropland Remaining Cropland	9.70	33.33
	3B2bi	Forest Land Converted to Cropland	0.37	1.53
	3B2bii	Grassland Converted to Cropland	0.23	1.38
	3B2biii	Wetlands Converted to Cropland	NA	NA

	3B2biv	Settlements Converted to Cropland	NA	NA
	3B2bv	Other Land Converted to Cropland	0.02	0.44
	Subtotal		**10.32**	**36.69**
3B3 Grassland	3B3a	Grassland Remaining Grassland	6.44	9.68
	3B3bi	Forest Land Converted to Grassland	3.60	6.49
	3B3bii	Cropland Converted to Grassland	<0.01	0.01
	3B3biii	Wetlands Converted to Grassland	NA	NA
	3B3biv	Settlements Converted to Grassland	NA	NA
	3B3bv	Other Land Converted to Grassland	<0.01	0.10
	Subtotal		**10.04**	**16.28**
3B4 Wetlands	3B4a	Wetlands Remaining Wetlands	0.51	NA
	3B4bi	Forest Land Converted to Wetlands	<0.01	<0.01
	3B4bii	Cropland Converted to Wetlands	NA	NA
	3B4biii	Grassland Converted to Wetlands	NA	NA
	3B4biv	Settlements Converted to Wetlands	NA	NA
	3B4bv	Other Land Converted to Wetlands	NA	NA
	Subtotal		**0.51**	**<0.01**
3B5 Settlements	3B5a	Settlements Remaining Settlements	5.92	2.60
	3B5bi	Forest Land Converted to Settlements	0.03	0.35
	3B5bii	Cropland Converted to Settlements	0.49	3.41
	3B5biii	Grassland Converted to Settlements	0.02	0.29
	3B5biv	Wetlands Converted to Settlements	NA	NA
	3B5v	Other Land Converted to Settlements	<0.01	<0.01
	Subtotal		**6.47**	**6.65**
3B6 Other Land	3B6a	Other Land Remaining Other Land	7.96	NA
	3B6bi	Forest Land Converted to Other Land	1.81	21.08
	3B6bii	Cropland Converted to Other Land	0.05	0.46
	3B6biii	Grassland Converted to Other Land	NA	NA
	3B6biv	Wetlands Converted to Other Land	NA	NA
	3B6v	Settlements Converted to Other Land	<0.01	<0.01
	Subtotal		**9.81**	**21.53**

5F.1 – Conversion from Wetlands

According to staff analysis, the 2001 mapping of wetlands was well matched with other datasets, including the National Wetlands Inventory and California Aquatic Resources Inventory. The 2010 mapping converted 99.98% of the wetland acreage mapped in 2001 to other land-use types, including wetland reserves such as the Suisun Marsh Reserve. To avoid enormous soil carbon losses from a clear geospatial modeling artifact, areas mapped as wetlands in 2001 were assumed to remain wetlands in 2010. Future iterations of the soil carbon inventory will attempt to address this issue, and all sections that were impacted by this mapping artifact are labeled To Be Determined (TBD). For further discussion see the "Future Refinements" section.

5F.2 – Uncertainty

The 3 major sources of uncertainty in the soil organic carbon inventory are uncertainty in land cover attribution, uncertainty in the initial stock estimate, and uncertainty in the factors used to calculate stock change. Uncertainty generated from land cover attribution mapping is ±25% and uncertainty in the initial soil organic carbon stock is ±70%; uncertainty for stock change factors is under development. Uncertainty in the resulting soil organic carbon (SOC) inventory is not formally quantified at this time because of the many methodologies used in unison to produce estimates of stock change. This version of the SOC inventory was designed to give CARB a broad understanding of where soil organic carbon stocks are located on the California landscape, the location and magnitude of stock change, and the major drivers of stock change. CARB staff will be strategically reducing uncertainty in the inventory by first focusing resources on the categories that were identified to have the largest potential stock changes: cultivation of drained organic soil, agriculture, grasslands, and other lands.

5G – Further Development

5G.1 – LANDFIRE Land Category Classifications

LANDFIRE geospatial products are evolving as the consortium expands its resource management capacity beyond wildfires. With each update, LANDFIRE endeavors to respond to requests for a variety of improvements. LANDFIRE vegetation mapping also abides by guidelines in the federal National Vegetation Classification System (NVCS). As a result, LANDFIRE has become a central clearinghouse of national vegetation mapping data. Consequently, continual modification of the Existing Vegetation Type (EVT) product is likely as user needs and standards change. The major source of uncertainty in ARB's land carbon quantification method is EVT classification (Battles, et al., 2013) (Gonzalez, et al., 2015).

Special attention will be paid to increasing the accuracy of wetlands mapping so that land-use change from this category can be included in future iterations of the inventory.

5G.2 – Tier 3 Biogeochemical Modelling

To improve the accuracy of California's soil carbon flux estimates, Tier 3 modeling will be adopted by IPCC land category in order of the category's contribution to the total annual soil carbon stock flux, pending data/calibrated model availability. The first expansion of Tier 3 methods will be applied to the Croplands Remaining Croplands category in the San Joaquin-Sacramento Delta, to more accurately represent the soil organic carbon losses from drained organic soils. The model currently under consideration for achieving this task is SUB-CALC (Deverel & Leighton, 2010) (Deverel, et al., 2016). SUC-CALC was specifically created to model CO_2 emissions from crop cultivation on the San Joaquin-Sacramento Delta and currently presents the best opportunity to quantify the Deltaic soil organic carbon fluxes with greater accuracy.

The planned next step is to model SOC fluxes using a vetted biogeochemical model such as DNDC (Li, et al., 1992) (Li, 2000) or DayCENT (Parton, et al., 1994) (Parton, et al., 2001). This process will be iterative and the inventory will move towards Tier 3 modeling for all land cover types in future versions of the inventory.

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