Biomass, Carbon Sequestration, and Avoided Emissions: Assessing the Role of Urban Trees in California

April, 2015

Report of the UC Davis Statewide Assessment of Urban Forests Project to the California Fire Urban and Community Forestry Program

A Cooperative Effort of the University of California Davis and the Forest Service Pacific Southwest Research Station

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EXECUTIVE SUMMARY

This report represents a collaborative effort between the Information Center for the Environment, Department of Environmental Science and Policy, University of California, Davis (UCD-ICE); the Urban Ecosystems and Social Dynamics Program, Pacific Southwest Research Station, USDA Forest Service (USFS-PSWRS); and the California Department of Forestry and Fire Protection, Fire and Resource Assessment Program (CAL FIRE-FRAP), to assess the current status of the tree canopy and associated benefits within the urban areas of California. In addition, the current status of environmental threats to the urban area population were also examined, in order to highlight the communities most vulnerable and potentially the most likely to benefit from tree plantings and maintenance.

Background

Urban forests make up only a small percentage of the total forested area of California. However, the proximity to trees and their ecological benefits are important for human health. Some of the known benefits of urban forests include:

- CO_2 storage and sequestration
- Avoided emissions through reduced energy use
- Air pollution removal through dry deposition
- Rainfall interception, reduction in flood risk and in water pollution
- Increased property value through curb appeal and neighborhood charm
- Improved human health through reducing air pollution, minimizing heat effects and reducing exposure to UV rays
- Improved quality of life through aesthetic value, noise reduction and reduction in stress.

While urban areas represent only about 5% of the land area of California, almost 95% of the state’s population resides in urban areas, which proportionally increases the benefits of urban trees and tree canopy to human populations. In addition, these urban areas have on average ~35% of their land area in impervious surfaces. Impervious surfaces combined with excessive heat can cause heat island effects, which can compound the effects of air pollution. Urban heat islands can affect human health by contributing to respiratory difficulties, heat cramps and exhaustion, non-fatal heat stroke and heat-related mortality. The effects of urban heat islands can be lessened with tree planting by increasing shade, reducing energy use and reducing or removing air pollution. Areas with the highest degree of heat island effects and air pollution were identified in this report to highlight priority landscapes for tree planting. In addition, areas with the highest amount of energy consumption and extreme heat were also identified for priority tree mitigation to help cool buildings through shade.

This project sought to assess the current extent and condition of urban forests within California, and to refine priority areas for future tree plantings and maintenance. Specifically, the goals of this project included to:

- Develop a statewide estimate of biomass, CO_2 stored, annual CO_2 sequestration and emissions avoided due to urban forests.
- Report on a range of environmental benefits including heat island mitigation and statewide estimates of urban trees contribution to removal of air pollution and improvements to water quality.

- Identify trends in urban areas, such as changes in population and geographic size, changes in impervious surface, and changes in the number of urban trees and related urban tree characteristics.
- Identify priority areas for tree planting using tree canopy and impervious data, as well as updated demographic, climate and air pollution data.

Summary of Findings

The study area for this analysis was the 2010 U.S. Census urban areas of California, which totals 21,538 km^2, a 4% increase from the 2000 U.S. Census urban areas. California urban areas accommodate an estimated 35,373,606 residents, a 10.6% increase from 2000. Impervious surface area also increased from 2000 to 2010, by 20% within urban areas, to 7,612 km^2.

To assess the urban tree canopy, biomass, CO_2 stored, CO_2 sequestered and CO_2 avoided, a 1-meter resolution dataset of tree canopy created by EarthDefine was combined with transfer functions calculated by the U.S. Forest Service and U.C. Davis. The urban tree canopy is estimated to occupy 3,204 km^2, an average of 15% of the all urban area, and approximately 90 m^2 of tree canopy per person, although the urban canopy is not evenly distributed.

This study found, the estimated amount of CO_2 stored in urban forests in California totaled 102,995,988 metric tons. Annually, the amount of CO_2 sequestered from urban forests is assessed at 7,225,191 metric tons/year. The amount of CO_2 avoided was estimated to be 1,300,883 metric tons/year. Assuming a price of $12.02/metric ton, these annual amounts are equal to $86,714,832/year for annual CO_2 sequestered, and $15,636,609/year for avoided emissions.

To assess pollution and health risks, several factors were examined, including the number of days in a year over 90^{o}F, the amount of impervious surface, the density of roads and the density of population. These measurements were combined to ascertain where the most vulnerable areas to pollution and heat effects were, in order to target tree planting and maintenance activities. For Analysis 1: Urban Tree Planting for Energy Conservation and Air Quality, 13.9% of California urban areas were determined to be high priority areas. For Analysis 2: Urban Tree Maintenance for Energy Conservation and Air Quality, 15.5% of California urban areas were considered to be high priority areas.

Another key finding includes the large proportion, 61%, of urban areas in California considered to have low tree canopy cover (2-10%). In addition, 40% of urban areas ranked high for the percent of days over 90^{o}F (high ranking is considered to be more than 74 days in a year with a maximum temperature greater than 90^{o}F), and 15% of urban areas ranked high for impervious surfaces (high ranking is considered to be where ≥70% of the total area is impervious). Together, these effects mean much of the urban areas in California are subject to high urban heat threat (40%). While we found considerable canopy extent in California's urban area, it tends to be concentrated in a subset of the urban areas. This analysis provides the opportunity to identify urban areas that could benefit from tree planting campaigns.

Recommendations
We found that the tree canopy is unevenly distributed within urban areas in the State of California. While the report summarizes the findings by urban area and by county, there are likely smaller geographies within these regions that differ considerably from the surrounding areas.

Because the priority landscapes in our analyses factor in the threats to human health and the environment as well as the population density of the immediate region, they are a good tool for identifying the most vulnerable urban areas of the state and areas most in need of urban tree planting and maintenance campaigns. In Analysis 1: Urban Tree Planting for Energy Conservation and Air Quality, the priority landscape identified the five urban areas with the highest risk ranking, meaning that the residents in these areas the most at-risk for health implications related to heat effects and air pollution, to be: Silver Lakes (San Bernardino County), Taft (Kern County), Mendota (Fresno County), Tipton (Tulare County) and Arvin (Kern County). The counties with the highest average priority landscape score include San Joaquin, San Bernardino, Stanislaus and Imperial. These areas represent highly populated, and in most cases growing, cities and counties. The San Joaquin Valley and Inland Empire are also known to have long, hot summers and poor air quality due to their valley locations away from the coast.

In Analysis 2: Urban Tree Maintenance for Energy Conservation and Air Quality, the results similarly highlighted areas within the San Joaquin Valley and Inland Empire. Urban areas with the highest priority score include Wasco (Kern County), Planada (Merced County) and Los Banos (Merced County). San Joaquin County, Stanislaus County, Kern County and Fresno County had the highest priority scores of the counties. While these urban areas and counties currently represent the most vulnerable spots in the state, all urban areas are evaluated in this report.

It is our recommendation that FRAP use the details within this report for resource allocation strategies within vulnerable communities in California. Ideally, as more priority areas are targeted for tree plantings and maintenance for climate mitigation, further studies are needed to test the performance of these measures, both at a local scale and statewide. Finally we recommend that a climate impacts assessment be conducted on existing urban forests, to determine in what areas altered management of urban forests may be needed to maintain the trees that are currently in place.

Methods
The methods for this study relied heavily on several key datasets: the EarthDefine 1 meter map of urban tree canopy; FIA tree plots, UFORE tree plots and municipal tree inventories; land use types within urban areas; climate zones within California; and several demographic datasets from the U.S. Census, including urban area boundaries and population by Census block. Additional datasets utilized were from the Air Resources Board, impervious surfaces from the NLCD which are derived from satellite imagery, and historic climate data that was downscaled to 270 meters, to analyze the pollution threats to urban areas.

Data Layers

To assess the condition and extent of urban tree canopy, the existing tree canopy extent was measured using EarthDefine data, a purchased presence/absence dataset at a 1-meter resolution. To characterize the urban tree canopy condition, tree surveys were used from plot inventories or municipal street tree inventories. The plot inventories consist of randomly sampled plots in which data are collected for all trees present. These data were used to calculate CO_2 stored and CO_2 sequestered, as well as avoided emissions from trees shading buildings, by land use and climate zone. The municipal inventories contain only trees along publicly maintained streets. These data were run through the i-Tree Streets model (http://www.itreetools.org/index.php) to calculate various co-benefits for each climate zone.

The plot data were collected under two different inventory protocols: the Urban Forest Effects Model (UFORE) and the US Forest Service's Forest Inventory and Analysis (FIA). For each tree in the plot data, species, diameter at breast height (dbh), height, and the distance and compass bearing relative to a building were collected. Data were also collected that describe the attributes of the entire plot, such as canopy covering the plot, and the land use of the plot.

Some of the estimation of urban tree canopy benefits, such as shading and energy savings, depended on the land use type of the area underlying the tree canopy. For this reason, a land use map of the urban areas was created using parcel data from Digital Map Products and CoreLogic/DataQuick. Land use types were categorized into six classes: Multi Family Residential; Single Family Residential; Commercial/Industrial/Institutional; Open Space; Water; and Transportation.

To account for the different climate regions within California and the different growing conditions of trees, building energy use patterns and rainfall, a subdivision of six climate zones was used.

To estimate the environmental benefits of urban tree canopy, transfer functions were developed to related field plot-based measures of CO_2 equivalent per hectare of urban tree canopy (UTC) and then aggregated and applied to the tree canopy area within each climate zone by land use class.

Developing Transfer Functions

Transfer functions were developed using data from UFORE and FIA tree plots for estimating the biomass, CO_2 stored, CO_2 sequestered and CO_2 avoided from tree canopy on a per-hectare basis. For environmental benefits, municipal tree data were used. Equations were developed using the following data:

- Tree species
- DBH
- Tree height
- Climate zone

A biomass calculator was created for this study, using a set of Excel spreadsheets relating different biomass values for different tree species, given tree height, dbh, estimated age and climate zone. For estimating CO_2 stored, sequestered and avoided emissions, the CUFR Tree Carbon Calculator (CTCC) application was used (http://www.fs.usda.gov/ccrc/tools/cufr-tree-carbon-calculator-ctcc), which also uses information on tree species, height, dbh and climate zone. The CTCC model uses different unit energy effects (UEEs) to adjust for different building types, heating and cooling types within buildings and building age. For additional co-benefits of tree canopy, municipal street tree inventories were run through the i-Tree Streets model for each climate zone. The co-benefits described in this report include energy effects, air quality, rainfall interception and property values.

To transfer these to map-based values, the transfer function values developed from the plot data were used as multipliers on the spatial extent of canopy within climate zone and land use type. The extent of canopy was extracted from the EarthDefine map for each land use, climate zone, and urban area. These canopy area values were multiplied by the kg values to produce kg of carbon or biomass/unit area of canopy (hectare).

Developing Priority Landscapes

Priority landscapes were developed for two separate sets of analyses: Analysis 1: Urban Tree Planting for Energy Conservation and Air Quality; and Analysis 2:Urban Tree Maintenance for Energy Conservation and Air Quality. For Analysis 1, a series of geographic layers were ranked into High, Medium and Low values, and then combined to identify areas of concern regarding high air pollutants, extreme summer heat, or areas with high percentages of impervious surfaces, which are known to cause a heat island effect. First, the percentage of tree canopy and the percentage of impervious surfaces were combined to create a heat island threat layer. This heat island layer was then combined with climate data showing areas with the number of days over 90^{o}F, culminating in an urban heat threat layer. To create an air pollution index layer, data on O_3, PM_{10}, and $PM_{2.5}$ were combined to form an overall pollution layer. Data for these layers were from the Air Resources Board and CalEnviroScreen. The air pollution index layer and an urban roads layer, which buffered highways and major roads based on the estimated pollution impact of road traffic, were then combined to show the overall air pollution threat, ranked as High, Medium and Low. The urban heat threat layer and air pollution threat layer were then combined to create a composite threat layer. A composite asset layer was created using urban housing and commercial density, again ranked into High, Medium and Low classes. The composite threat and composite asset layers were then combined to form an overall priority landscapes layer.
A similar process was done for Analysis 2. First, housing density and the percent of days over 90^{o}F were combined to create an energy consumption threat layer. The same air pollution threat layer was used from Analysis 1, and together the two layers formed a composite threats layer. A composite asset layer was created using the urban population asset from Analysis 1 plus the percent of urban tree canopy. The composite threat layer and composite asset layer were combined to form an overall priority landscape layer for Analysis 2.

Chapter 1 INTRODUCTION

The benefits of urban trees are many, including aesthetic, shading, interception of particulate matter, increased value of properties, habitat, and a variety of ecosystem services. The environmental benefits from these urban forests (UF) are often overlooked, and include: air pollution removal, carbon dioxide (CO_2) sequestration, regulating air temperature, reducing energy use, improving water quality, and reduced noise pollution.

In order to take full advantage of these attributes, the public and government agencies are becoming increasingly engaged in the management and planning of urban and community forests. In California, there is increasing need for statewide data on the extent of urban trees to support these activities, and to provide a baseline from which future benefits resulting from tree planting and management campaigns may be assessed. This type of information could also be used to educate communities and decision makers about the importance of urban forestry in local, regional, state, and national plans and policies.

Current California urban tree data is fragmented at a local level. It consists of some urban area studies including Los Angeles, San Jose, Sacramento, and an ongoing effort in Sonoma county (McPherson et al. 2013), as well as over 50 inventories of municipal street trees from individual towns and cities, that contain varying levels of detail and information. Two previous assessments covered all of California, both published in 2010.

The federal USDA Forest Service Northern Research Station General Technical Report (NRS-65), “Urban and Community Forests of the Pacific Region” (Nowak and Greenfield 2010a), provided information that identifies priority urban areas based on population density and tree canopy, and carbon calculations. That report relied on 2001 NLCD imagery (which was published in 2007) for tree canopy cover, at 30 meter resolution, and 2007 U.S. Census data for demographic data, and covered the states of California, Washington and Oregon. The values for urban tree benefits for the prior study were based on a national average of tree attributes and do not appear to be particularly well calibrated for California, which has a different climate from many of the regions used in the Forest Service’s national evaluation. The NRS-65 study provides urban and community forest information by state, county, and community, but identifies priority urban areas for tree planting based on population density, green space, and canopy per capita. CO_2 sequestration estimates were based on a national average that included data from two cities in California that are located in the same climate region. However, California has six climate regions representing different conditions. In addition, the NLCD 2001 data used to derive tree canopy for that study was found to underestimate tree canopy by a national average of 9.7% (Nowak and Greenfield 2010b).

The California Department of Forestry and Fire Protection, Fire and Resource Assessment Program evaluated UF conditions and identified priority areas for urban tree planting and maintenance based on an asset-threat approach in California’s Forests and Rangelands: 2010 Assessment. The 2010 Assessment report is also based on the NLCD map of canopy. The report compiled a wide variety of data types and used them to map and rank urban areas in terms of their tree planting needs.

This report (UCD-USFS) provides an update and extends information provided in the 2010 California state report. Many of the resources available for this update are more detailed and were not available previously, so the extent and condition of urban forests, and the ecosystem services described are not directly comparable to the 2010 Assessment report. Therefore, trends are also difficult to establish. Effort has been made in this version of the report to permit greater replicability for the next edition going forward.

In 2010, California's urban areas cover 8,316 square miles (~5%) of the land and supported 94% of the state's population and 93% of the housing (Census 2010). Urban area has expanded by about 325 square miles. This report focuses on California's current urban areas (Figure 1-1) and aims to provide base information that can be used by state and local agencies in the development of urban tree planting and management plans and programs. Applications of the information in the report can be used to update priority areas for urban tree planting, and potentially as input for calculations of statewide carbon balance under California's new cap and trade system.

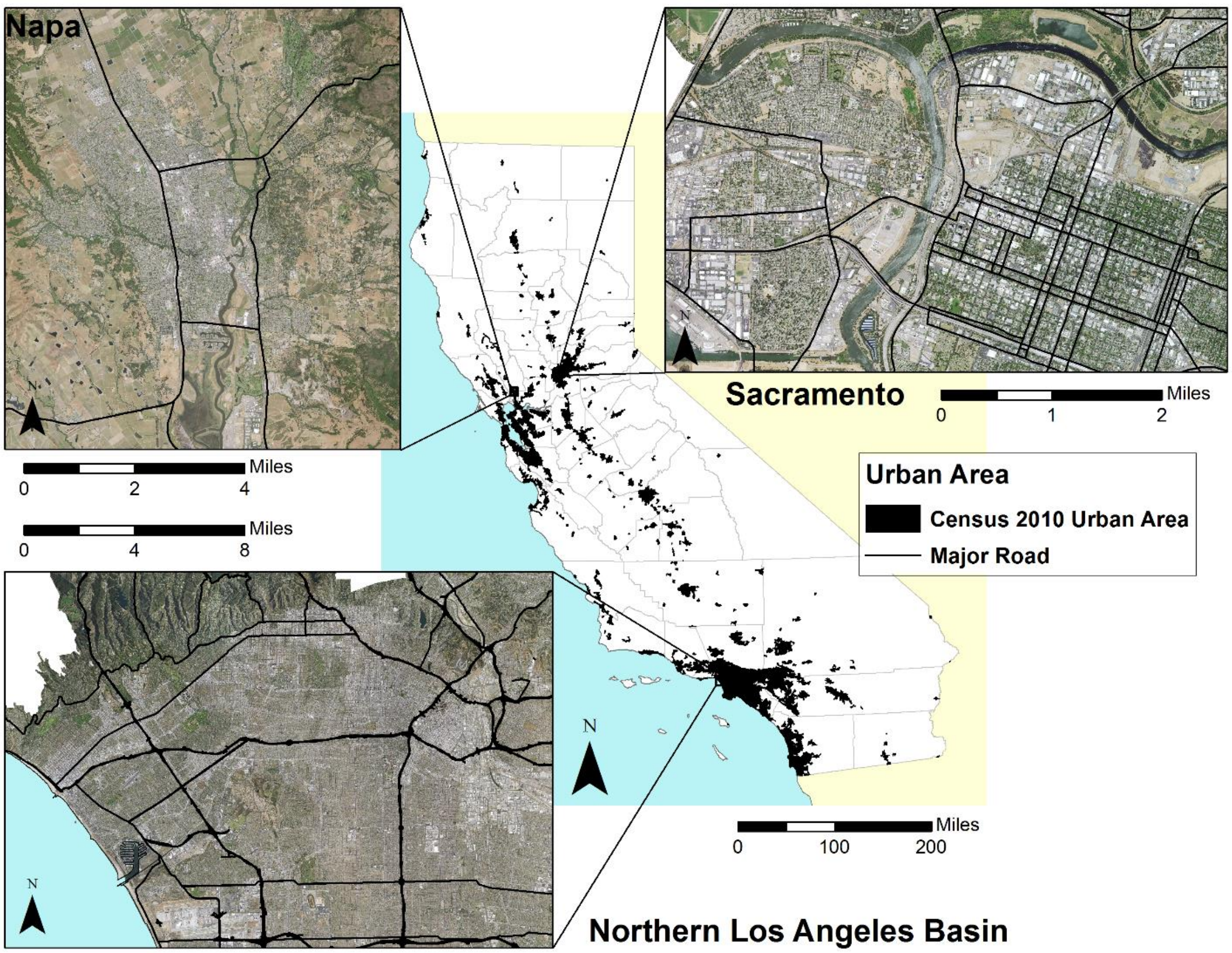


Figure 1-1. California urban areas (project map).

The development of the analyses presented in this report required the development and compilation of a variety of data types. Among them, we created a land use map that generalizes parcel information into six land use categories for the state's urban areas. We also compiled weather data to develop maps of the days over 90°F, based on daily values and summarized for

2004-2013, as well as two previous decades.We are additionally thankful to the California Air Resources Board for providing information on Ozone, and particulate matter in the 2.5 and 10 micron sizes. We further compiled information from 49 urban street tree inventories conducted in various towns and cities in the state, and made use of two sets of urban tree surveys that use a plot-based approach, the U.S. Forest Service's Forest Inventory and Analysis program (FIA, plots n = 682), and the U.S. Forest Service's Urban Forest Effects Model program (UFORE n = 703).

An urban tree canopy baseline was compiled from the existing California tree inventories, databases, and combined with data from a new 1-meter resolution map product of tree canopy, from EarthDefine (2013). EarthDefine data is based on 2012 NAIP imagery, and its high resolution will enable improved future statewide change detection of urban forest conditions, as well as serve to identify where more data is needed to enable monitoring, and for ranking of locations for various tree-related government services.

We updated a series of transfer functions, which are used to calculate various urban tree attributes. The FIA and UFORE plots were used to generate estimates of biomass (tons), CO_2 stored (tons), annual CO_2 sequestered (tons/year), and CO_2 emissions avoided (tons/year) because of shade and climate effects on buildings, which influence their energy use. The municipal street tree data were used to generate an estimate of a wide range of other ecosystem services or co-benefits including: rainfall interception, air pollutant removal and release, effects on property values and other benefits.

Finally, this report specifies delivery to FRAP of a combination of analyses and data products, including:

- A comprehensive set of data layers for use by government and non-profit entities to support management decisions
- A compilation of local tree inventory data and Urban Tree Canopy (UTC) assessments.

Chapter 2, the Methods Section, presents the data and its preparation, including tree plot data, land use data, climate data, ancillary data as well as the development of the transfer functions for the analysis of biomass, CO_2 stored, sequestered and avoided emissions. CO_2 stored refers to the amount of CO_2 accumulated over many years in standing trees. The methods for calculating additional transfer functions for co-benefits as well as an overview of how the different analyses were translated to spatial data layers are also included in this section.

Chapter 3, the Results Section, is divided into three subsections: Part 1. CO2 Inventory, Part 2. Priority Landscapes and Part 3. Trends in Urban Forests. Part 1 is an overview of the results of the tree canopy, biomass and CO_2 inventory for the statewide urban areas. The data are summarized for each section and maps showing the statewide extent as well as three different detail views of Sacramento, Napa and the Northern Los Angeles Basin are provided, as a way to visually compare each variable. Part 2 provides the summarized results for two sets of analyses aimed at identifying priority areas for targeting urban forestry investments and efforts in the future. Analysis 1 describes the process for identifying priority landscapes for urban tree planting, as well as summarizing results for the intermediary layers that are created during the process. Analysis 2 is a similar process but for identifying priority landscapes for urban tree maintenance. The last section of Chapter 3 provides State summary results for changes and trends in urban areas including; area growth, population growth, and change in percent of impervious surfaces.

Chapter 4, the Next Steps Section, provides a summary of the results from the UCD-USFS study, compares them to the previous NRS-65 study, and briefly presents possible applications of the new data.

Due to the large datasets used for this analysis, complete tables and ancillary data can be found in a number of appendices. Some data are described in the appendices and referenced to an external digital file, if too large for the document.

Chapter 2 METHODS

Input Data and Data Preparation

The report required the acquisition, modification and in some cases the creation of many different datasets and data layers. This section describes this process for the major data sections, including tree plot and canopy data, the creation of transfer functions and allometric equations for developing biomass, as well as some of the ancillary data that was acquired and developed, such as climate data, land use layer, and air pollution data.

Tree Plot Data

Tree surveys used in the analysis can be characterized as either plot inventories or municipal street tree inventories. The plot inventories consist of randomly sampled plots in which data are collected for all trees present. These data were used to calculate biomass, CO_2 stored and CO_2 sequestered, as well as avoided emissions from trees shading buildings, by land use and climate zone. The municipal inventories contain only trees along publicly maintained streets. These data were run through the I-Tree Streets model (http://www.itreetools.org/index.php) to calculate various co-benefits for each climate zone.

The plot data were collected under two different inventory protocols: the Urban Forest Effects Model (UFORE) and the US Forest Service's Forest Inventory and Analysis (FIA) (Table 2-1) (Nowak, 2005; "Forest Inventory," n.d.). For each tree in the plot data, species, diameter at breast height (dbh), height, and the distance and compass bearing relative to a building were collected. Data were also collected that describe the attributes of the entire plot, such as canopy covering the plot, and the land use of the plot.

The UFORE protocol requires that plots are circular in shape, are 0.04 ha. in size, and are randomly located and surveyed (Nowak et al., 2008). Plots located in non-urbanized areas were excluded from this analysis. In Los Angeles, 323 plots were measured during 2007 and 2008, with information recorded for 675 trees. In Sacramento, 276 plots were measured during 2007 and data recorded on 626 trees. In Santa Barbara, 104 plots were measured during 2012 and data recorded on 612 trees. In Sacramento and Los Angeles, a GIS analysis was conducted to determine the average age of development for buildings in or near the plot (McPherson, Xiao & Aguaron, 2013).

An additional 682 plots were inventoried in urban areas throughout 35 California counties using the FIA protocol. Each FIA plot consists of four subplots, which are established 120 ft. (36.6 m) from the center subplot at 120°, 240°, and 360° azimuths (Nowak et al., 2008). These subplots are 24 ft. (7.3 m) in radius and cover .0168 ha. Each FIA plot covers a total of area of .067 ha.

In addition, 56 municipal street tree inventories from across California were collected for analysis (Table 2-1). Seven of these inventories were removed due to missing data, or if they were collected prior to 2005. Also, many of the inventories contained trees not along publicly maintained streets. Because these trees were located in parks, natural areas or areas where benefits were thought to be different from the rest of the street trees, these trees were removed from the dataset (McPherson et al., 2015). In total, the final 49 inventories comprise 908,304 trees.

Table 2-1. Summary of plot and municipal inventory data

		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

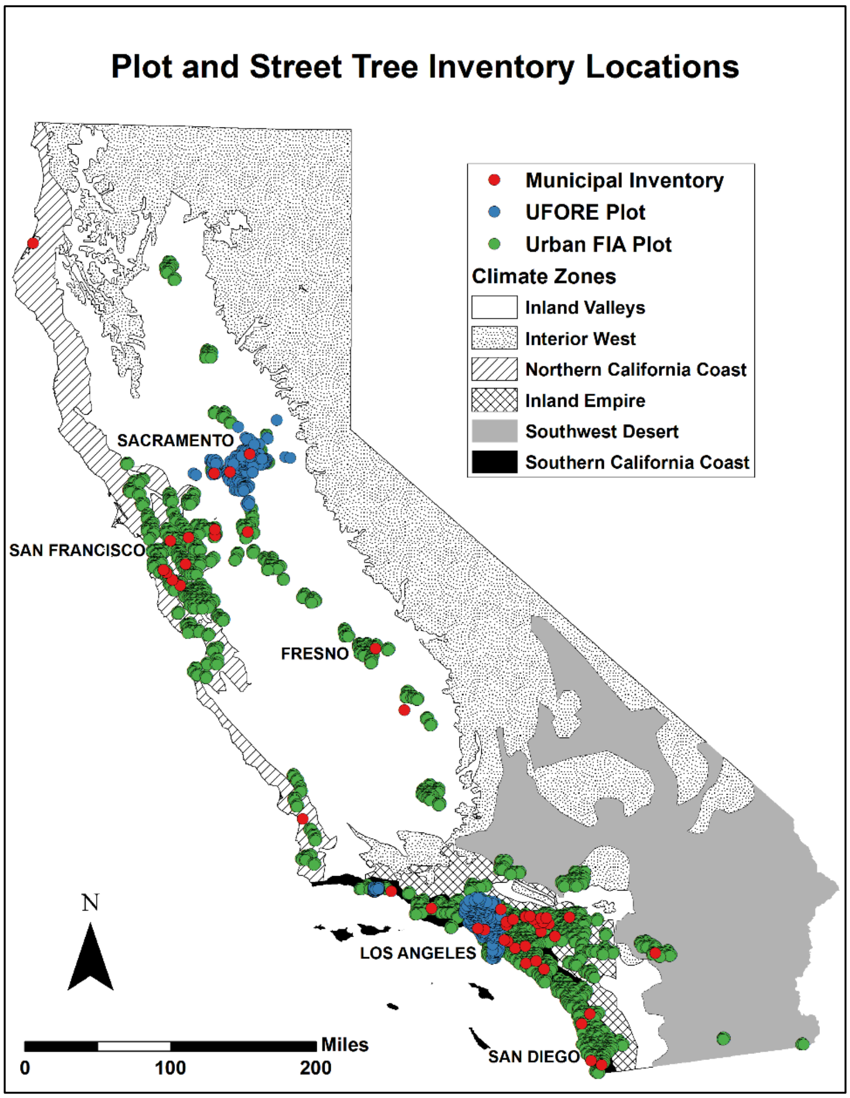


Figure 2-1. Climate zones, plot data, and municipal tree inventories locations (project map).

Parcel Data and the Generation of Land Use

The FRAP 2010 Assessment analysis incorporated land use in the estimation of tree canopy benefits, such as shading and energy savings, and it was preferred for the statewide analysis to also include a comprehensive, statewide land use layer. Additionally, some of the tree plot data and tree inventory data also incorporated a land use class component. For this report a similar statewide estimate of tree canopy benefits was needed. We therefore developed a statewide land use map for urban area.

Requirements for the land use data layer needed for this project were that it had to be:

- A statewide layer,
- Recent (within the past 5 years),
- Able to be cross-walked to the existing land use classes used by the tree plot and tree inventory data sets, and
- A high spatial resolution data layer.

Land use categories are useful for summarizing projections of urban tree benefits for the urban areas of California, because different land use classes typically have different tree densities. This study uses six land use classes: Multi Family Residential; Single Family Residential; Commercial/Industrial/Institutional; Open Space; Water; and Transportation. We used parcel data purchased by the State of California's Department of Technology as follows: parcel boundaries were purchased from Digital Map Products (08/2013), and attributes were purchased from CoreLogic/DataQuick (08/2013). These were available by county for all of California. Each county had different classification schemes, and the GIS line work was typically not in a final useable form. We therefore conducted a county-by-county update of the parcels data, in order to complete a uniform map of parcels that could be used in calculations of urban tree benefits (See Appendix 1: Geo-processing steps to render parcel-level data to land use classes for a detailed description of how the land use class layer was created.

Climate Data

Climate data were used for informing the transfer functions for CO_2 inventory as well as for the creation of a statewide layer of urban heat islands, an energy consumption layer and ultimately factored into the priority landscapes layers.

Climate Zones

California was subdivided into six climate zones (Table 2-2). The climate zone map (Figure 2-1) outlines the zones based on conditions that influence tree growth, building energy use patterns, and rainfall. The zones are based largely on the Sunset National Garden Book's 45 climate zones (Brenzel 1997). Ecoregion boundaries as delineated by Bailey (2002) and Breckle (1999) were included to a lesser extent. Reference cities are where extensive tree growth measurements were made and benefit modeling was conducted as a basis for application to other communities in the same climate zone. Cooling degree days (CDD) and heating degree days (HDD) are indicators of building heating and cooling loads. The CDD value is the summation of degrees of the average temperature per day above 80° F for the year, and the HDD value is the summation of degrees of the average temperature per day below 65° F for the year (Pacific Energy Center, 2006).

Table 2-2. Characteristics of California climate zones used in this study.

Climate Zone	Reference City	CDD[1]	HDD[2]	Sunset Zones
Inland Empire	Claremont	1863	1475	18,19,20,21
Inland Valleys	Modesto	1248	2666	7, 8, 9, 14
North Cal Coast	Berkeley	142	2862	15, 16,17
South Cal Coast	Santa Monica	679	1274	22, 23, 24
Southwest Desert	Glendale, AZ	4364	1027	11,12,13
Interior West	Albuquerque, NM	1290	4315	2, 10
[1]CDD - Cooling Degree Days				
[1]HDD - Heating Degree Days				
Western Regional Climate Center 1971-2000 normals, 65°F baseline				

Historic and Current Climate

A 270m version of the Daily PRISM (PRISM Climate Group, http://www.prism.oregonstate.edu/; downscaling detailed in Flint et al. 2013) data between 1981 and 2013 was used to determine: the number of days in a year where the maximum temperature exceeded 90° F (Figure 2-2), the number of days in a year where the maximum temperature exceeded 5° C, the number of days in a year where the minimum temperature exceeded 20° C, and temperate ranges (maximum temperature minus minimum temperature) for the year and 3 summer periods (June 1 – Aug 31, July 1 – Sept 30, June 21-Sept 21) (Figure 2-3). The analyses were performed in R and resulted in yearly datasets. These were fed into a linear regression model which produced a 30-year and three 10-year averages over the 1984-2013 time period.

For this report, the 1981-2013 spatial values of days over 90°F were used.

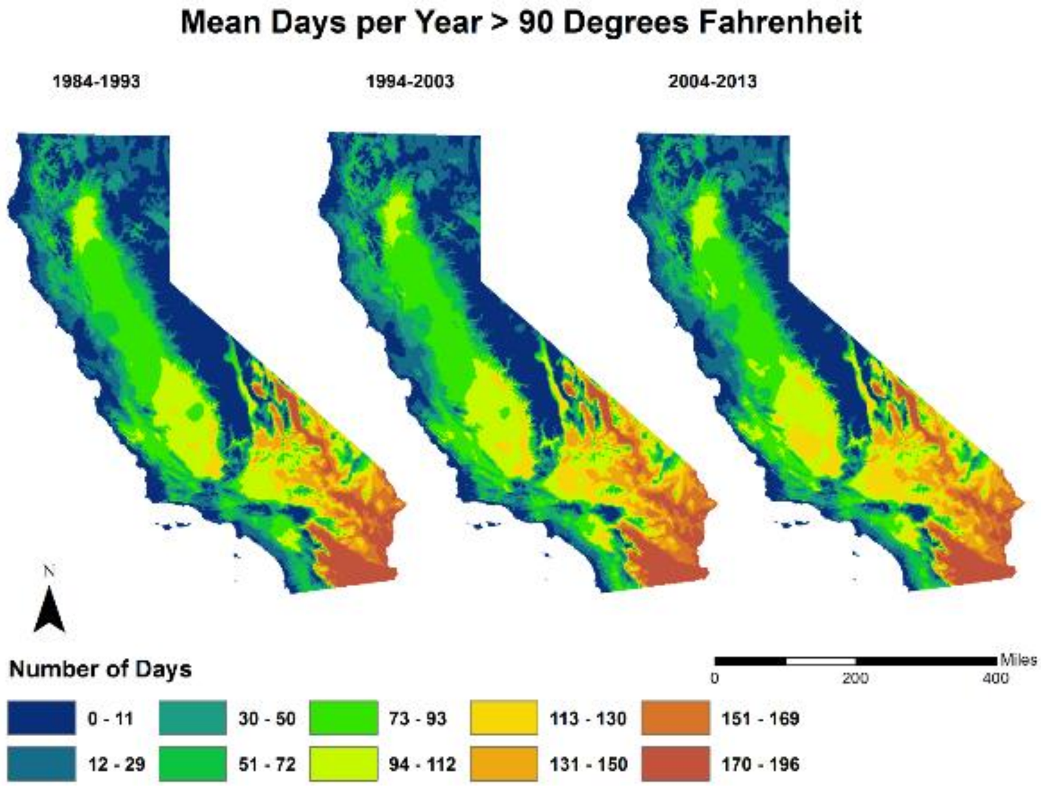


Figure 2-2. California extent of the mean number of days per year greater than 90° F (map).

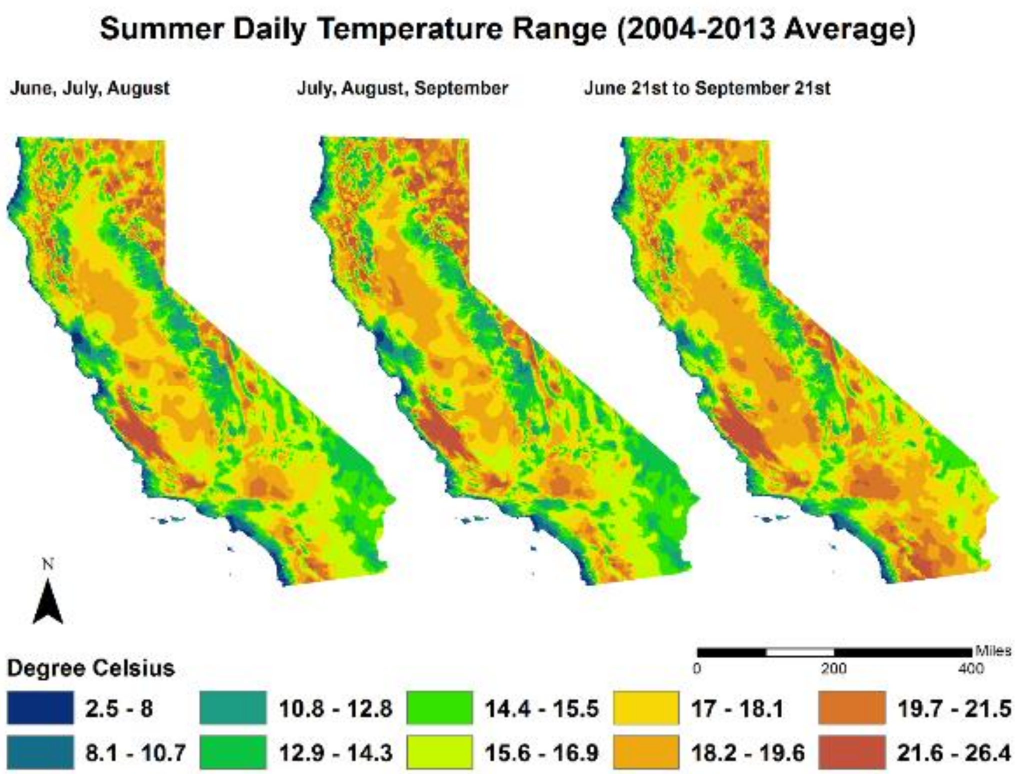


Figure 2-3. California extent of the daily summer temperature range (2004-2013) (map).

Urban Tree Canopy Map

We used a tree canopy map developed by EarthDefine (2013), which processed National Agricultural Imagery Program (NAIP) 1 m^2 aerial imagery into a map of canopies using segmentation analysis. The EarthDefine map is based on 2012 NAIP imagery, which includes four multispectral bands (blue, green, red and near infrared) with 1-m ground sample distance (GSD). The EarthDefine methods use object-based image analysis, which depends on image segmentation to combine adjacent grid cells that fall into the same class (http://www.earthdefine.com/spatialcover_landcover/).

Accuracy assessments were conducted by climate zone and land use class for treed and non-treed areas within urban extents. Our independent accuracy assessment of tree canopy cover across land use classes produced an overall user accuracy of 82.4% (see Appendix 2: Evaluation of the EarthDefine accuracy in mapping urban tree canopy in California).

Data Processing & Analyses

Transfer Functions

In this study, transfer functions are defined as a way to convert individual tree-based measurements to a variety of attributes and values. This report contains transfer functions addressing two main categories of attributes. In this section, we use field plot-based measures to assess biomass, CO_2 currently stored and annual sequestration, and avoided emissions. In the next section below, street tree inventories were used for calculating other co-benefits of urban trees. Additional information on transfer functions can be found in

To derive UTC-based transfer functions, CO_2 storage, sequestration and avoided emission values are calculated for trees in each UFORE and FIA plot and divided by the plot's UTC. Plot data are aggregated by land use class for each climate zone and descriptive statistics are applied to determine sample means and standard errors. Four main data tables were included in this database: a species code table, a table giving the equation types and coefficients for the biomass, a table giving equation types and coefficients relating growth by age to the size of the tree, and a table giving the minimum and maximum tree sizes and corresponding ages to bound the range over which the equations are applicable.

Urban-based biomass equations were developed from street and park trees measured in California (Pillsbury, Reimer, & Thompson, 1998) and Colorado cities (Lefsky & McHale, 2008). Inputs to calculations for biomass, CO_2 stored and CO_2 sequestered were the tree species, the climate zone, the tree dbh, and the tree height. Trees with sizes that were outside the minimum or maximum size range were respectively set to their minimum or maximum size value for their species and climate zone. The biomass calculator contains functions for 14 different equation types, with the functions parameterized at each function call through a lookup into the biomass coefficient table. The carbon sequestration calculator uses functions for 12 different equation types relating tree size to age.

The steps in this calculation were the following:
1) Determine age of the tree given the tree size (dbh and height).
2) Subtract 1 from this age to set up the calculations in the previous year.
3) Use the current dbh and height to calculate biomass and CO2 equivalent for the current year.
4) Calculate the dbh and height of the tree in the previous year.
5) Calculate the biomass and CO2 equivalents for the previous year.
6) Subtract (5) from (3) to determine carbon sequestered over the year.

Because the functional form of the growth equations predicts dbh or height from tree age, step (2) poses a challenge because it asks for the inverse relationship. In the previous generation of these tools, this inverse relationship was handled using a set of lookups into precomputed growth tables. In this Python version of the calculator, the inverse computation was made using numerical root solving techniques. Two different root solvers from the SciPy library were used in this calculation (fsolve and brentq), the choice of which being dependent on the equation type. By avoiding using precomputed growth tables, the calculator can easily be updated, for instance by changing the equation coefficients in the database.

Two types of allometric biomass equations were used to yield aboveground volume and dry weight of a tree. The methodology to convert green volume into biomass and eventually to stored CO_2 is well established (Jenkins, et al., 2003a, 2003b; Markwardt and Wilson, 1935; Simpson, 1993) and entailed calculating total dry weight biomass, then standing carbon and sequestered CO_2 equivalents. The conversion from carbon to CO_2 equivalent uses the following equation: Carbon * 3.67 = CO_2. Converting the fresh weight of green volume into dry weight required use of species specific dry weight density conversion factors. The amount of belowground biomass in roots of urban trees is not well researched. This study assumed that root biomass was 28% of total tree biomass (Cairns, et al., 1997; Husch et al., 1982; Wenger, 1984). Wood volume (dry weight) was converted to C by multiplying by the constant 0.50 (Lieth et al, 1975).

The amount of CO_2 sequestered in year *x* was calculated as the amount stored in year *x+1* minus the amount stored in year *x*. To project tree size at year *x*+1 we used growth curves developed from samples of about 700 street and park trees representing the 20 to 22 predominant species in each climate zone's reference cities (Peper et al., 2001a, 2001b). Each tree in the sample plots was matched to one of the representative species, to ensure that the appropriate allometric and growth equations were applied to calculate biomass and annual sequestration rates

Avoided emissions from power plants from effects of each sampled tree on building energy use were calculated based on data from the CUFR Tree Carbon Calculator (CTCC) (McPherson et al., 2008). The CTCC, a free Excel spreadsheet application, was produced by US Forest Service researchers. It uses information on climate zone, species, and size to calculate standing carbon, sequestered carbon, and avoided emissions. Since the application only accepts inputs for one tree at a time, a script was written to automate these calculations.

The estimated value of CO_2 sequestered and avoided emissions assumed a price of $12.02 per ton CO_2, the annual metric ton average in 2014 (California Carbon Dashboard, http://calcarbondash.org/).

For a more detailed methodology on how the transfer functions were developed, see Appendix 3: Detailed methods on the development of transfer functions.
For the complete table of transfer functions, including those for co-benefits, the SQLite database with plot data used in the creation of the transfer functions and the R file of code used to calculate transfer functions, see Appendix 4: Transfer function table including other benefits.

Transfer Functions for Co-Benefits
Lacking numerical models directly applicable to plot data for transfer functions for co-benefits, such as rainfall interception, air quality effects and property values, transfer functions were calculated from municipal street tree inventory data run through the i-Tree Streets model for each climate zone. A dollar value was assigned to each resource unit (RU) based on local costs (Table 2-3). We also estimated rainfall interception, property values, aesthetics and other benefits. Methods for those analyses can be found in Appendix 4: Transfer function table including other benefits. The complete table of transfer functions for co-benefits can be found in Appendix 5: Transfer function development for co-benefits.

Energy effects
Calculations of energy effects of trees on residential buildings were based on the previously described computer simulations that incorporated tree data from the UFORE and FIA field plots. The dollar values of electrical energy and natural gas were based on retail residential electricity and natural gas prices obtained from each utility (Table 2-3).

Table 2-3. Prices used to monetize selected urban forest services. All prices in dollars per metric ton unless otherwise noted.

	Inland Empire	**Inland Valleys**	**Interior West**	**Northern CA Coast**	**Southern CA Coast**	**Southwest Desert**
Electricity ($/MWh)	$150.00	$136.27	$149.24	$136.27	$150.00	$149.24
Natural gas ($/GJ)	$8.79	$9.30	$7.76	$9.30	$8.79	$8.79
Rain Interception ($/m3)	$1.91	$2.01	$1.32	$1.06	$1.91	$1.27
CO_2 ($/t)	$12.02	$12.02	$12.02	$12.02	$12.02	$12.02
O_3 ($/t)	$51,966.26	$51,966.26	$51,966.26	$51,966.26	$51,966.26	$51,966.26
PM10 ($/t)	$44,120.01	$44,120.01	$44,120.01	$44,120.01	$44,120.01	$44,120.01
NO_2 ($/t)	$51,966.26	$51,966.26	$51,966.26	$51,966.26	$51,966.26	$51,966.26
SO_2 ($/t)	$72,665.46	$72,665.46	$72,665.46	$72,665.46	$72,665.46	$72,665.46
VOC ($/t)	$47,878.89	$47,878.89	$47,878.89	$47,878.89	$47,878.89	$47,878.89

Air quality
The hourly pollutant dry deposition per tree was expressed as the product of deposition velocity $V_d = 1/(R_a+R_b+R_c)$ (where R_a, R_b, and R_c are aerodynamic, boundary layer, and stomatal

resistances), pollutant concentration, canopy projection area, and a time step. Hourly deposition velocities for ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter of <10-micron diameter (PM_{10}) were calculated from the i-Tree Streets Model by using estimates for the resistances R_a, R_b, and R_c for each hour throughout a "base year" (Scott et al., 1998). Deposition velocities accounted for each species' leaf area during the in-leaf and out-of-leaf seasons. Hourly meteorological data and pollutant concentrations were obtained from local monitoring stations when pollutant concentrations were near average. Deposition was calculated for dry periods only.

Energy savings result in reduced emissions of criteria air pollutants (volatile organic hydrocarbons [VOCs], NO_2, SO_2, PM_{10}) from power plants and space-heating equipment. These avoided emissions were calculated using i-Tree Streets emission factors for electricity and natural gas heating fuel (Table 2-4 and Table 2-5). Here again the estimated value of avoided CO_2 emissions due to energy effects and CO_2 sequestered assumed a price of $12.02 per ton CO_2, based on the California Carbon Allowance Futures annual average for 2014 (California Carbon Dashboard, Accessed on Dec. 8, 2014 at: http://calcarbondash.org/).

Table 2-4. Electricity emissions factors by climate zone (kg/MWh).

	Inland Empire	Inland Valleys	Interior West	North Cal Coast	South Cal Coast	Southwest Desert
CO_2	335.2	290.9	286.2	290.9	335.2	286.2
NO_2	0.807	0.662	2.297	0.202	0.807	1.540
SO_2	0.481	0.000	2.086	0.061	0.481	0.928
PM10	0.056	0.034	0.448	0.077	0.056	0.054
VOC	0.024	0.245	0.446	0.020	0.024	0.009

Table 2-5. Natural gas emissions factors by climate zone (kg/GJ).

CO2	56.5
NO2	0.0489
SO2	0.0003
PM10	0.0036
VOC	0.0026

The monetary value of tree effects on air quality reflects the value that society places on clean air, as indicated by willingness to pay for pollutant reductions. Air quality benefits were monetized as the mean cost of pollution offset transactions. California requires air quality management districts that are not in attainment of ambient air quality standards to adopt emission reduction credit banking programs. Stationary source owners can purchase offsets that are valid for the lifetime of the permitted source. The California Air Resources Board's (2011) most recent report found that 666 transactions took place in California in 2008. Mean values that represent the statewide average cost of a transaction were used in this study (Table 2.6).

Table 2-6. Table of 2008 prices paid in dollars per transaction per ton of offsets, from CARB 2011.

	NO_x	PM_{10}	SO_x
Mean	$47,143	$40,025	$65,921

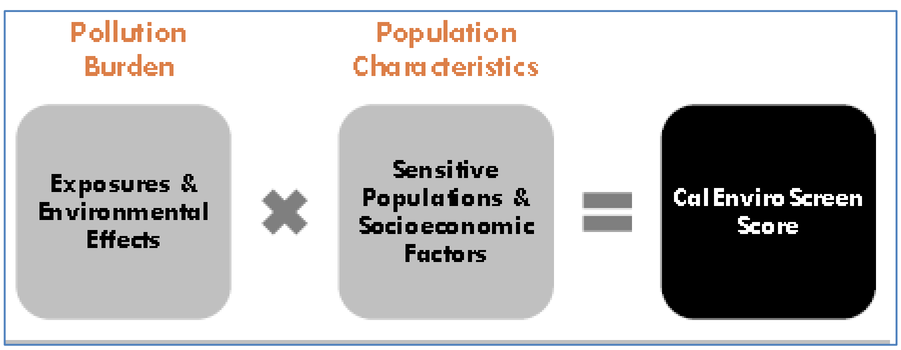
Ancillary Data

Roads

Roads were used to evaluate air pollution as it related to the proximity to primary and secondary transportation corridors. Areas within 300 meters of an interstate, freeway or expressway were considered to be ranked high in terms of air pollution while areas within 150 meters of an urban principal arterial road were considered medium. The dataset chosen for this analysis was the ArcGIS North American Streets Cartographic layer, from ESRI. Primary roads were classified as cartographic classes 1 and 2, which include Primary Limited Access and Primary U.S. State Highways. Secondary roads were classified as cartographic class 3, which included Secondary State and County Roads.

CalEnviroScreen

The California Communities Environmental Health Screening Tool, CalEnviroScreen (CES), was developed by the Office of Environmental Health Hazard Assessment (OEHHA) at the request of the California Environmental Protection Agency (CalEPA) in order to identify communities in California that are most burdened by pollution and that are most vulnerable to its effects. Version 2.0, released in November, 2014, was used for this analysis. The overall CES Score was used in this analysis, which uses the following formula:



The overall score is provided for each CES geography, using a scoring system to weight and sum each set of pollution and population indicators. For the complete CES results table and report, see Appendix 6: CalEnviroScreen and California Air Resources Board information. The CES 2.0 Percentile Range contains the percentile of the CES score, grouped by 5% increments. The overall ranking for this project was as follows: Low (0-45%), Medium (46-75%) and High (76-100%) (Figure 2-4).

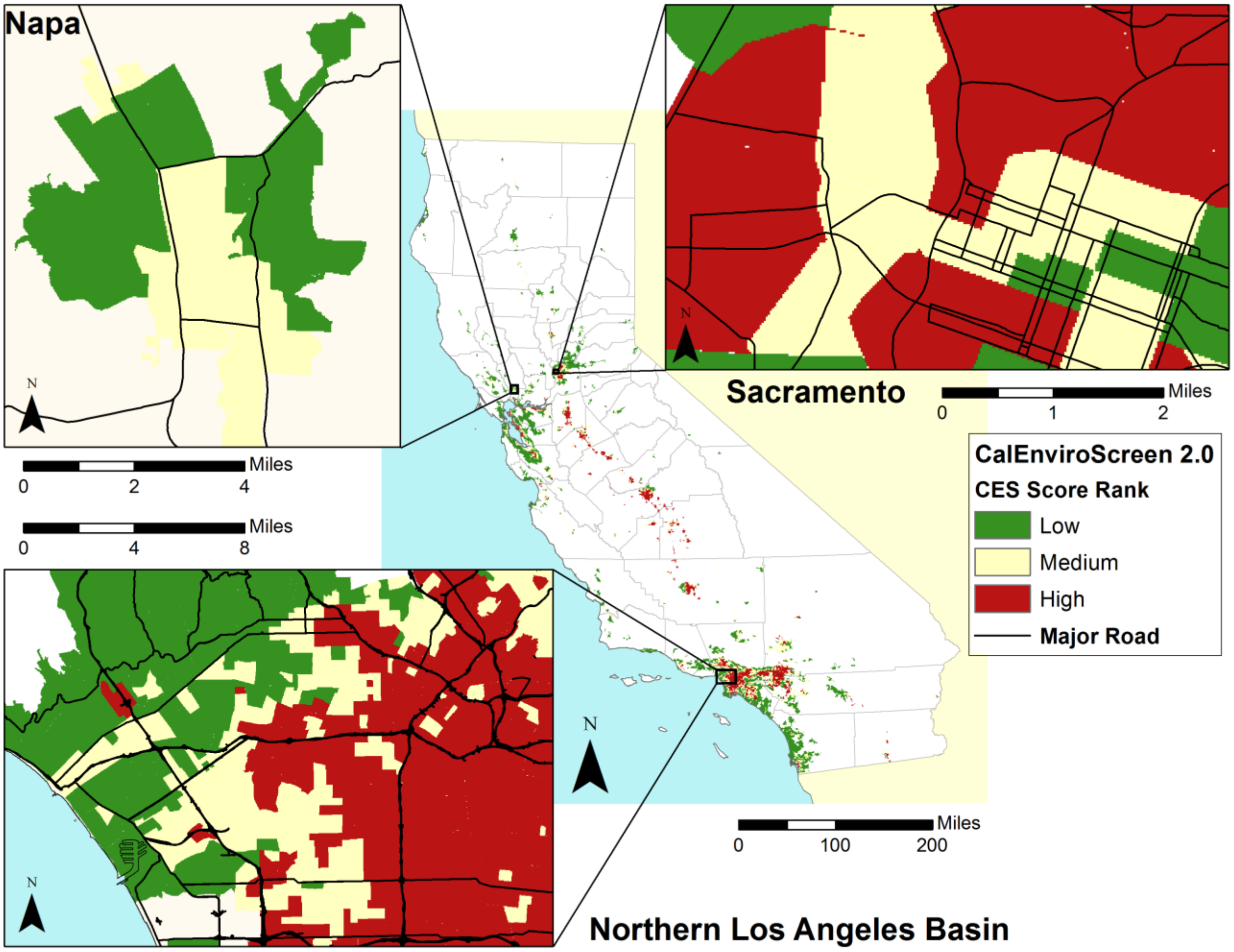


Figure 2-4. CalEnviroScreen (CES) score rank for urban areas (map).

Air Quality Reference Data

Air quality reference data were obtained from the California Air Resources Board (ARB). These data represent three measures of air quality: ozone, particulate matter <2.5 microns and particulate matter <10 microns. However, monitoring stations in California do not cover all areas in the state, and as a result some regions have no data.

Ozone and PM 2.5 were available through the CalEnviroScreen data layer. That layer had many topological errors, including overlaps and gaps, which were too time consuming to fix. We therefore converted the CalEnviroScreen 2.0 layer to two 30-meter rasters, one for ozone values and one for PM 2.5 values. Areas with no data were removed from the output. Using the zonal statistics as table tool, the mean value of ozone and PM 2.5 within each unique community/urban area/county geography was calculated, and the resulting table was joined back to the 2010 Census urban area layer.

PM 10 values were also considered to influence air quality, and these values were acquired through the Air Resources Board directly. We used the maximum value for the National

Maximum 24-Hour PM 10 Average for each combination of county and air basin from the available years between 2010 and 2013, and converted the table to GIS points using the latitude/longitude fields. The points containing PM 10 maximum values were then averaged for the geographies within the community/urban area/county layer.

The community/urban area/county layer was divided into three equal categories; with the lowest third having a rank value of 1, the next-highest 2, and the highest values were given a rank of 3. For values with no data, no rank was given. The three rank values were then averaged together to give an overall pollution rank. For areas with no data present in one of the categories, then only two values were averaged. If the average rank was 1.0-1.3, the final rank was low. If the average was 1.7-2.0, the final rank was medium. And if the average was 2.7-3.0, the final rank was high.

Scale up to landscapes

Transfer function equations were created using spatial data in the form of forest inventory plots, climate zones and land use classes. Once they were developed, an additional process was needed to convert these equations back to spatial data for the statewide urban areas. Similarly, environmental and demographic data layers were combined and classified into high, medium and low categories to create priority landscape layers. Those processes are described below.

Steps for scaling up CO_2 stored, sequestered carbon, and CO_2 avoided emissions

The objectives were to develop estimates of biomass, CO_2 stored, CO_2 sequestered and associated avoided emissions from shading. To do this, we integrated the urban forest inventory plots by climate zone and land use category to develop transfer functions for these variables.

All FIA and UFORE plots were assessed by how much canopy and how much biomass they had. If a plot had no biomass, it was ranked “0”. All plots were considered. Biomass, canopy, carbon (sequestered, stored, avoided) were summed for all plots by land use and climate zone. We took the sum of carbon and biomass results and divided by the sum of all canopy cover (see Appendix 4: Transfer function table including other benefits for R code used in analysis). Additionally, for CO_2 avoided analysis, cooling reductions (Megawatts) and heating reductions (Gigajoules) were quantified by summing each value across all plots within the same land use and climate zone and then divided by the total canopy cover for that land use.

For climate zones without tree data or measured plots, an average transfer function was calculated using data from similar climate zones. For the Interior West, averages were calculated using data from the Inland Empire, Inland Valley and Southwest Desert. For the Southwest Desert, averages for multi-family land use class were calculated using data from the Inland Empire and Inland Valley.

To transfer these to map-based values, the transfer function values developed from the plot data were used as multipliers on the spatial extent of canopy within climate zone and land use type. The extent of canopy was extracted from the EarthDefine map for each land use, climate zone, and urban area. These canopy area values were multiplied by the kg. values to produce kg. of carbon or biomass/unit area of canopy (hectare).

Scale-up steps for developing Priority Landscapes for Analysis 1 and Analysis 2

Environmental data layers including tree canopy, air pollution and climate data were combined with demographic and infrastructure layers, such as population density and roads in different ways in order to develop composite threat layers and composite asset layers for urban areas in the state. These layers were then combined to develop overall priority landscape layers to identify the most vulnerable areas in the state to target resources for tree planting and tree maintenance. Two sets of analyses were performed; Analysis 1: Urban Tree Planting for Energy Conservation and Air Quality and Analysis 2: Urban Tree Maintenance for Energy Conservation and Air Quality. The different data layers were combined in steps toward one final priority landscape layer for each analysis. The steps are outlined below (Figure 2-5 and Figure 2-6).

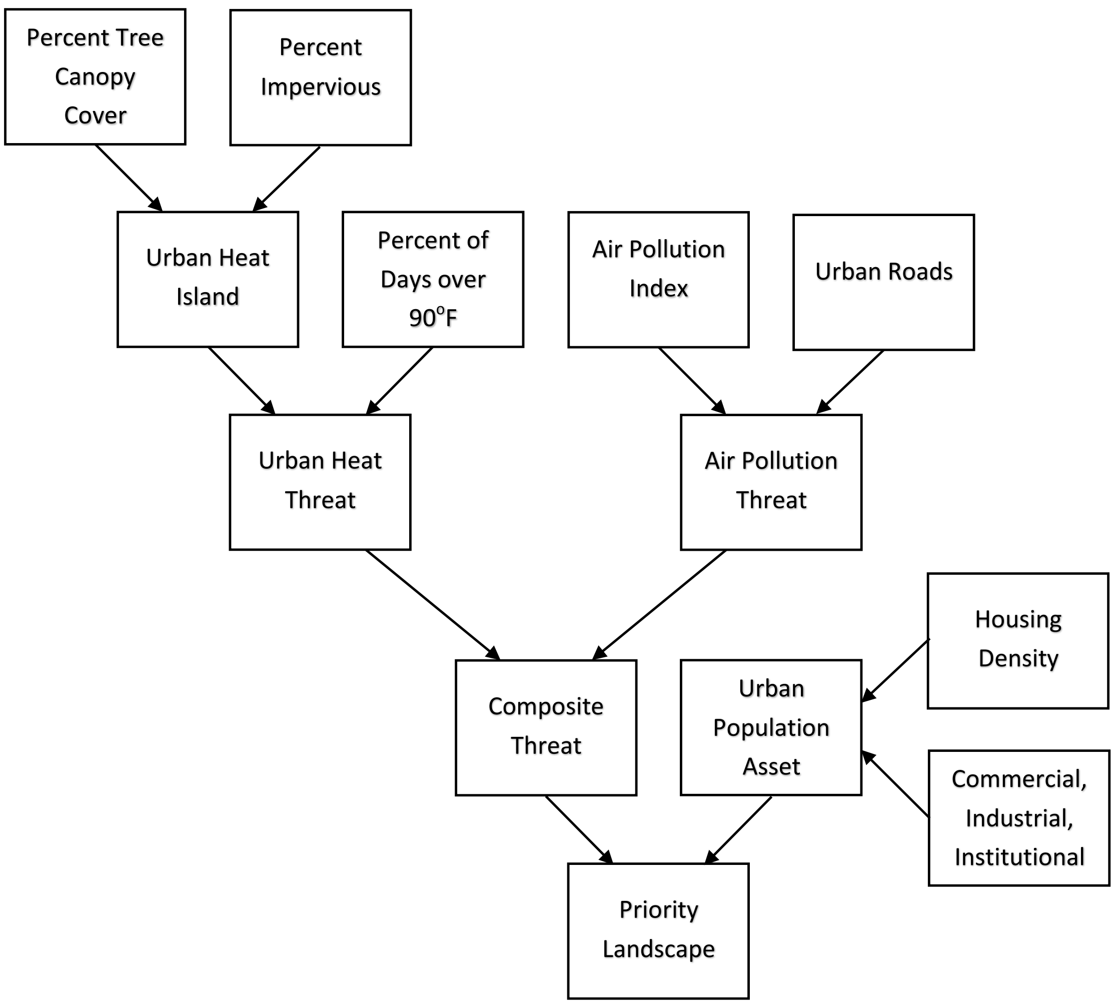


Figure 2-5. Analysis 1: urban tree planting priority landscape development (flow chart).

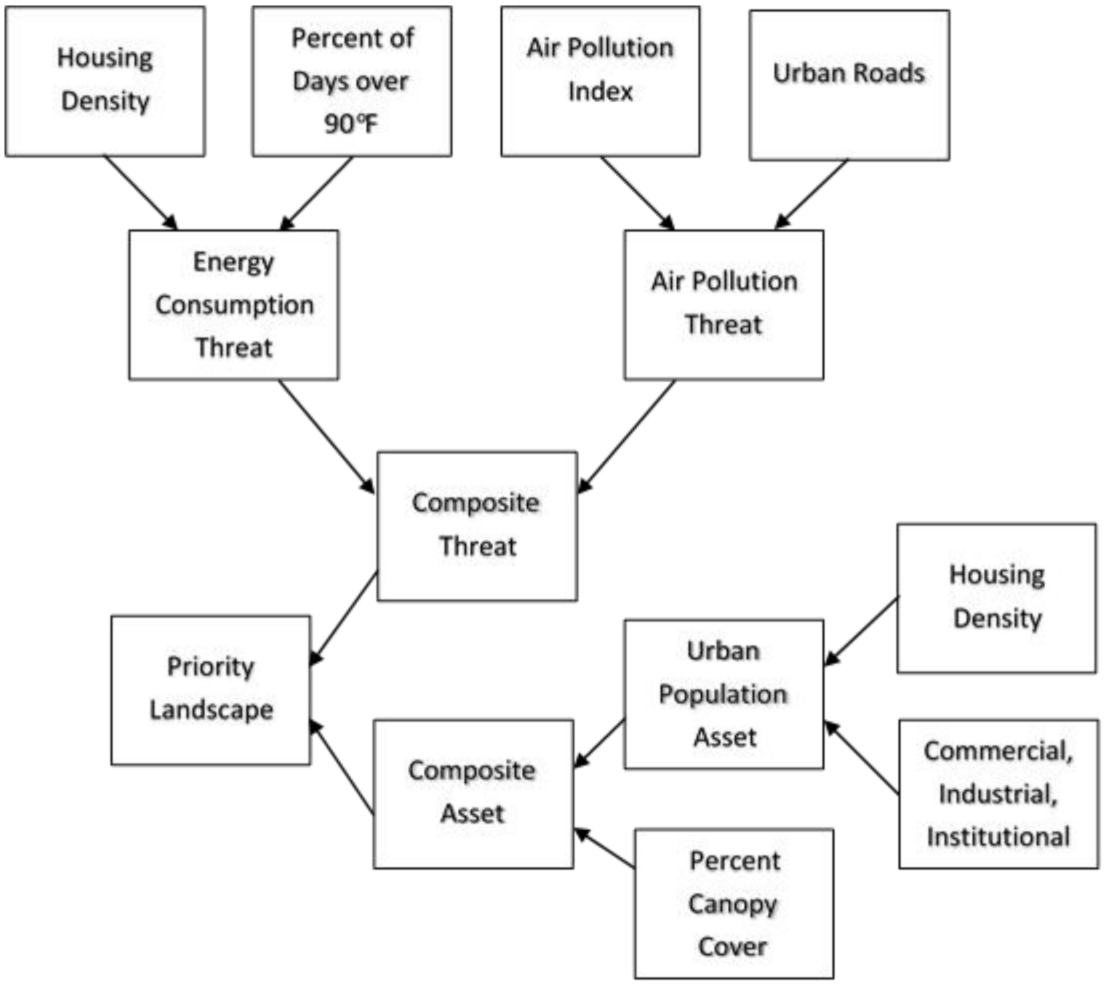


Figure 2-6. Analysis 2: urban tree maintenance priority landscape development (flow chart).

Chapter 3 RESULTS

The results section is broken into three parts. Part one addresses the mapped urban tree canopy, and transfer functions associated with carbon dioxide stored in trees: biomass, CO_2 stored, CO_2 sequestered, and avoided CO_2 emissions due to shading from trees. CO_2 stored refers to the amount of carbon that is stored in the tree woody mass or wood products long-term, but is eventually released back into atmosphere as part of the carbon cycle. CO_2 sequestered is the rate at which the carbon is accumulated for storage, but does not factor in an annual tree mortality figure. Avoided carbons are emission reductions that occur outside of a product's life cycle or value chain, but as a result of the use of that product (tree shading). The benefit calculations represent an initial baseline estimate that may be subject to change as new methods and information become available.

Part two provides some information about the geographic distribution of environmental health threats, such as air pollution and urban heat island effects as well as the distribution of both human population and tree canopy as assets throughout urban areas of the state. These threats and assets are combined to create overall priority landscapes for both tree planting and tree maintenance. In parts one and two, we present summarized data at the state level. Summarized data include the area within each low, medium and high ranked category as well as a percentage of area for the entire urban area for the state, 21,538 km^2 (Table 3-1). Data were summarized at the Urban Area level (Census 2010) and County level (Census 2012). A map is also included showing the extent of each variable. Note that the three levels of urban mapping: Napa, Sacramento and Northern Los Angeles Basin, can be used to examine patterns of the reported variables. The complete dataset from which the summary data were calculated can be found in Appendix 7: Tree Canopy, Biomass and CO_2 Inventory by Community, Urban Area and County.

Part three describes some of the demographic characteristics of the urban areas in California, and how some of them have changed over time.

Part One: Inventory

The following section reviews the results from the rollup of transfer functions to spatial units and summarizes the distribution of tree canopy, biomass and carbon inventory for urban areas and counties in California. Tabular results are given as a per-acre value so that large and small geographic units can be compared. Mapped results show values per 30 m^2 grid cell.

Table 3-1. Summary table of demographic, tree canopy and associated benefits for California (2 pages).

			Urban Area Metrics by Climate Zones					
	Statewide	**UA State Total**	**Inland Empire**	**Inland Valleys**	**Interior West**	**N. CA Coast**	**S. CA Coast**	**SW Desert**
Population								
2010	**37,254,503**	35,373,606	8,826,385	7,556,268	249,482	6,913,793	10,583,707	1,100,041
2000	**33,871,648**	31,989,663	6,864,872	6,204,443	198,972	6,574,937	11,243,661	842,688
% change (2000-2010)	**10.0%**	10.6%	28.6%	21.8%	25.4%	5.2%	-5.9%	30.5%
% Total Population (2010)	**100%**	95.0%	23.7%	20.3%	0.7%	18.6%	28.4%	3.0%
Total Urban Area (water + land)								
km^2 (2010)	**423,970**	21,538	4,744	6,231	365	3,840	5,087	1,189
km^2 (2000)	**423,970**	20,696	4,191	5,435	600	3,762	5,168	1,613
Urban Land Area								
km^2 (2010)	**403,466**	21,280	4,712	6,189	361	3,806	5,030	1,183
% land area (2010)	**100%**	5.3%	1.2%	1.5%	0.1%	0.9%	1.2%	0.3%
km^2 (2000)	**404,362**	20,542	4,143	5,397	593	3,706	5,094	1,609
% land area (2000)	**100%**	5.1%	1.0%	1.3%	0.1%	0.9%	1.3%	0.4%
% change (2000-2010)	**-0.2%**	3.60%	13.70%	14.70%	-39.10%**	2.70%	-1.30%	-26.50%**
Population Density (people/land area km2)								
2010	**92**	1,662	1,873	1,221	691	1,817	2,104	930
2000[2]	**84**	1,560	1,657.00	1,149.60	335.5	1,774.00	2,207.10	523.7
% change (2000-2010)	**10.2%**	6.6%	13.0%	6.2%	106.0%	2.4%	-4.7%	77.6%
Tree Canopy Cover (EarthDefine 2012)								
km^2	**n/a**	3,200	469	1,080	51	845	698	57
% land area	**n/a**	15.0%	10.0%	17.5%	14.1%	22.2%	13.9%	4.8%
Per capita (m^2/person)	**n/a**	90	53	143	204	122	66	51
Total Green Space (CPAD 2012)								
km2 green space	**199,332**	1,437	275	245	33	352	510	12
% land area	**49.4%**	6.8%	5.8%	4.0%	9.1%	9.2%	10.1%	1.0%
km^2 tree canopy within green space	**n/a**	288	35	57	12	103	81	1
% canopy green space	**n/a**	20.0%	12.6%	23.1%	35.2%	29.4%	15.8%	6.2%
Impervious Surface								
km^2 (2010)	**9,822**	7,612	1,555	1,925	69	1,395	2,337	323
% land area (2010)	**2.4%**	35.8%	33.0%	31.1%	19.1%	36.7%	46.5%	27.3%
Per capita (m^2/person) (2010)	**264**	215	176	255	277	202	221	293
km^2 (2001)	**8,413**	6,364	1,258	1,469	62	1,249	2,178	233
% change (2001-2010)	**16.7%**	19.6%	23.6%	31.1%	11.8%	11.7%	7.3%	38.2%

Data Sources: 2000 and 2010 Census (urban and rural); EarthDefine (2012 Tree Canopy), CPAD 2012 (Green Space), USDA, Forest Service (Climate Zones and Benefit Data).

Data Notes: ** Census Urban 2000 definition of Urban included prisons, while 2010 did not. This resulted in large drops of urban areas in smaller climate regions with numerous prisons. In addition, there was a reduction in urban military base property in the 2010 Census.

	UA State Total	Urban Area Tree Benefits by Climate Zones Inland Empire	Inland Valleys	Interior West	N. CA Coast	S. CA Coast	SW Desert
Urban Tree Canopy (ha)	320,048	46,932	108,045	5,089	84,484	69,837	5,662
Carbon							
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)	7,225,191	785,169	2,171,692	92,592	2,745,568	1,340,972	89,198
CO_2 sequestered ($1000/yr)	$86,715	$9,438	$26,060	$1,113	$32,913	$16,118	$1,072
Pollution							
CO_2 avoided (metric tons/yr)	1,300,883	443,020	561,056	21,109	165,304	74,964	35,430
CO_2 avoided ($1,000/yr)	$15,637	$5,325	$6,744	$254	$1,987	$901	$426
NO_2 removed (metric tons/yr)	6,481	1,280	2,308	119	800	1,819	156
NO_2 removed ($1,000/yr)	$69,298	$13,690	$24,672	$1,269	$8,550	$19,450	$1,667
O_3 removed (metric tons/yr)	11,293	2,121	4,902	100	1,103	2,977	90
O_3 removed ($1,000/yr)	$120,747	$22,677	$52,416	$1,069	$11,791	$31,828	$966
SO_2 removed (metric tons/yr)	2,331	1,044	481	89	271	343	103
SO_2 removed ($1,000/yr)	$34,851	$15,610	$7,188	$1,324	$4,055	$5,132	$1,543
PM_{10} removed (metric tons/yr)	7,030	1,284	3,066	53	726	1,808	93
PM_{10} removed ($1,000/yr)	$63,819	$11,653	$27,833	$484	$6,587	$16,414	$847
Net VOC removal (BVOC + VOC) (metric tons/yr)	-23,599	-6,282	-5,505	-76	-7,924	-3,464	-349
Net VOC removal (BVOC + VOC) ($1,000/yr)	-$232,476	-$61,882	-$54,229	-$744	-$78,061	-$34,119	-$3,442
Total pollutant removal (tons/yr)	3,537	-553	5,252	285	-5,025	3,484	93
Total pollutant removal ($1,000/yr)	$56,239	$1,749	$57,879	$3,403	$-47,077	$38,706	$1,580
Energy savings							
Cooling (MWh)	3,850,640	1,371,903	1,886,367	65,996	233,536	175,165	117,672
Cooling ($1,000/yr)	$548,350	$205,785	$257,055	$9,849	$31,824	$26,275	$17,561
Heating (GJ)	2,181,498	-337,016	239,757	521	1,928,127	321,410	28,697
Heating ($1,000/hyr	$20,280	-$2,962	$2,230	$4	$17,931	$2,825	$252
Total Energy Savings ($1,000/yr)	$568,630	$202,824	$259,285	$9,850	$49,755	$29,100	$17,813
Stormwater Runoff Reduction							
Interception (m^3)	195,963,847	42,129,470	48,707,690	1,187,552	60,550,834	40,194,111	3,194,190
Interception ($1000)	$324,628	$80,466	$97,791	$1,569	$63,983	$76,769	$4,050
Aesthetic and Other Benefits							
Property Value ($1,000)	$7,234,068	$1,058,217	$2,249,998	$11,234	$1,673,360	$2,131,974	$109,285
Replacement Value ($1,000)	$181,011,970	$28,980,830	$49,464,742	$978,331	$31,915,429	$61,558,295	$8,114,344

Data Notes: Carbon valued at $12.02 per ton, the annual metric ton average in 2014 (California Carbon Dashboard). Energy savings value estimated using UFORE and FIA plot data. The benefit data represents an initial baseline estimate that may be subject to change as new methods and information become available.

Tree Canopy

Total urban tree canopy for the 2010 Census Urban Areas covered approximately 3,204 km^2 out of the total 21,538 km^2 of urban area, or 15.1% (Table 3-2). The mean urban tree canopy cover for Census 2010 urban areas was 15.7% and the median 9.9%. By county, the urban area canopy cover was 19.5%, with a median of 15.5%.

Table 3-2. Urban tree canopy (UTC) data summarized by 2010 Census urban areas and counties.

Urban Tree Canopy	UTC Urban Area	UTC County
Mean	15.7%	19.5%
Median	9.9%	15.5%
Standard Deviation	14.5%	12.8%
Minimum	0.3% (Fort Irwin)	3.5% (Imperial)
Maximum	71.7% (Paradise)	66.5% (Tuolumne)
Range	71.4%	63%

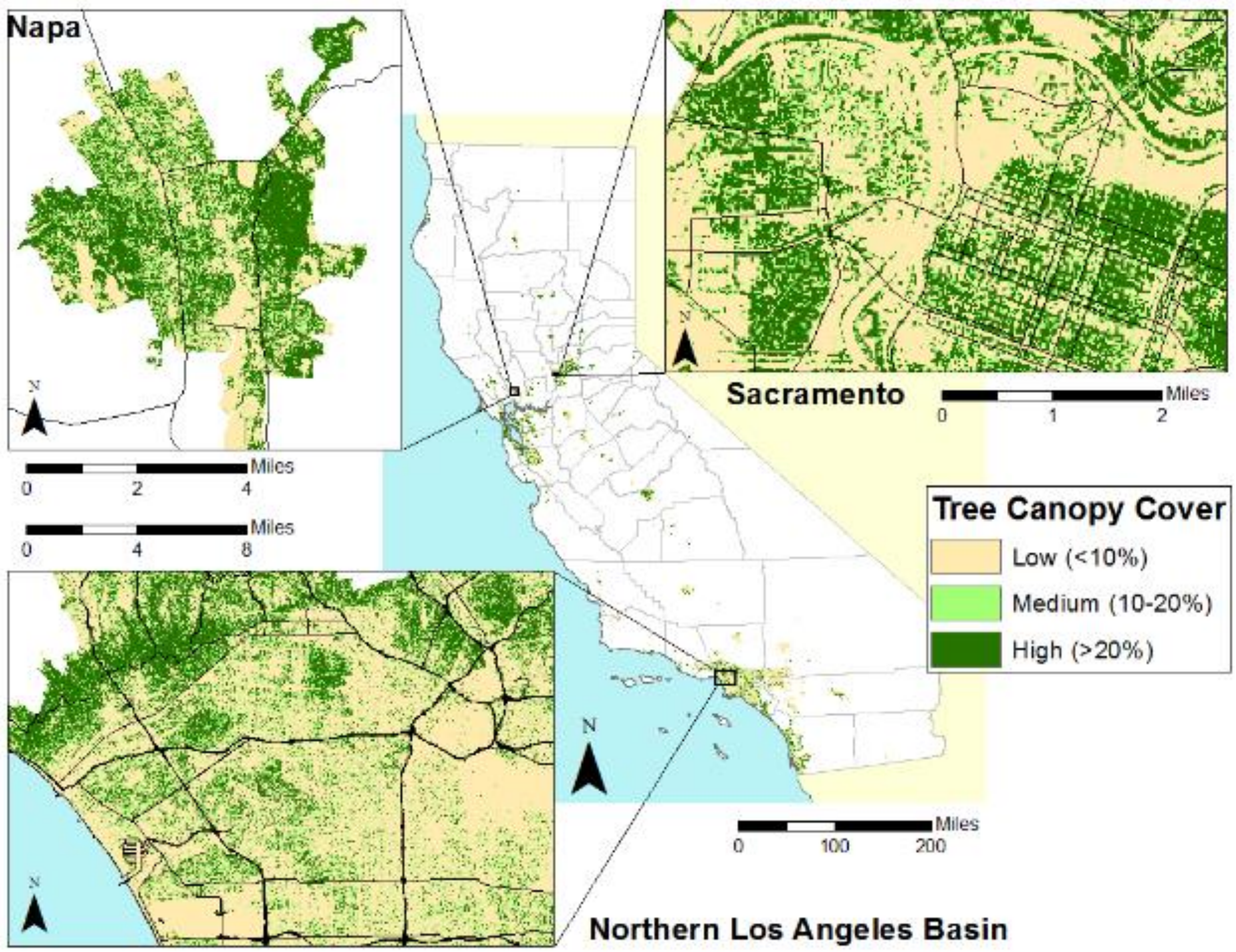


Figure 3-1. Percent tree canopy cover within California urban areas (map).

Tree canopy was also ranked into high, medium and low categories for use in further analysis presented in Part 2, such as urban heat effects (Figure 3-1). Using these rankings, 61.4% of urban areas had tree canopy cover that was considered to be low, 12.8% of areas medium, and 25.9% high (Table 3-3).

Table 3-3. Urban Tree Canopy (UTC) area and percentage associated with high, medium and low ranks.

Urban Tree Canopy	Percent Tree Canopy	Area (km^2)	Percent of Urban Area
Low	<10%	13,214.3	61.4%
Medium	10-20%	2,747.7	12.8%
High	>20%	5,576.8	25.9%

Biomass

Biomass for urban areas was calculated based upon transfer functions created using the tree species, the climate zone, the tree dbh, and the tree height from FIA and UFORE plots and the amount of urban tree canopy for a given area (see Methods section for more detail). Total urban biomass for the 2010 Census Urban Areas was 43,780,627 tons (Table 3-1). The mean biomass value for Census 2010 urban areas was 9.07 tons/acre and the median 5.44 tons/acre, and for counties the mean biomass value was 11.49 tons/acre and the median 8.70 tons/acre (Table 3-4).

Table 3-4. Biomass (tons/acre) summarized by 2010 Census urban areas and counties.

Biomass	UTC Urban Area (tons/acre)	UTC County (tons/acre)
Mean	9.07	11.49
Median	5.44	8.70
Standard Deviation	9.09	8.37
Minimum	0.12 (Fort Irwin)	0.87 (Imperial)
Maximum	41.94 (Paradise)	36.99 (Tuolumne)
Range	41.82	36.1

The regions of the state with the smallest amount of tree canopy cover, the Imperial Valley, also have the lowest levels of biomass (Figure 3-2). The urban area of Paradise, in Butte County had the highest per acre value of biomass, while a county comparison showed Tuolumne County had the highest per acre value of biomass among counties. The Urban Area of Fort Irwin, located in San Bernardino County had the lowest per acre value of biomass, with Imperial County having the lowest value at the county level.

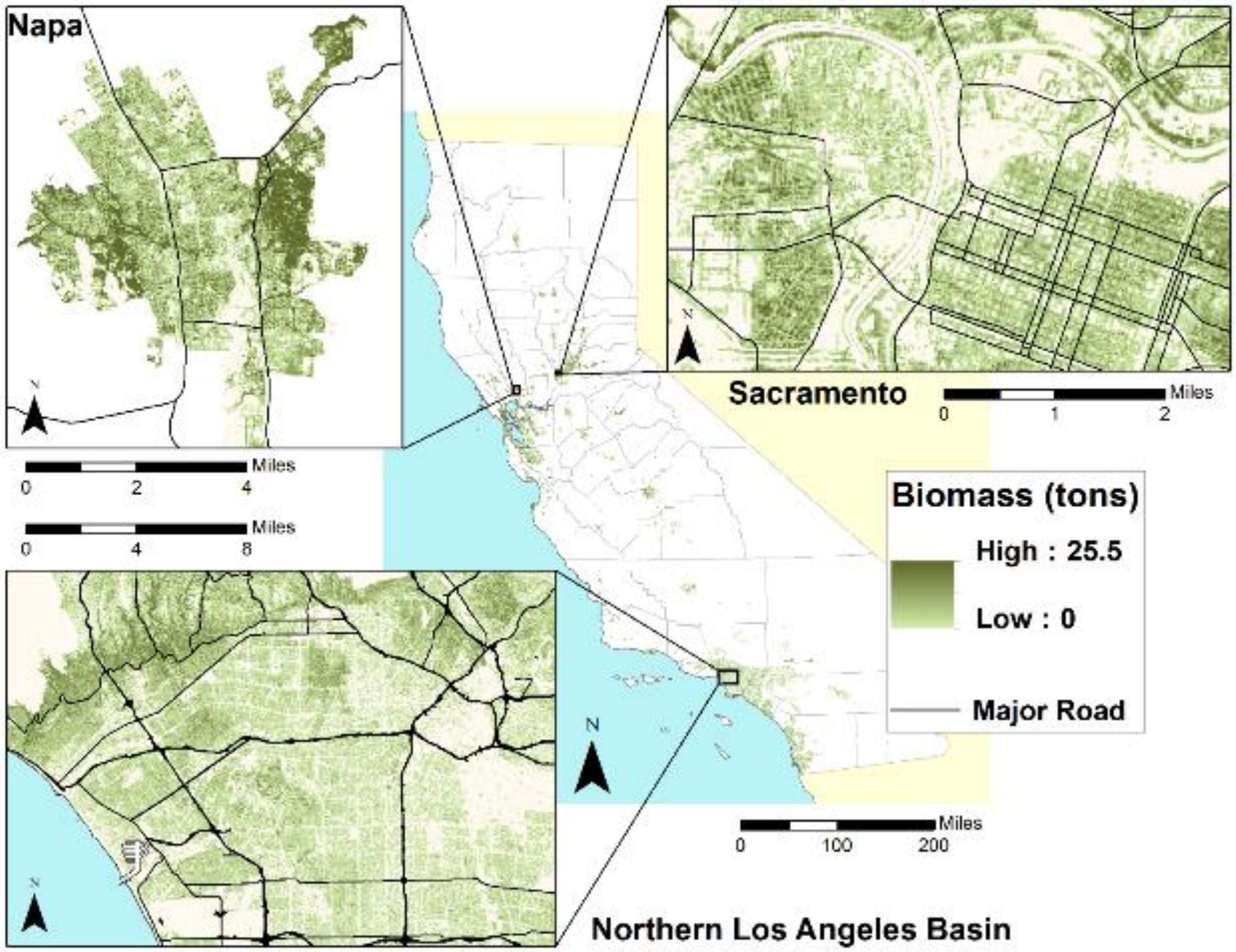


Figure 3-2. Estimated biomass (tons/grid cell) within California urban areas (map).

Carbon Stored

The total estimated CO_2 stored value for all California urban areas was 102,995,988 tons (Table 3-1). The mean CO_2 stored value for Census 2010 urban areas was 21.32 tons/acre and the median 12.79 tons/acre, and for counties the mean CO_2 stored value was 27.01 tons/acre and the median 20.46 tons/acre (Table 3-5).

Table 3-5. CO2 stored (tons/acre) summarized by 2010 Census urban areas and counties.

CO_2 Stored	UTC Urban Area (tons/acre)	UTC County (tons/acre)
Mean	21.32	27.01
Median	12.79	20.46
Standard Deviation	21.39	19.70
Minimum	0.00 (Vandenberg AFB)	2.04 (Imperial)
Maximum	98.68 (Paradise)	87.01 (Tuolumne)
Range	98.68	84.97

Paradise, in Butte County, had the highest per acre value of CO_2 stored amongst urban areas. The county with the highest amount of CO_2 stored was Tuolumne County. The urban area of Fort Irwin, located in San Bernardino County had the lowest per acre value of CO_2 stored, with Imperial County having the lowest value at the county-level.

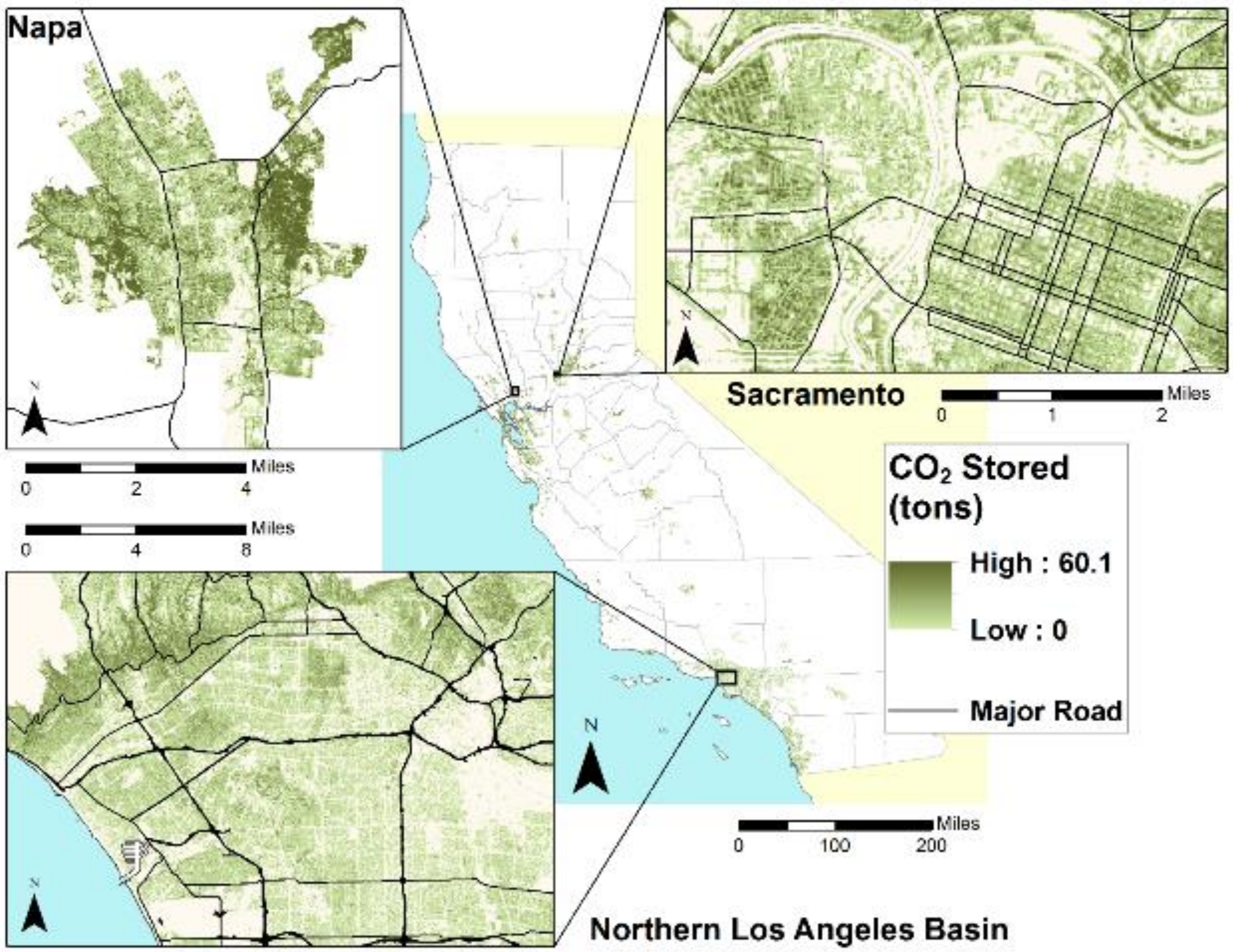


Figure 3-3. Estimated CO_2 stored (tons/grid cell) within California urban areas (map).

Carbon Sequestered

The annual CO_2 sequestered by trees in all California urban areas was 7,225,191 tons/year, worth an estimated $ 86,714,832 (Table 3-1). The mean CO_2 sequestered value for Census 2010 urban areas was 1.46 tons/year/acre and the median 0.8 tons/year/acre, and for counties the mean CO_2 sequestered value was 1.87 tons/year/acre and the median 1.26 tons/year/acre (Table 3-6).

Table 3-6. CO2 sequestered (tons/year/acre) summarized by 2010 Census urban areas and counties.

CO_2 Sequestered	UTC Urban Area (tons/year/acre)	UTC County (tons/year/acre)	UTC Urban Area ($/year/acre)	UTC County ($/year/acre)
Mean	1.46	1.87	$17.50	$22.45
Median	0.80	1.26	$9.56	$15.20
Standard Deviation	1.52	1.45	$18.30	$17.47
Minimum	0.02(Fort Irwin)	0.20 (Imperial)	$0.00 (Vandenberg AFB)	$2.38 (Imperial)
Maximum	7.63 (Guerneville)	6.22 (Marin)	$91.68 (Guerneville)	$74.76 (Marin)
Range	7.61	6.02	$91.68	$72.39

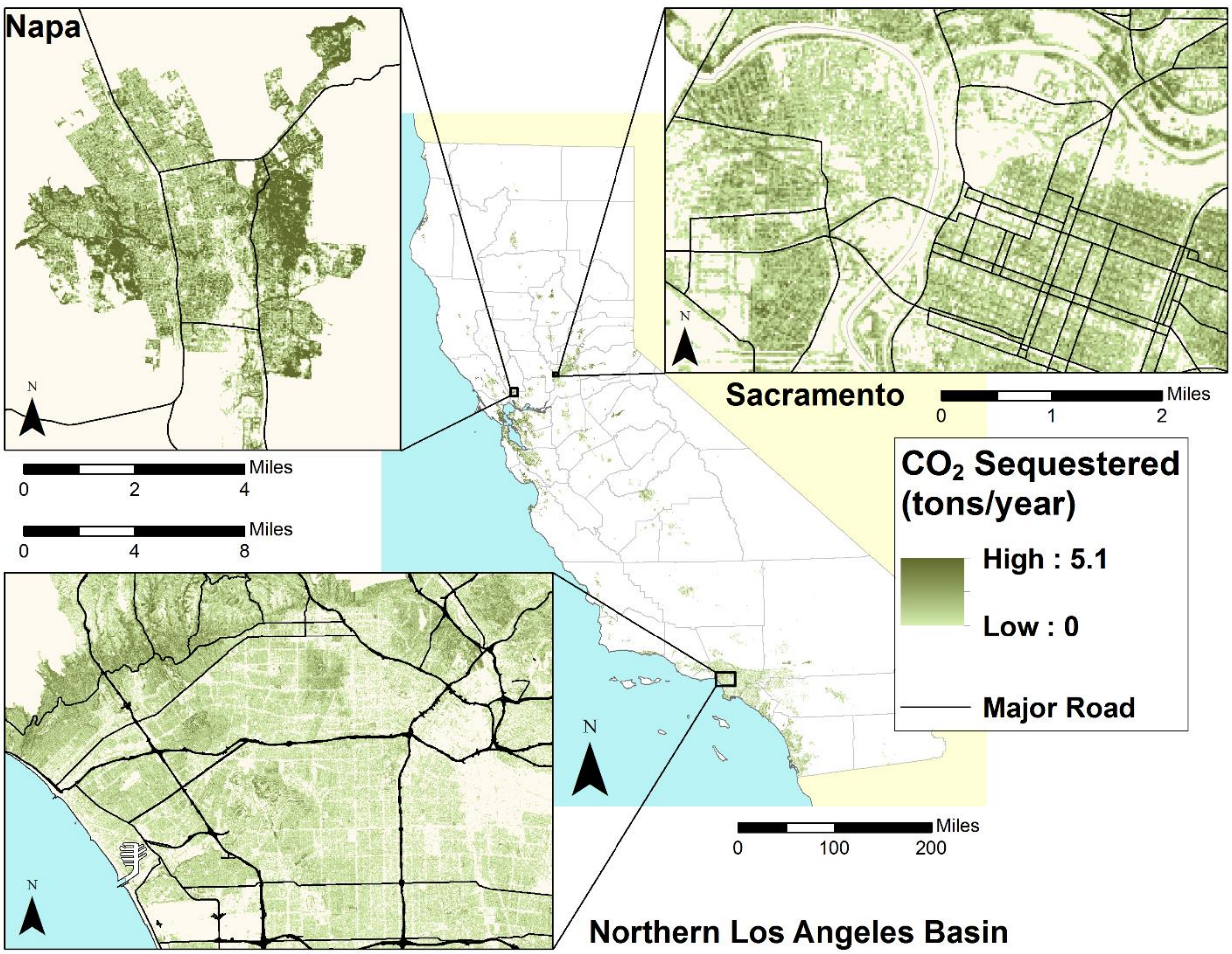


Figure 3-4. Estimated CO2 sequestered (tons/year/grid cell) within California urban areas (map).

The urban area of Guerneville, in Sonoma County had the highest per acre value of carbon sequestered, while overall the county with the highest amount of carbon sequestered was Marin County. The urban area of Fort Irwin, located in San Bernardino County had the lowest per acre value of carbon sequestered, with Imperial County having the lowest value at the county-level (Figure 3-4).

CO_2 Emissions Avoided

The total value of estimated CO_2 emissions avoided due to tree shading that reduces energy demand for cooling structures, for all California urban areas combined was 1,300,883 tons/year, worth an estimated $15,636,609 (Table 3-1). The mean CO_2 avoided value for Census 2010 urban areas was .27 tons/year/acre and the median .19 tons/year/acre, and for counties the mean CO_2 stored value was .33 tons/year/acre and the median .25 tons/year/acre (Table 3-7).

Table 3-7. CO_2 emissions avoided (tons/year/acre) summarized by 2010 Census urban areas and counties.

CO_2 Avoided	**UTC Urban Area (tons/year/acre)**	**UTC County (tons/year/acre)**	**UTC Urban Area ($/year/acre)**	**UTC County ($/year/acre)**
Mean	0.27	0.32	$3.19	$17.58
Median	0.19	0.24	$2.29	$13.82
Standard Deviation	0.28	0.25	$3.40	$11.93
Minimum	0.00 (Twentynine Palms Base, Vandenberg AFB)	0.06 (Orange)	$0.00 (Twentynine Palms Base/ Vandenberg AFB)	$3.80 (Imperial)
Maximum	1.82 (Paradise)	1.37 (Tuolumne)	$21.93 (Paradise)	$56.16 (Tuolumne)
Range	1.82	1.31	$21.93	$52.37

The urban area of Paradise, in Butte County had the highest per acre value of CO_2 emissions avoided. The county with the highest amount of carbon sequestered was Tuolumne County. The urban areas of Twenty nine Palms Base, located in San Bernardino County and Vandenberg AFB in Santa Barbara County had the lowest per acre values of CO_2 emissions avoided. Since it is probable that the Twenty Nine Palms base, located in the desert, requires cooling of buildings, the 0 values are likely due to the land use classifications of military bases being “Open Space” or “Other”, both of which result in 0 avoided emissions. Orange County had the lowest value at the county level for CO_2 avoided emissions (Figure 3-5).

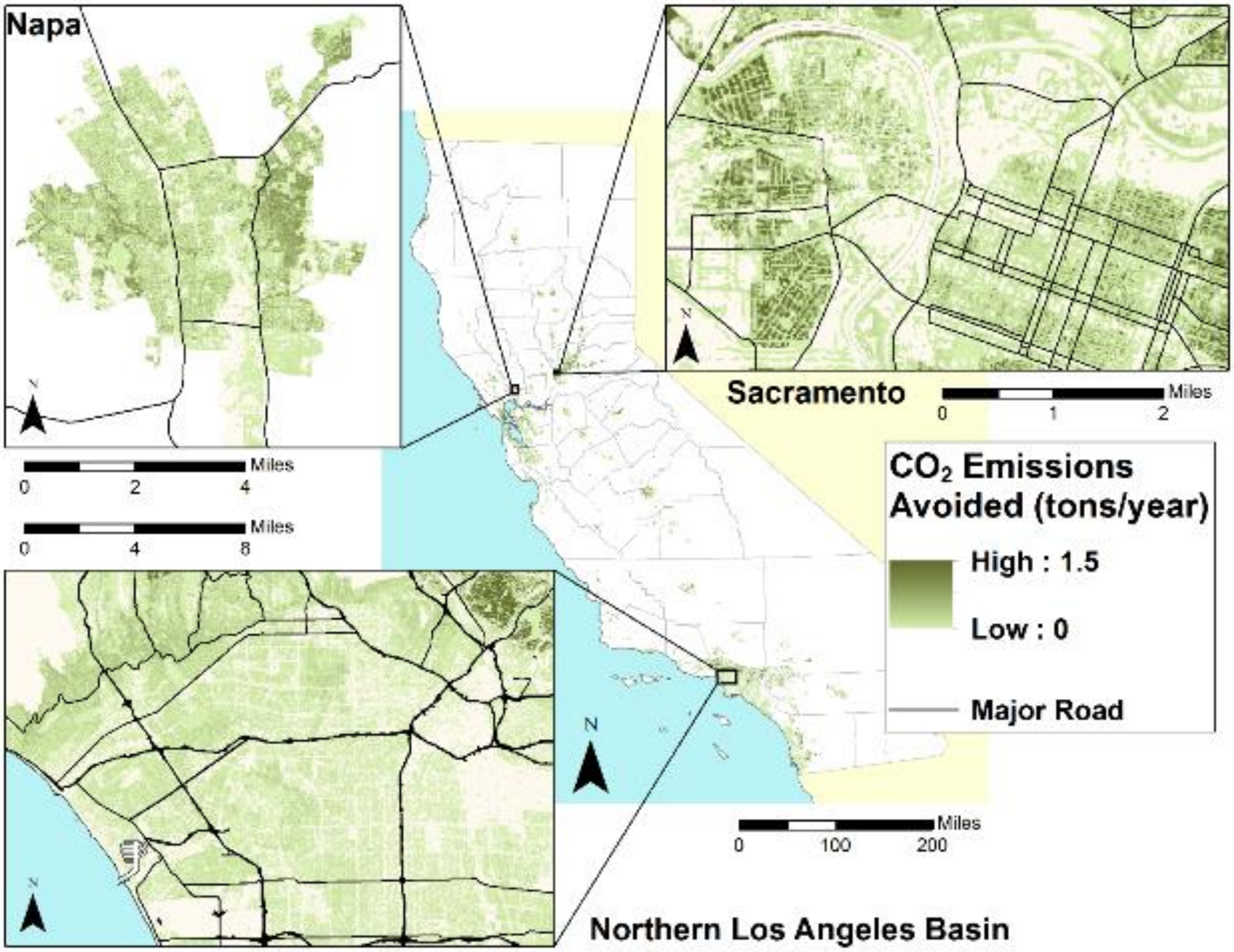


Figure 3-5. Estimated CO_2 emissions avoided (tons/year/grid cell) within California urban areas (map).

Part Two: Priority Landscapes

This section of the results presents two major analyses requested by FRAP, and also a number of the component parts that were required to develop the analyses. The first analysis is to identify priority landscapes as they relate to tree planting. The second analysis is to identify priority landscapes as they relate to tree maintenance. Both analyses rely on the calculation of component parts such as air pollution threat and urban population density, which are also reported here. While this report encompasses all urban areas within the State of California, the condition of urban forests is not consistent across all areas, and some priority landscapes were identified for future investment in urban tree planting and improved management. To distinguish these areas, a number of environmental threats related to climate, air pollution and urban heat island effects were examined. In addition, urban areas across the state were classified by population density, so that areas where environmental threats were disproportionately affecting larger numbers of people could be identified. Together, the threats and assets give an overall rank to the urban areas in California, and highlight specific communities or areas that could benefit the most from targeted programs.

Analysis 1: Urban Tree Planting for Energy Conservation and Air Quality

Priority landscapes for urban tree planting for energy conservation and air quality contains several layers relating to climate and population density that are combined in a way to produce composite threat and asset layers. These layers are then combined to create an overall priority landscape layer identifying the most vulnerable areas in the state.

Urban Heat

The urban heat threat includes an urban heat island layer and a climate layer to show areas of the state most impacted by urban heat. The urban heat island layer was created by ranking the state according to the percent of impervious surface and combining that with a ranking of the percent urban tree canopy cover (Table 3-8).

Table 3-8. The urban heat island rank, using tree canopy cover and impervious surface.

	% Tree Canopy Cover		
% Impervious	**L (Trees<10%)**	**M (10-20%)**	**H (>20%)**
H (>70%)	H	M	L
M (30-70%)	H	M	L
L (<30%)	M	L	L

Areas with both a high percentage of impervious surface and low tree canopy cover were considered to have a high urban heat island effect, while areas with a high tree canopy were considered to have a low urban heat island effect. Figure 3-6 shows the statewide view of urban heat island threat, with zoomed in areas around Napa County, downtown Sacramento and the Northern Los Angeles Basin.

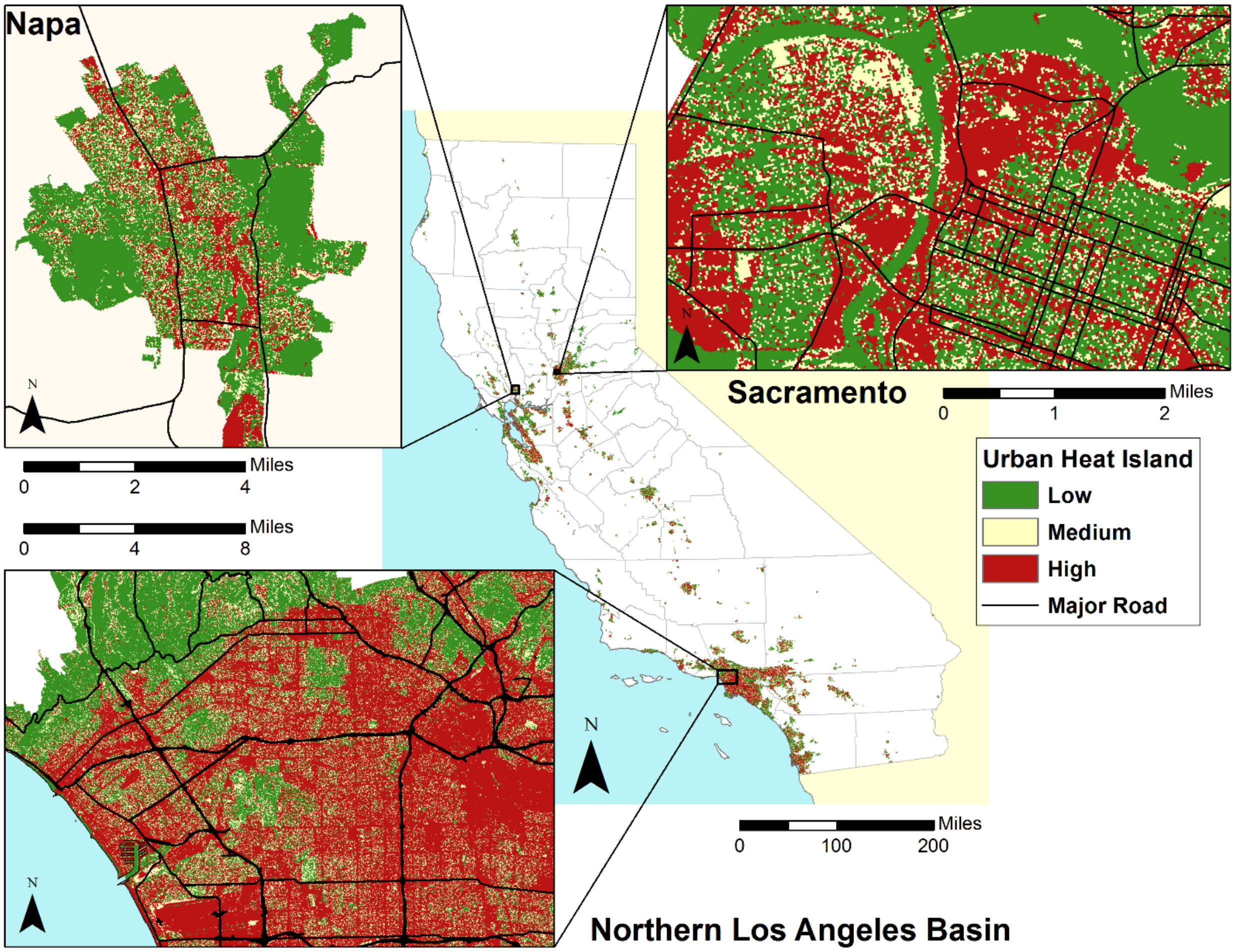


Figure 3-6. Urban heat island effect (map).

Urban heat island effects are only part of the story when determining an index of overall urban heat threat. A more complete picture can be achieved by incorporating climate data. A climate layer was created to rank the average percent of days per calendar year over 90 degrees Fahrenheit. This metric was used to evaluate severe health concerns, as they are associated with prolonged excessive heat, especially for vulnerable population. Using a 270m downscaled version of the PRSM daily maximum temperatures between 2004 and 2013, the number of days exceeding 90 degrees was calculated per year. These 10 years were then averaged and ranked (Table 3-9).

Table 3-9. Ranking of PRSM climate data.

Days Over 90 Rank	% of Days over 90ºF
L	<8% (0-29days/year)
M	9-20% (30-73days/year)
H	>20% (74+ days/year)

Combined with the urban heat island rank, areas can now be identified that have a high percentage of impervious surface, low tree canopy cover and a higher percentage of days over 90° (Table 3-10). The combination of these three variables results in overall urban heat threat.

Table 3-10. Urban heat threat rank, using urban heat island and climate data.

	Urban Heat Island Rank		
% of days >90° F	**H**	**M**	**L**
L (<8%)	M	M	L
M (9-20%)	H	M	L
H (>20%)	H	H	L

Figure 3-7 shows the final urban heat threat index. The same regions as Figure 3-6 are displayed, but this figure includes the added temperature effect. Whereas the Northern Los Angeles Basin showed some risk of having a high urban heat island effect, the effect of coastal temperatures reduce the overall threat, while in Sacramento the urban heat threat remains high due to the high air temperatures in that region.

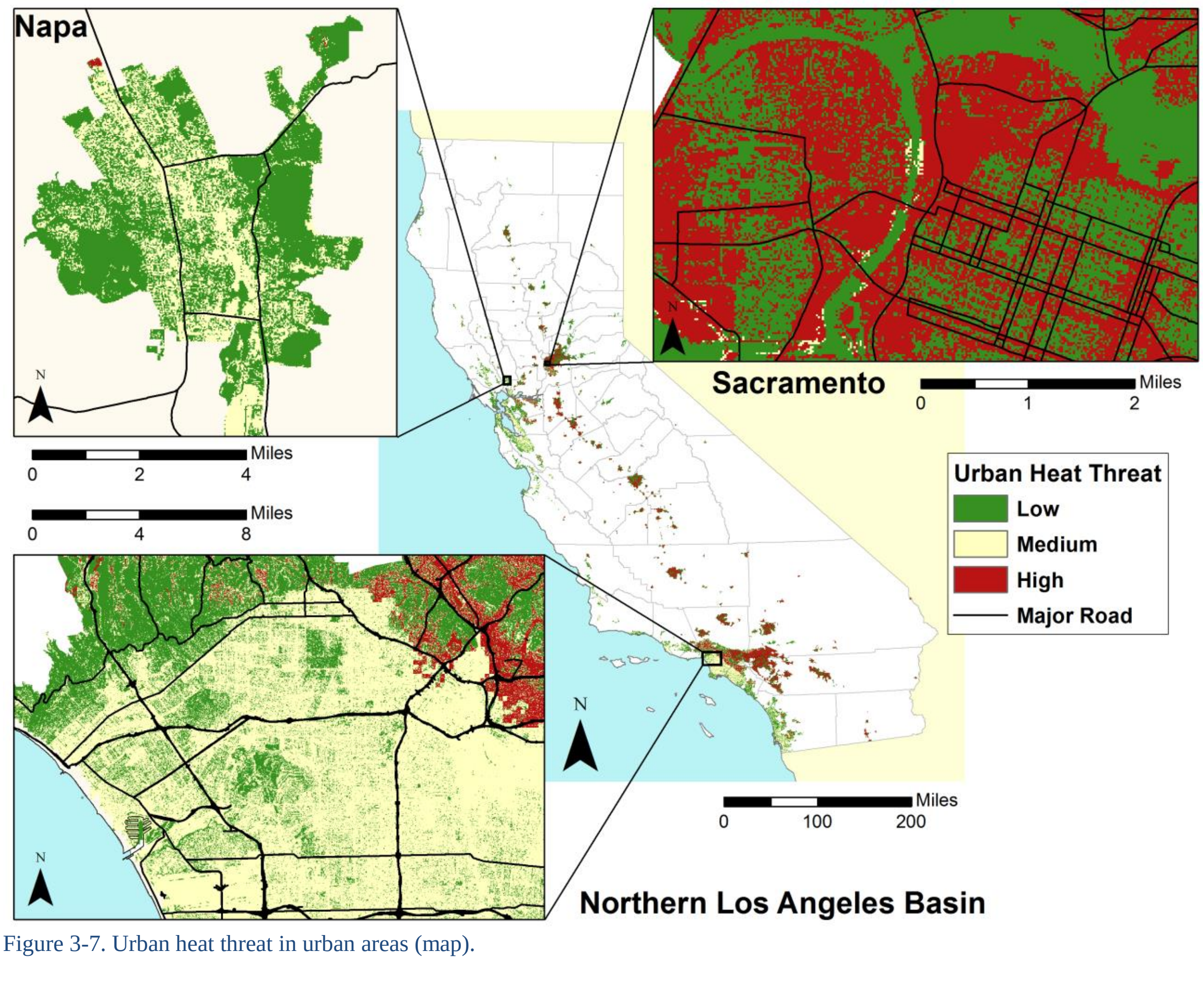


Figure 3-7. Urban heat threat in urban areas (map).

The results indicate that the overall urban heat threat and percent of days over 90° F match closely, with just over 39% in the high rank category, roughly 21% in the medium rank category and 38% in the low category, for the urban areas in California (Table 3-11).

Table 3-11. Extent of different environmental measures, in km^2 and percent of total urban area.

	Tree Canopy (km^2)	Tree Canopy (%)	Impervious (km^2)	Impervious (%)	Days Over 90° (km^2)	Days Over 90° (%)	Urban Heat Threat (km^2)	Urban Heat Threat (%)
Low	13,214.3	61.4%	4,985.7	23.1%	8,254.9	38.6%	8,254.9	38.3%
Medium	2,747.7	12.8%	8,333.4	38.7%	4,612.6	21.6%	4,612.6	21.4%
High	5,576.8	25.9%	3,163.4	14.7%	8,513.6	39.8%	8,513.6	39.5%

Air Pollution

Another threat to urban areas is air pollution, here described by levels of particulate matter (PM) at 2.5 microns and 10 microns, as well as ozone. First, the statewide urban areas were ranked using a combination of these three air pollution variables, described in greater detail in the methods section. Then, the air pollution ranks were merged with an urban roads layer, which ranked areas by proximity to interstate highways and principal arterial roads (Table 3-12). Thus, areas that rank high in air pollutants and are situated near major roads or expressways are considered more vulnerable to issues related to poor air quality.

Table 3-12. Air pollution threat rank, using proximity to major roads and air pollution levels.

	Air Pollution		
Urban Road Density	**H**	**M**	**L**
L (>150 m of principal arterial)	H	M	L
M (<150 m of principal arterial)	H	H	M
H (<300 m of interstate, freeway or expressway)	H	H	M

The results show that more than half (56.6%) of the urban areas analyzed were considered to have a high air pollution threat level (Table 3-13). This is due mostly to poor air quality, as the air pollution index shows 43.7% in the High category, and another 34.1% in the Medium category. Some areas of the state could not be ranked due to a lack of air quality monitoring or data available from the Air Resources Board.

Table 3-13. The extent of different environmental threats, in km^2 and percent of total urban area.

	Air Pollution Index (km^2)	Air Pollution Index (%)	Urban Road Density (km^2)	Urban Road Density (%)	Air Pollution Threat (km^2)	Air Pollution Threat (%)
Low	4,773.4	22.2%	13,458.4	62.5%	2,899.0	13.5%
Medium	7,349.8	34.1%	5,542.6	25.7%	6,440.9	29.9%
High	9,412.2	43.7%	3,346.1	15.5%	12,193.1	56.6%

Figure 3-8 shows the air pollution threat levels for urban areas statewide as well as three zoomed in areas. Areas with poor air quality and a high density road network, such as the Northern Los Angeles Basin, are ranked a high air pollution threat, while more rural areas, such as Napa County, are given a low rank for air pollution threat levels.

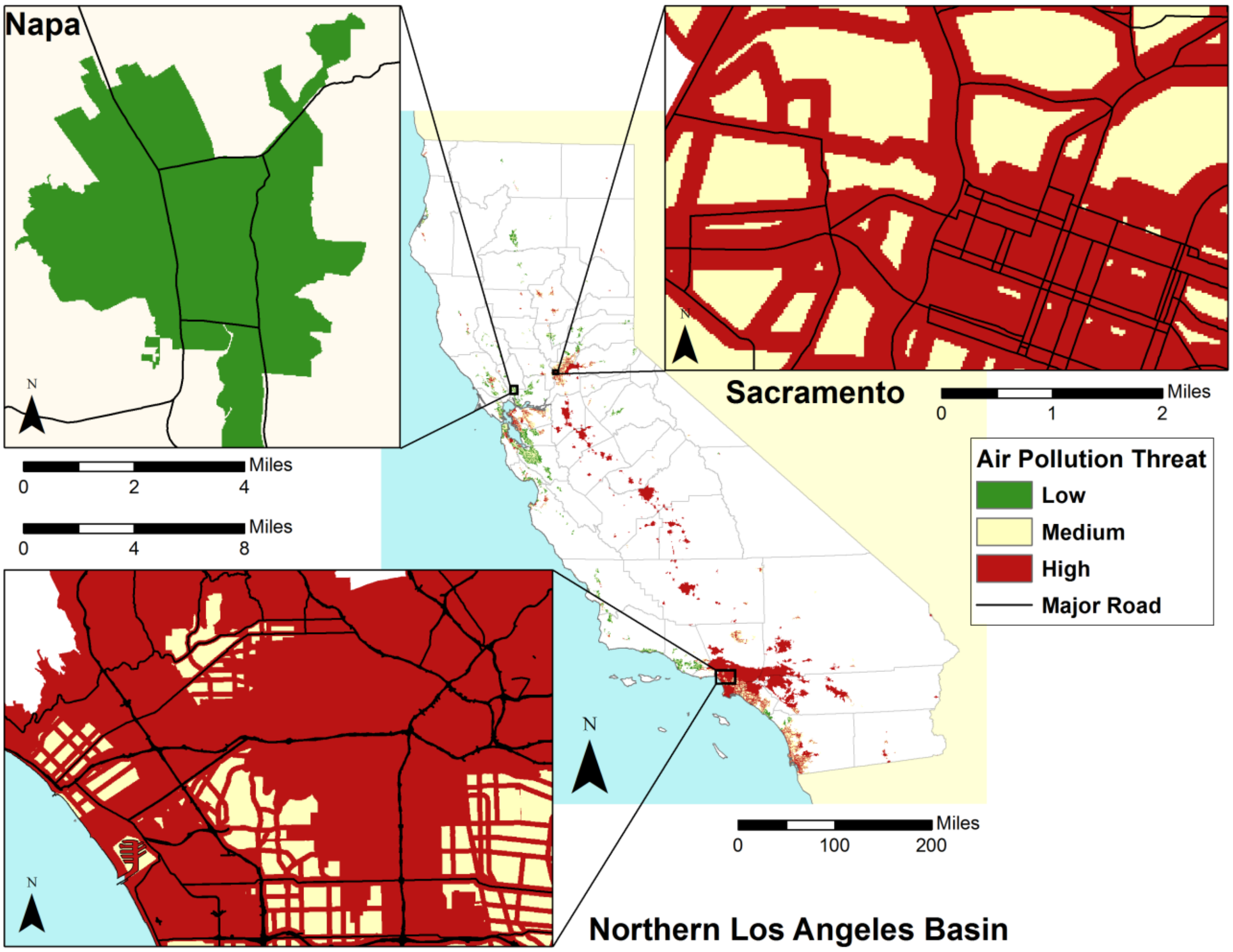


Figure 3-8. Air pollution threat index levels in urban areas (map).

Composite Threat

The urban heat and air pollution threat layers were merged into a single composite threat using equal weights. All urban areas were categorically ranked by high, medium or low vulnerability to the composite threat (Table 3-14). Areas with high threats in both pollution and urban heat were given the highest rank.

Table 3-14. The composite threat layer rank, using urban heat threat and the air pollution threat.

	Air Pollution Threat		
Urban Roads	**H**	**M**	**L**
L	L	L	L
M	M	L	L
H	H	M	L

The results show that most of the urban areas fall into the low threat level (61.7%), although there is a considerable amount of area within the high threat levels (23.1%) (Table 3-15). These areas would be the most vulnerable to both urban heat effects and poor air quality.

Table 3-15. The extent of composite urban heat and air pollution threats for urban areas in California.

	Composite Threat (km^2)	Composite Threat (%)
Low	13,197.8	61.7%
Medium	3,240.2	15.2%
High	4,937.4	23.1%

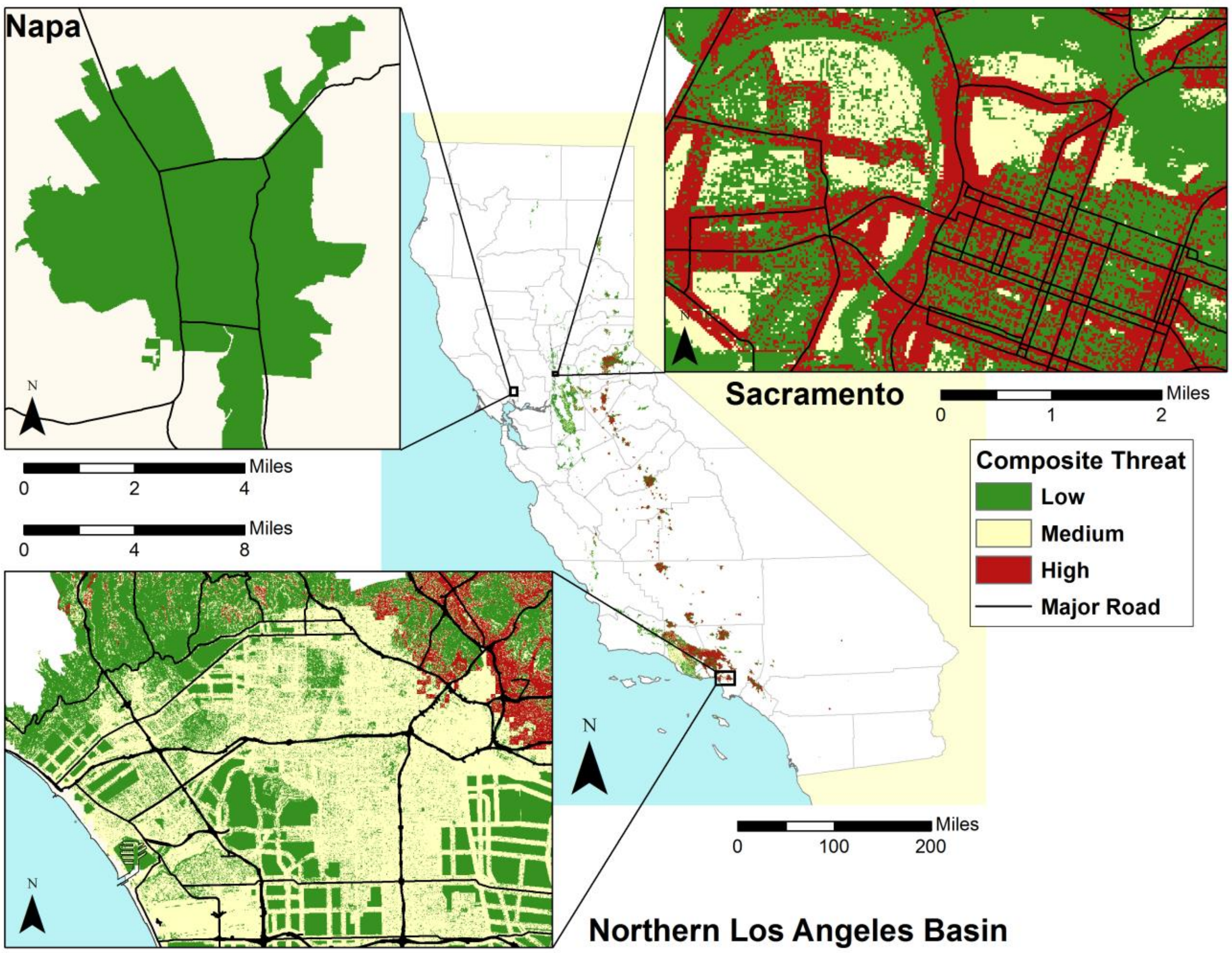


Figure 3-9. Air pollution and urban heat threat levels (map).

Urban Population
To prioritize enhancement of urban trees in areas that are the most heavily populated, an urban population layer was created to measure housing and population density as well as commercial development. This analysis factored housing density by measuring the number of housing units per acre, and land use classification to generate an overall rank of urban population density (Table 3-16).

Table 3-16. Urban housing density rank, using parcel size and land use type.

	Urban Housing Density		
	L (SF 1-5 acre parcels)	M (SF .2-1 acre parcels)	H (SF <.2 acre parcels, MF and C/I/I)
Residential	L	M	H
Commercial	H	H	H

The lowest residential category or urban housing density was considered to include single family residential types with 1-5 acre parcel size. Medium density includes single family residential types 0.2-1 acre parcels in size. The high density category included single family residential <0.2 acres in size, multi-family residential, and all commercial/industrial/institutional types.

Table 3-17. The extent of urban housing density rank, in km^2 and percentage of total.

	Urban Housing Density (km^2)	Urban Housing Density (%)
Low	2,404.3	17.6%
Medium	2,686.7	19.7%
High	8,533.6	62.6%

The results show that the majority (62.6%) of the urban areas are considered to have a high urban housing density (Table 3-17).

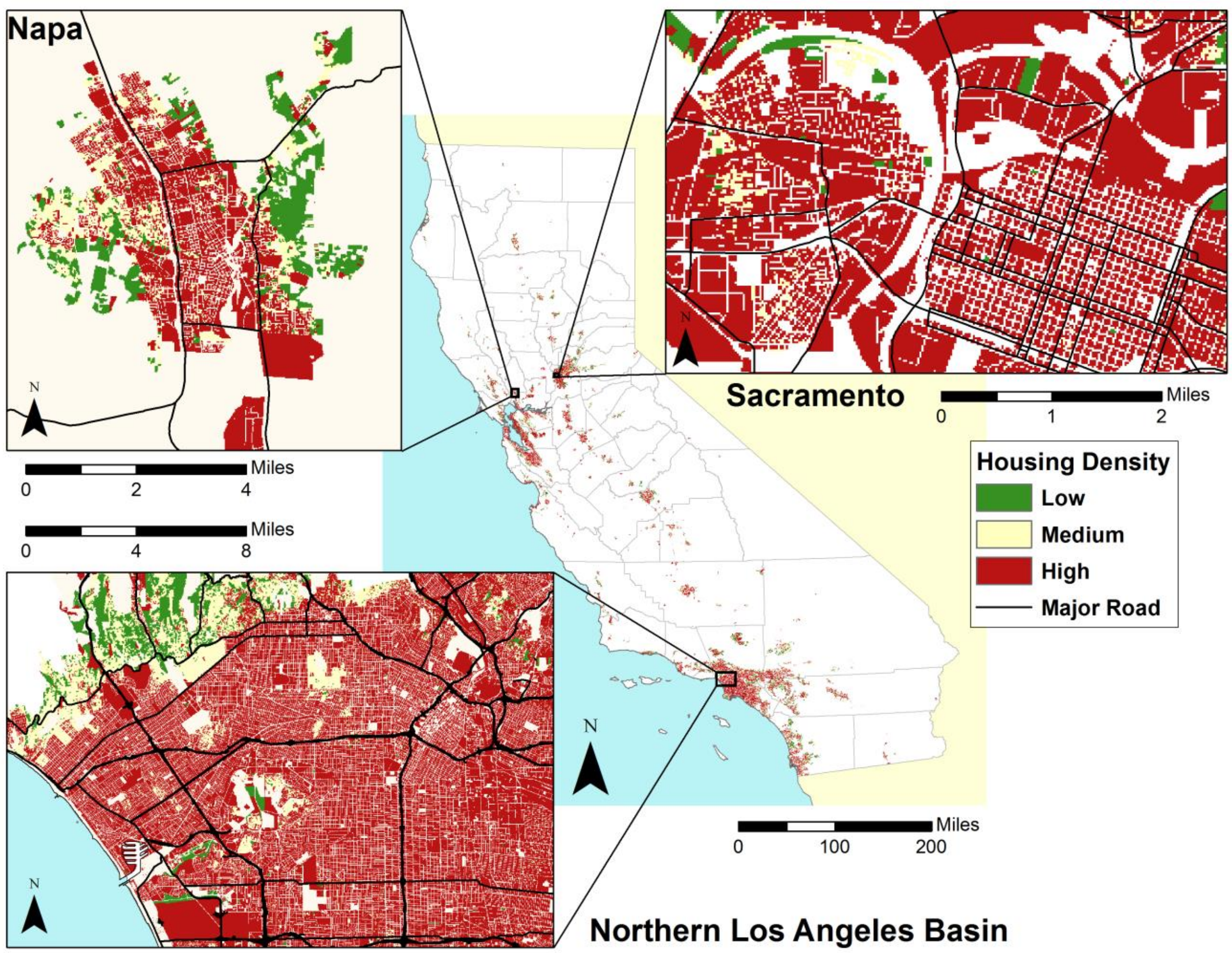


Figure 3-10. Urban housing density (map).

Priority Landscapes for Urban Tree Planting

A final merging of layers was produced with urban population, urban heat and air pollution, in order to consider where poor air quality and urban heat might disproportionately affect the most people (Table 3-18). These areas are priority areas for urban tree planting.

Table 3-18. Analysis 1, priority landscapes for urban tree planting rank.

	Urban Housing Density		
Composite Threat	**H**	**M**	**L**
L	L	L	L
M	M	L	L
H	H	H	L

The results show that 40.8% of the urban areas in California would be considered low priority and 13.9% would be considered high priority landscapes, meaning they are densely populated with considerable air pollution and/or urban heat island effects (Table 3-19).

Table 3-19. Analysis 1, priority landscape extent by km^2 and percentage of total.

	Priority Landscape (km^2)	**Priority Landscape (%)**
Low	8,780.4	40.8%
Medium	1,786.9	8.3%
High	2,996.1	13.9%

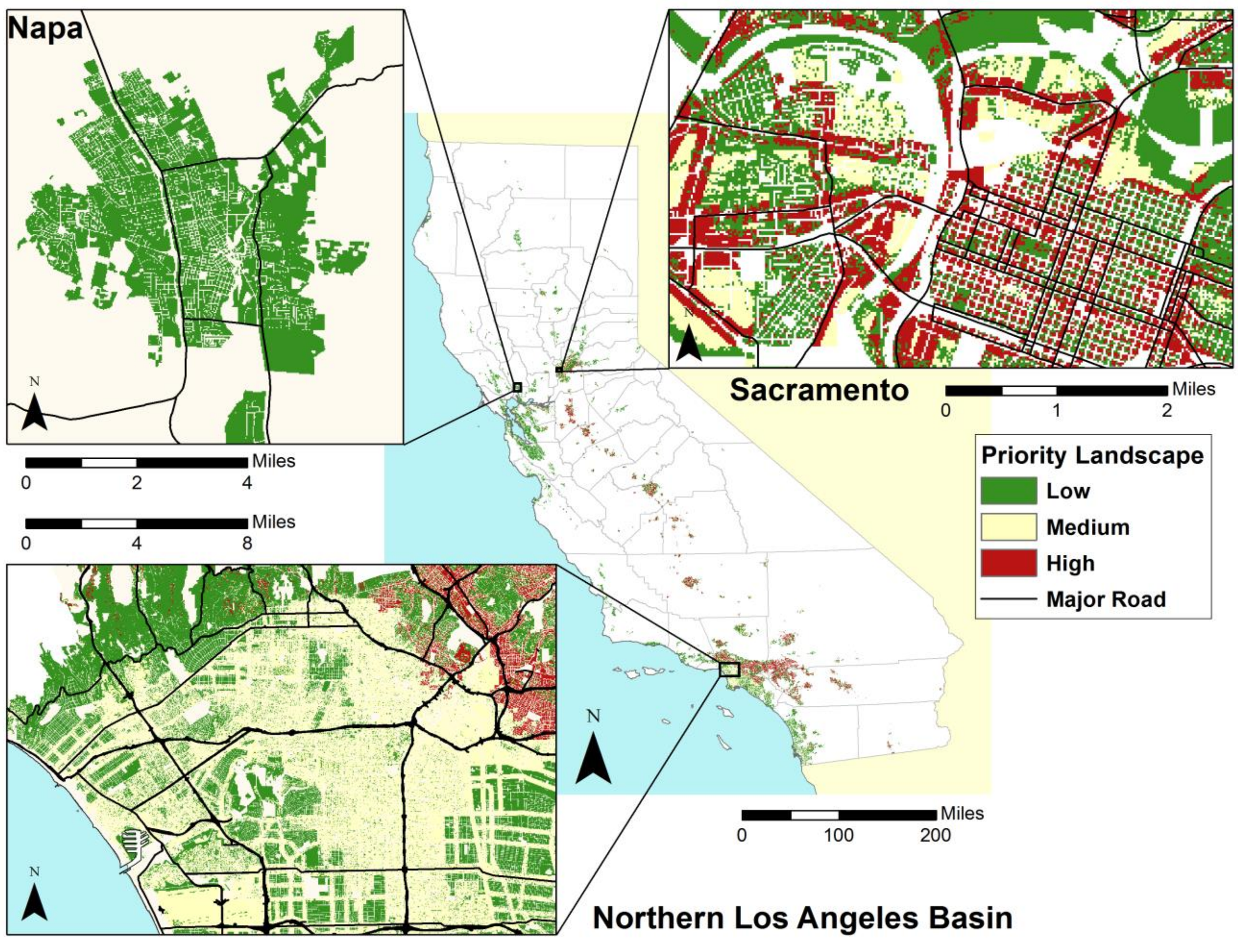


Figure 3-11. Analysis 1: urban tree planting priority landscape (map)

Analysis 2: Urban Tree Maintenance for Energy Conservation and Air Quality

A second set of analyses provide information on urban tree maintenance for energy conservation and air quality. Similar to the first analysis, Analysis 2 also draws upon several subcomponent layers relating to the environment and population distribution within urban areas.

Energy Consumption Threat

Energy consumption was derived using a combination of housing density and days over 90° Fahrenheit. Areas with high housing density and many days over 90° were ranked highest, while low housing density with fewer days over 90° were ranked lower (Table 3-20).

Table 3-20. The energy consumption threat rank, using urban housing density and the percent of days over 90° F.

	Urban Housing Density		
% Days over 90° F	**H**	**M**	**L**
L <8% (0-29days)	M	L	L
M 9-20% (30-73days)	H	M	L
H >20% (74+ days)	H	H	L

Energy consumption was found to be high or medium for much of the urban areas in the state (27.7% and 20.3%) (Table 3-21).

Table 3-21. The extent of energy consumption threat rank, in km^2 and percentage of total.

	Energy Consumption (km^2)	**Energy Consumption (%)**
Low	3,237.0	15.0%
Medium	4,371.7	20.3%
High	5,957.2	27.7%

Because the energy consumption rank was dependent on both population density and high temperatures, areas with lower populations, such as Napa, or areas along the coast, such as the Northern LA Basin were ranked low or medium (Figure 3-12). Sacramento and other areas in the Central Valley that are both densely populated and have more days over 90° F were ranked high.

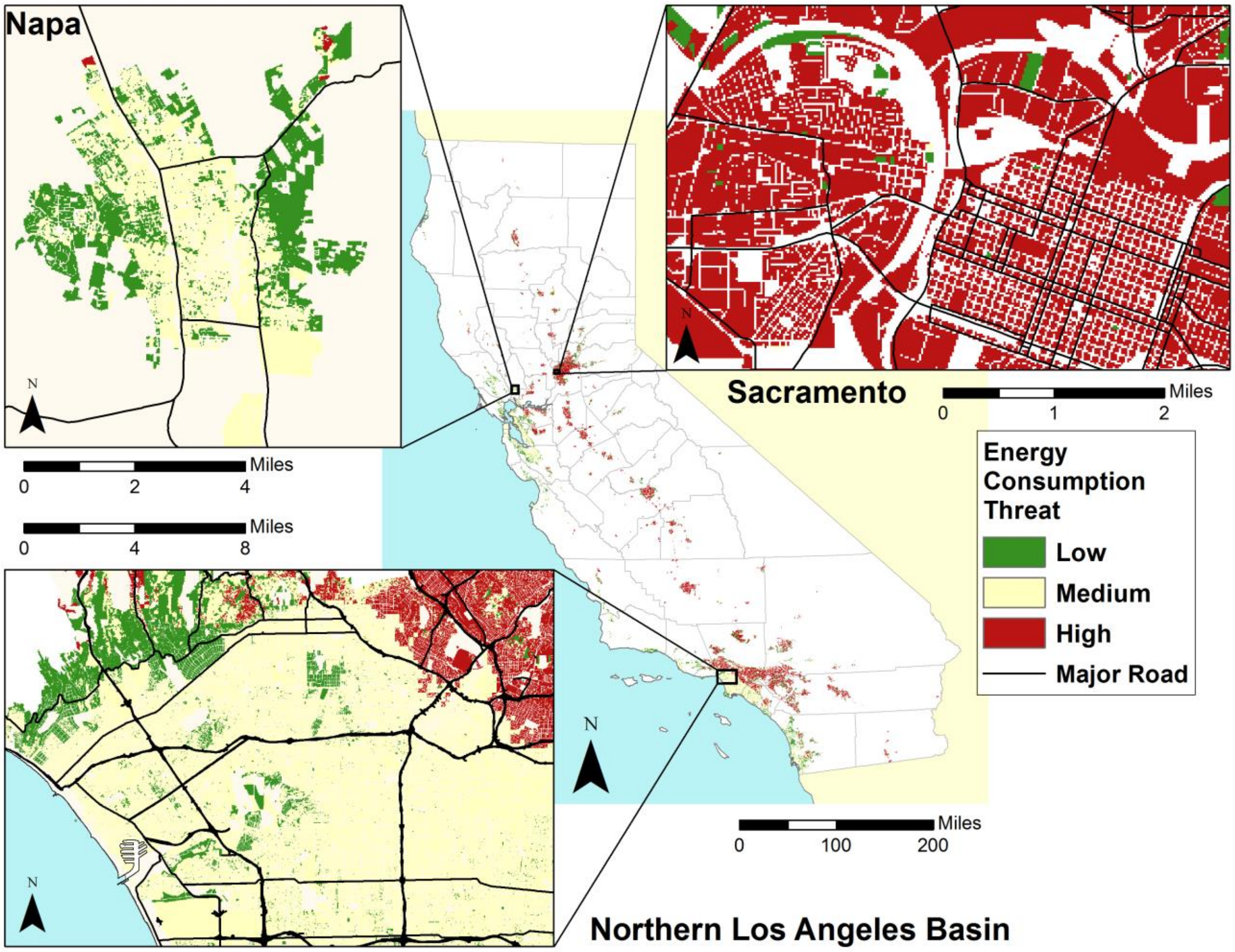


Figure 3-12. Energy consumption threat in urban areas (map).

A second composite threat layer was created for Analysis 2 to show areas of high energy consumption in relation to areas of high air pollution threat (Table 3-22). The air pollution threat layer was the same as in Analysis 1 (Figure 3-8.).

Table 3-22. The composite threat rank, using the energy consumption threat and the air pollution threat.

	Energy Consumption Threat		
Air Pollution Threat	**H**	**M**	**L**
L	L	0	0
M	M	L	L
H	H	M	L

The Composite Threat results show that the urban areas are somewhat evenly split among the high, medium and low categories, with slightly less in the medium rank (Table 3-23).

Table 3-23. The extent of the composite threat rank, in km^2 and percentage of total.

	Composite Threat (km^2)	**Composite Threat (%)**
Low	4,644.7	21.6%
Medium	2,946.6	13.7%
High	4,492.8	20.9%

Areas that are closest to major roads or highways become a higher threat, which can be seen when the Composite Threat layer is mapped (Figure 3-13).

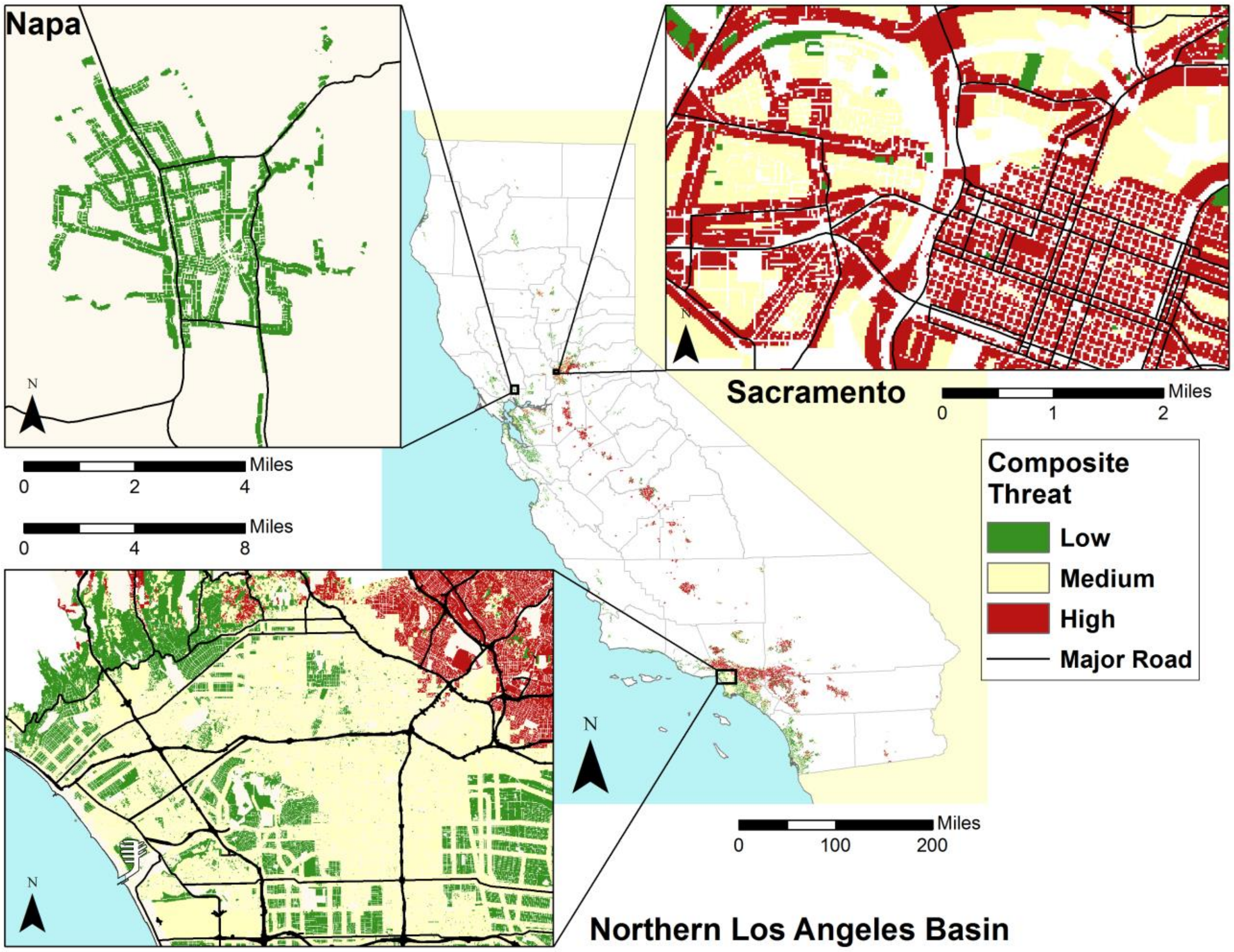


Figure 3-13. Air pollution and energy consumption threat in urban areas (map).

To show areas that are considered to be both densely populated as well as containing resources relating to tree canopy coverage, a Composite Asset layer was created using two previously mapped layers: Urban Population and Tree Canopy (Table 3-24). Areas with high housing density and high tree canopy were considered to have a high Composite Asset rank.

Table 3-24. The composite asset rank, using tree canopy cover and housing density.

	Tree Canopy Coverage		
Housing Density	**L (2-10%)**	**M (10-20%)**	**H (>20%)**
L	L	L	M
M	L	H	H
H	M	H	H

The results show that 21.3% are considered to be ranked high as assets both in terms of tree canopy cover and housing density, for all urban areas in California (Table 3-25).

Table 3-25. The composite asset extent for urban areas in km^2 and percentage of total.

	Composite Asset (km^2)	Composite Asset (%)
Low	952.7	4.4%
Medium	2,432.4	11.3%
High	4,584.1	21.3%

By looking at the results on a map (Figure 3-14), highly populated areas such as the northern LA basin and heavily treed areas, such as the City of Napa, tend to have High Composite asset ranks.

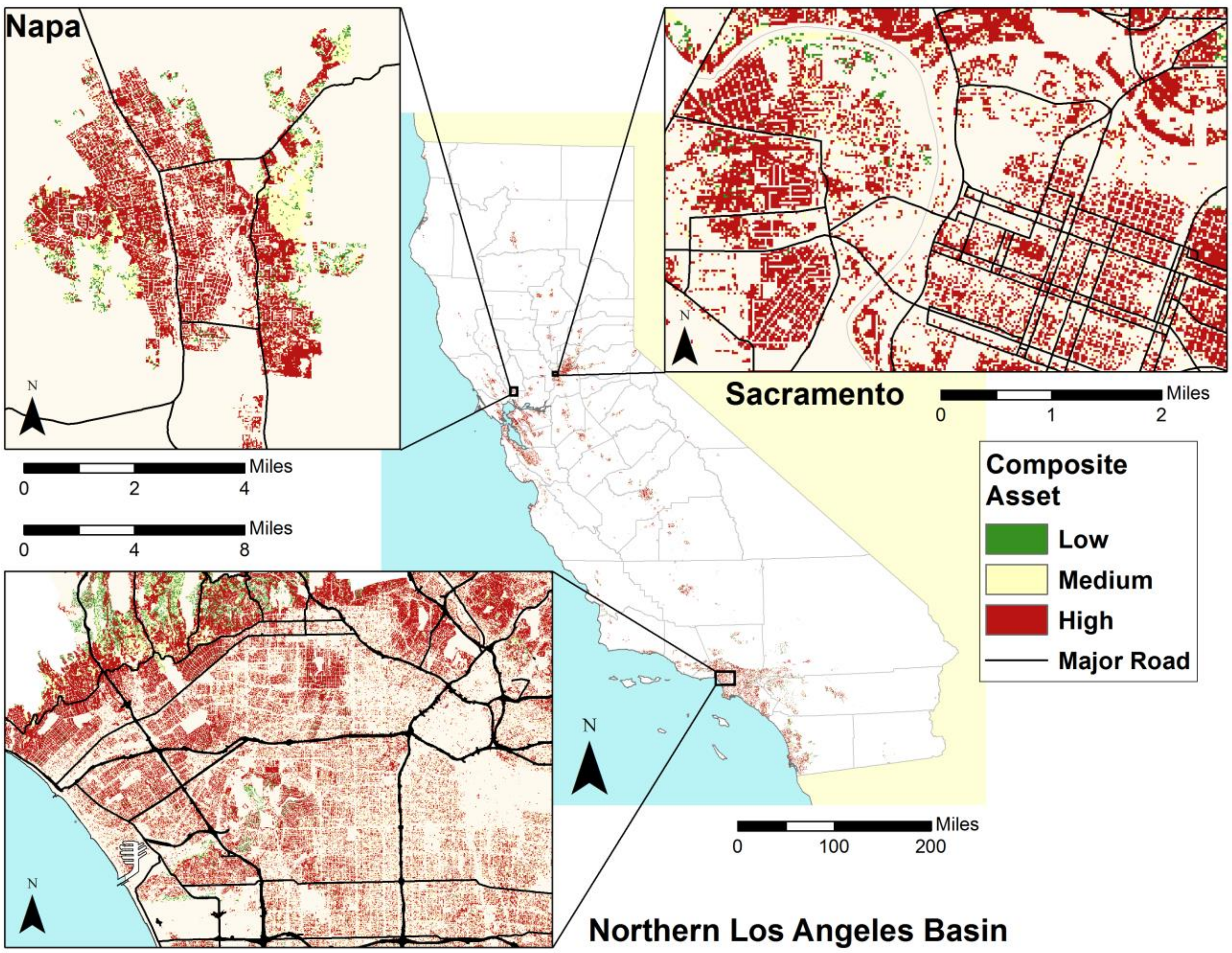


Figure 3-14. Tree canopy percent and housing density asset in urban areas (map).

Priority Landscape for Urban Tree Maintenance

The identification of priority areas that are high in energy consumption, poor air quality yet also densely populated and with existing tree coverage is important for directing resources for tree maintenance. A Priority Landscape layer was created by combining the Composite Threat layer and Composite Asset layer (Table 3-26).

Table 3-26. Analysis 2, priority landscapes for urban tree maintenance rank.

	Composite Asset		
Composite Threat	**L**	**M**	**H**
L	0	L	L
M	L	M	H
H	M	H	H

The combination of the Composite Asset layer and Composite Threat layer show 15.5% of California Urban Areas are considered to be Priority Tree Maintenance Landscapes (Table 3-27).

Table 3-27. Analysis 2, priority landscape extent by km^2 and percentage of total.

	Priority Landscape (km^2)	Priority Landscape (%)
Low	2,437.2	11.3%
Medium	601.7	2.8%
High	3,344.6	15.5%

Because urban population and housing density are considered for both the Composite Asset and Composite Threat layers, the highly populated downtown areas of large cities tend to have a high Priority Landscape rank (Figure 3-15).

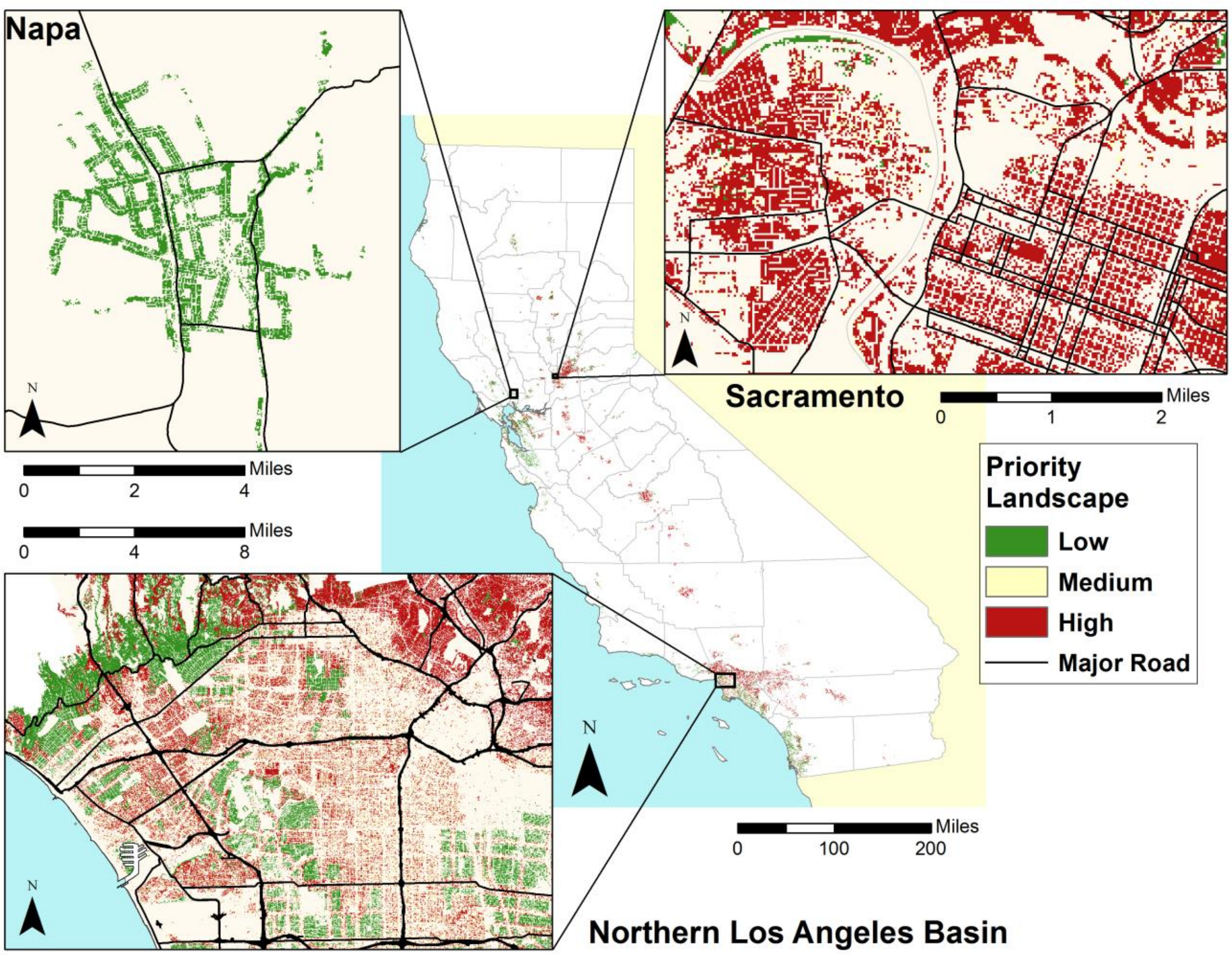


Figure 3-15. Analysis 2: urban tree maintenance priority landscape (map).

Part Three: Trends in Urban Forests

This section describes some of the demographic characteristics of the urban areas in California, and how some of them have changed over time.

Change in Urban Area

The overall change in population for all urban areas in the state was an increase of 3,383,943 people, or 10.6% (Table 3-1) and there were an additional 842.6 km^2 of urban area than in 2000. However, some regions in California saw a larger than average increase in population between 2000 and 2010, such as the Sacramento region and the San Joaquin Valley (Table 3-28). The Sacramento region (El Dorado, Placer, Sacramento, Sutter, Yolo and Yuba Counties) saw a 22.52% increase while urban areas in the 8-County San Joaquin Valley (Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanislaus and Tulare) saw a 13.22% increase from 2000 to 2010. In Southern California, the population of the urban areas in the Los Angeles region (Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties) grew by 9.3% while the San Diego region grew by 8.3%. The complete table can be found in Appendix 8: Urban Area Trends.

Table 3-28. Population change by region (Census 2000 and 2010 data).

Region	Included Counties	Urban Area Change km^2	2000 Population	2010 Population	Pop Change	% Pop Change
San Francisco Bay Area	Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara	212.1	5,718,028	6,060,956	342,928	6.0%
Sacramento Area	El Dorado, Placer, Sacramento, Sutter, Yolo, Yuba	336.5	1,738,017	2,129,432	391,415	22.5%
San Joaquin Valley	Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanislaus, Tulare	302.6	3,516,297	3,981,095	464,798	13.2%
Los Angeles Area	Los Angeles, Orange, Riverside, San Bernardino, Ventura	29.2	16,091,551	17,593,821	1,502,270	9.3%
San Diego	San Diego	-148.0	2,761,907	2,990,897	228,990	8.3%

Impervious Surface

Table 3-29 (complete table in Appendix 8: Urban Area Trends) presents summary data by county for the extent and percent of impervious surfaces (as measured using the NLCD 2011), percent of protected areas (as measured from the CPAD 2014 data) and percent of urban tree canopy by county. The average area of impervious surface was 392 km^2, or roughly 28% of the total area (Table 3-29). Each county had an average of 4.7% protected open space and 19.5% tree canopy cover.

Table 3-29. Summary data of impervious surface, green space and tree canopy by county.

	Area (km^2) of Impervious Surface	% Impervious	% CPAD/open Access	% Urban Tree Canopy
Mean	391.6	28.1%	4.7%	19.5%
Median	181.5	27.3%	3.1%	15.5%
Standard Deviation	648.1	10.8%	4.9%	12.8%

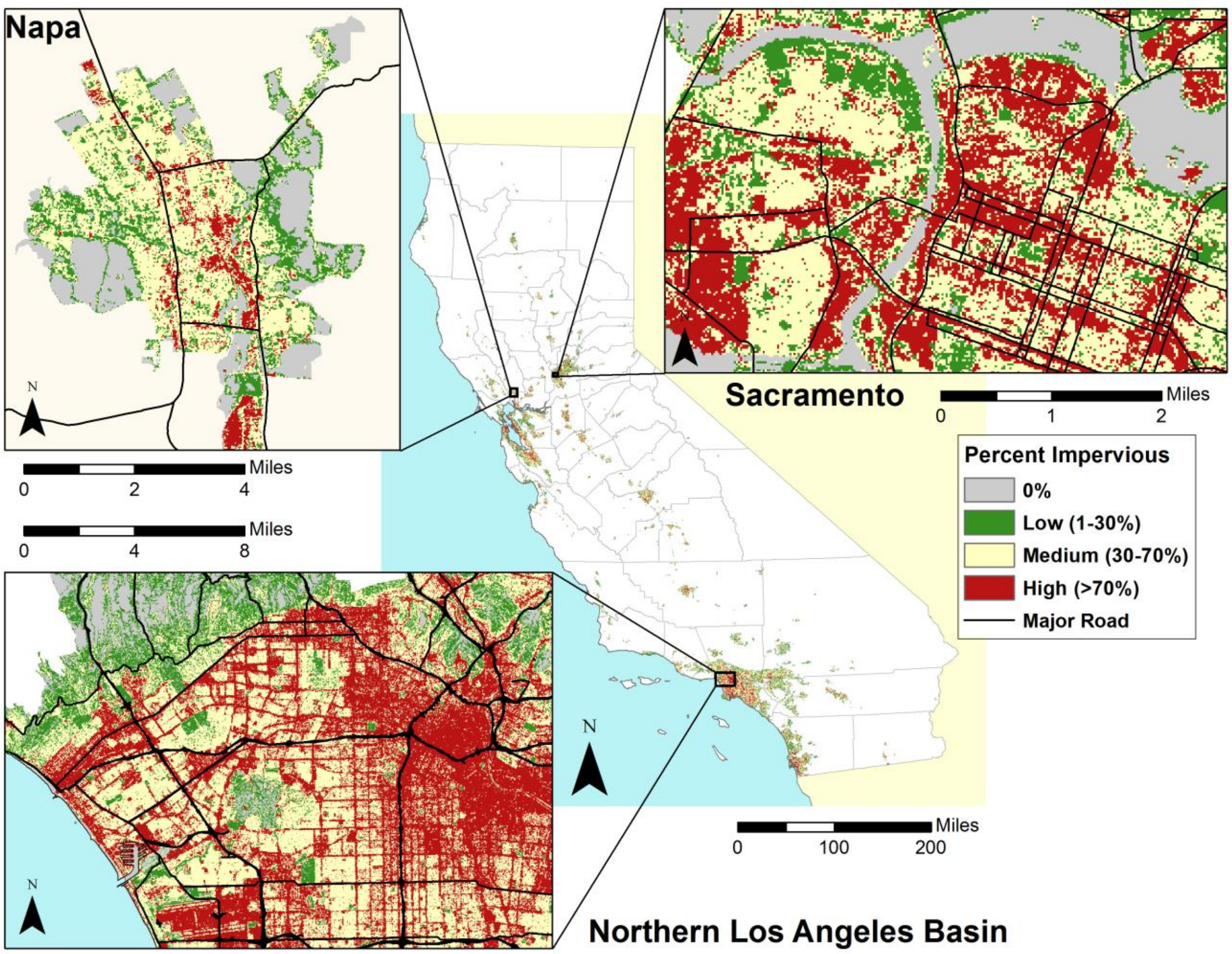


Figure 3-16. Percent impervious surfaces in urban areas (map).

Land Use

A summary of the 2010 Census urban areas reveals that 35.49% of land use in urban areas is single family residences, followed by Open Space (25.43%), and Commercial/Industrial/Institutional (17.13%) (Table 3-30). A complete table is located in Appendix 8: Urban Area Trends.

Table 3-29 uses the CPAD definition of open space which is protected areas such as national/state/regional parks, forests, preserves, and wildlife areas; large and small urban parks that are mainly open space (as opposed to recreational facility structures); land trust preserves owned outright; special district open space lands (watershed, recreation, etc.) and other types of open space. Table 3-30 uses our parcel data definition of open space that includes all areas not considered to be water, transportation corridors, or developed with building structures. For this reason, the percent of open space in these two figures are not comparable.

Table 3-30. Summary of land use classes within each Census Urban Area.

	Unclassified (0) %	**Multi Family Res (1) %**	**Single Family Res (2) %**	**Commercial/Industrial/ Institutional (3) %**	**Open Space (4) %**	**Water (5) %**	**Trans-portation Corridors (6) %**
Mean	0.71%	5.64%	35.49%	17.13%	25.43%	1.51%	14.09%
Median	0.28%	5.16%	35.86%	16.71%	22.91%	0.14%	13.85%
Standard Deviation	1.36%	3.95%	12.85%	9.40%	14.69%	7.43%	5.29%

Chapter 4 SUMMARY

This study (UCD-USFS) presents a baseline of the extent and characterization of urban trees in California, including the environmental and other co-benefits provided by urban tree canopy, such as CO_2 stored, sequestered and emissions avoided, pollution removal and energy savings. The UCD-USFS report differs from previous studies detailing the benefits of California urban trees in that urban tree canopies were mapped at an order of magnitude higher spatial resolution. In addition, individual tree-based measurements used to derive the environmental benefits were obtained from two systematic urban tree survey programs as well as 49 urban street tree inventories, and results were projected for six climate zones in California, a state known for its climatic variability.

A previous study, the USDA Forest Service Northern Research Station General Technical Report (NRS-65) (Nowak and Greenfield, 2010a), also provided information on urban tree canopy extent. That 2010 report relied on NLCD 2001 satellite imagery for tree canopy cover, and U.S. Census data from the year 2000. The NRS-65 reports on urban forest benefits in California, Oregon and Washington, and as the predecessor for the UCD-USFS study, it is an important base for comparison. However, due in large part to differences in datasets used in each study, the UCD-USFS report should not be considered to present a formal change analysis, as much as a more detailed inventory for tree canopy extent. The 2001 NLCD data used in the NRS-65 report is a 30-meter resolution satellite imagery dataset that was found underestimate tree canopy (Nowak and Greenfield, 2010b). In contrast, the EarthDefine tree canopy dataset used for the UCD-USFS study, which became available in 2014, has a 1-meter resolution. The tree canopy extent for urban areas in California was estimated for the UCD-USFS study to total 3,200 km^2 out of 21,538 km^2 of urban area, or 15.0%. While the NRS-65 study found less tree canopy cover for urban areas in California (6.7%), this is likely due at least in part to the differences in resolution of the imagery datasets used to derive the tree canopy.

Urban tree benefits were categorized as 'benefits' for CO_2-related measures, and 'co-benefits' for a number of other measures. On the benefits side, the total CO_2 currently stored for urban area trees in this analysis was estimated at 102,995,988 metric tons, compared to 45,837,500 metric tons estimated from the NRS-65 study. This difference can largely be explained by the difference in urban tree canopy area. The UCD-USFS study also projects yearly CO_2 sequestered totaled 7,225,191 metric tons, or $86,714,832. And, we also calculated yearly CO_2 emissions avoided because of canopy shade to be 1,300,883 metric tons, or $15,636,609.

Urban tree benefits appear to have increased in dollar value from the NRS-65 study, even after accounting for the difference in tree canopy. For example, the NRS 65 report found the total yearly CO_2 sequestered for urban areas in California from the NRS-65 study was found to equal 1,518,138 metric tons, or roughly $25,094,821. The differences are likely explained by the region-specific data used for our study. Carbon storage and sequestration rates for the NRS-65 report were estimated using studies from 17 different cities across the United States, while this report derived the rates using tree data sampled from 1,385 plots, representing 3,803 trees, located within California urban areas. To estimate the dollar value for CO_2 sequestered for the UCD-USFS study, the 2014 annual per ton value of $12.02 was used for the state of California

(California Carbon Dashboard). The NRS-65 study used a national average of $28.1/ton C, a 2001-2010 projected cost from a 1994 study by Samuel Fankhauser.

Four co-benefits were the primary focus of the co-benefit analysis: O_3, NO_2, SO_2, and PM10. For co-benefits, pollution removal estimates from the previous NRS-65 study relied on state pollutant flux rates which were derived from a study of national pollution removal rates. The UCD-USFS study relied on 49 municipal street tree inventories, consisting of 908,304 trees. Again, accounting for the difference in urban tree canopy between the two studies, the amount of some co-benefits were roughly equivalent; however, the dollar values were considerably higher. For O_3, removal by urban trees for the NRS-65 study was estimated to be 6,973 metric tons/year, or $69,075,000, while the UCD-USFS study estimates O_3 removal to be 11,293 metric tons/year, or $120,746,679. For NO_2, the NRS-65 estimated 2,666 metric tons/year are removed due to urban tree canopy, a value of $26,404,600/year, while the UCD-USFS study estimates those values to be 6,481 metric tons/year and $69,298,304/year. For SO_2, the NRS-65 reported 896 metric tons/year were removed, or $2,173,000/year, while the UCD-USFS study found 2,331 metric tons/year were removed, or $34,851,328/year. And for PM_{10}, the NRS-65 estimated that 5,822 metric tons/year were removed as a result of the urban tree canopy, or $38,509,800/year, while the UCD-USFS reported those numbers to be 7,030 tons/year and $68,818,904/year. The difference in dollar value is likely attributable to the different sources used to estimate dollar value: the UCD-USFS study relied on a California-specific per/ton value while the NRS-65 study used national median values. Dollar values for the UCD-USFS study were taken from a statewide study of 666 purchased pollution offset transactions (CARB, 2011). The NRS-65 study used 1994 national median externality values, adjusted to 2007 dollars based on the producer price index.

The study quantifies the magnitude of benefits provided to Californians by their urban trees; for sequestering CO_2, reducing energy demand by shading buildings, offsetting pollutants and improving air quality, and improving the quality of life and health for humans. These data represent the most accurate estimate of the condition and extent of California's urban trees to date, which is important for enacting policy decisions at the state and local levels and establishing a baseline from which we can measure changes over time.

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Chapter 6 APPENDICES

Appendix 1: Geo-processing steps to render parcel-level data to land use classes
Appendix 2: Evaluation of the EarthDefine accuracy in mapping urban tree canopy in California
Appendix 3: Detailed methods for the development of transfer functions
Appendix 4: Transfer function table including other benefits
Appendix 5: Transfer function development for co-benefits
Appendix 6: CalEnviroScreen and California Air Resources Board information
Appendix 7: Tree Canopy, Biomass and CO_2 Inventory by Community, Urban Area and County
Appendix 8: Urban Area Trends

Appendix 1: Geo-processing steps to render parcel-level data to land use classes

There were several drawbacks with using the Digital Map Products dataset (08/2013 version used) for this analysis. First, there were a large number of graphical errors in the geospatial data, called topology errors. Topology errors occur when a data layer does not maintain certain geometric properties, such as connectivity. It is common for parcel layers to exhibit topology errors due to the fact that some parcel areas share multiple land owners, which is a necessity to document for county assessor's offices but becomes a hindrance for analytical purposes. A common example is a high-rise condominium, which could have multiple properties, each with separate owners and Assessor Parcel Numbers (APNs). Second, there were many parcels that were left unclassified, with no assigned land use code. These parcels, especially those unclassified parcels covering a large geographic area, needed to be visually checked using satellite imagery and assigned a land use code. Third, the Digital Map Products dataset does not include roads. Transportation corridors are intentionally left as gaps in the dataset, as they are not considered owned property.

The data processing to address these limitations was one of the more time consuming parts of the study. In addition to the spatial issues of the parcel dataset, the attribute data, from CoreLogic/DataQuick (08/2013 version used) had missing attributes for many of the parcels. We assigned land use codes to unclassified parcels 5 acres or larger, and processed the parcel data for subsequent incorporation into the Urban Tree Canopy benefits calculations by aggregating adjacent parcels with the same land use definitions. Unclassified parcels smaller than 5 acres were not assigned a land use code, resulting in a statewide mean of 0.39% of urban areas unclassed. Among California's 58 counties, the median urban area excluded from our analysis is 0.23% (Table 6-2 lists the extent of each county's urban area that was not classified). However, many counties had very few unclassified parcels, and five out of the 56 counties with urban areas had zero unclassified parcels.

Prior to any parcel work, the Information Center for the Environment (ICE) corrected the statewide parcel dataset topologically, which was fraught with overlapping polygons, slivers, and incomplete polygons. Because of the dataset's size and complexity, the ICE used the following steps to prepare the data for manual processing.

<u>Preprocessing: Topology Correction of State Parcel Dataset (Planarization)</u>
The following steps were automated using Python to process the dataset loaded into a PostGIS 2.1 Geodatabase.
Using a 2010 Census Tract dataset downloaded from the US Census Bureau the following was done for each census tract.

- All parcels with centroids within the census tract were extracted from the statewide dataset.
- Each ring from every parcel was extracted into a line feature type and merged so that all of the boundaries of every parcel in the tract formed a single mass of lines.
- This mass was then reassembled so that every non-overlapping polygon described by the parcel boundaries was a new polygon.
- The resultant polygons were inserted into a new polygon dataset.

This process results in a dataset where all polygons in the tract are guaranteed to be non-overlapping. In effect, each set of unique overlaps between parcels became a new polygon. Earlier attempts at creating this non-overlapping parcel dataset failed for a variety of reasons including: ESRI's ArcGIS Topology engine returned errors when operating on many of the portions of the state's parcel dataset, and computer memory size limitations. As a result of the memory limits, ICE selected tracts as the geographic sub-unit to process when some counties turned out to have too many parcels to manage step 1b and 1c in memory on the available computing hardware.

The flattening or planarization process did not result in a perfect dataset. The primary remaining issue, being that large parcels that extend beyond the tract boundary (notably the negative space parcels describing roads or other rights of way) could create polygons that would have overlaps with polygons in adjacent tracts. ICE manually identified and fixed these problems in later processing.

ICE joined Land use code, APN, and year of construction attributes from the CoreLogic/DataQuick (2013) dataset back to the corrected polygon, based on a priority list of the land uses.

This means that each polygon was assigned a land use code based on the highest priority land use in the polygons that overlap it (Table 6-1).

Table 6-1. Parcel Land Use Codes, Descriptions and Priorities

priority	code	Description	UF_ code	UF_Description
0			0	Unclassified
1	CMOB	Mobile Home Parks, Trailer Parks	1	Residential - MF
2	RAPT	Multi-Family Res (5+ Units)	1	Residential - MF
3	RCON	Condominium, PUD	1	Residential - MF
4	RCOO	Cooperative	1	Residential - MF
5	RDUP	Duplex	1	Residential - MF
6	RMFD	Multi-Family Dwelling (2-4 Units	1	Residential - MF
7	RMOB	Mobile / Manufactured Home	1	Residential - MF
8	RQUA	Quadraplex	1	Residential - MF
9	RTRI	Triplex	1	Residential - MF
10	RTIM	Timeshare	2	Residential - SF
11	RMSC	Miscellaneous Residential	2	Residential - SF
12	RSFR	Single Family Residence	2	Residential - SF
13	VRES	Residential	2	Residential - SF
14	CAUT	Auto sales, services	3	Commercial/Industrial/Institutional
15	CCAS	Casino	3	Commercial/Industrial/Institutional
16	CCOM	Store / Office Combo	3	Commercial/Industrial/Institutional
17	CDEP	Department Store	3	Commercial/Industrial/Institutional
18	CEAT	Restaurant, Bar, Food Services	3	Commercial/Industrial/Institutional
19	CFIN	Financial Building	3	Commercial/Industrial/Institutional
20	CFOO	Food Store, Market	3	Commercial/Industrial/Institutional
21	CHOS	Hospitals, Convalescent Homes	3	Commercial/Industrial/Institutional
22	CHOT	Hotel / Motel	3	Commercial/Industrial/Institutional
23	CLAU	Laundry, Dry Cleaning	3	Commercial/Industrial/Institutional
24	CMED	Medical Buildings	3	Commercial/Industrial/Institutional
25	CMSC	Miscellaneous Commercial	3	Commercial/Industrial/Institutional
26	CNUR	Nursery	3	Commercial/Industrial/Institutional
27	COFF	Office Building	3	Commercial/Industrial/Institutional
28	CSER	Service Station, Gas Station	3	Commercial/Industrial/Institutional
29	CSHO	Shopping Center	3	Commercial/Industrial/Institutional
30	CSTO	Stores, Retail Outlet	3	Commercial/Industrial/Institutional
31	CVET	Veterinary	3	Commercial/Industrial/Institutional
32	IFOO	Food Processing	3	Commercial/Industrial/Institutional
33	IHEA	Heavy Industrial	3	Commercial/Industrial/Institutional
34	ILIG	Light Industrial	3	Commercial/Industrial/Institutional
35	ILUM	Lumber, Building Materials	3	Commercial/Industrial/Institutional

36	IMSC	Miscellaneous Industrial	3	Commercial/Industrial/Institutional
37	IPET	Petroleum, Gas	3	Commercial/Industrial/Institutional
38	IPUB	Public Storage, Mini Warehouse	3	Commercial/Industrial/Institutional
39	IWAR	Warehouse, Storage	3	Commercial/Industrial/Institutional
40	IWIN	Winery	3	Commercial/Industrial/Institutional
41	MBOW	Bowling Alley	3	Commercial/Industrial/Institutional
42	MCLU	Clubs, Fraternal Organizations	3	Commercial/Industrial/Institutional
43	MCMN	Communications	3	Commercial/Industrial/Institutional
45	MGOV	Governmental, Public	3	Commercial/Industrial/Institutional
46	MMAR	Marina	3	Commercial/Industrial/Institutional
47	MREL	Religious	3	Commercial/Industrial/Institutional
48	MSCH	School	3	Commercial/Industrial/Institutional
49	MTHE	Theaters	3	Commercial/Industrial/Institutional
50	MTRA	Transportation, Air, Rail, Bus	3	Commercial/Industrial/Institutional
51	MUTI	Utilities	3	Commercial/Industrial/Institutional
52	VCOM	Commercial	3	Commercial/Industrial/Institutional
53	VIND	Industrial	3	Commercial/Industrial/Institutional
44	MGOL	Golf Course	4	Open Space
54	ADAI	Dairy	4	Open Space
55	AFAR	Farms, Crops	4	Open Space
56	ALIV	Livestock, Animals	4	Open Space
57	AMSC	Miscellaneous Agricultural	4	Open Space
58	AORC	Orchards, Groves	4	Open Space
59	APAS	Pasture	4	Open Space
60	APOU	Poultry	4	Open Space
61	ATIM	Timber	4	Open Space
62	AVIN	Vines and Bush Fruits	4	Open Space
63	CCEM	Cemeteries, Mortuaries	4	Open Space
64	CPAR	Parking Lot, Parking Structure	4	Open Space
65	IMIN	Mineral, Quarries, Mining	4	Open Space
66	MNAT	Natural Resource Rights	4	Open Space
67	MREC	Recreational	4	Open Space
68	VAGR	Agricultural / Rural	4	Open Space
69	VMSC	Miscellaneous Vacant Land	4	Open Space
70	VREC	Recreational	4	Open Space
71	VWAS	Waste Land / Marshes	4	Open Space
72	MMSC	Miscellaneous, Miscellaneous	5	Water/Other
73	Other	blank Unknown	5	Water/Other
74	MROA	Roadways	6	Transportation Corridors

The resultant dataset was exported to an ESRI FileGeodatabase for further use.

Automated Processing for Each County

For each county the following scripted process was run prior to manual review and editing of land use attributes.

- Each county's parcels were extracted to a new ESRI FileGeodatabase
- The parcels were clipped to the US Census Bureau defined urban areas
- The land use priorities table was joined to the clipped parcels dataset
- The parcels were unioned with the US Census Bureau defined urban areas to fill any gaps between parcels
- The parcels were then clipped to the US Census Bureau defined urban areas
- The parcel dataset was coerced into a single-part polygon dataset to avoid having multiple parts to the same polygon
- The California Protected Areas Database (CPAD) was used to overwrite parcel boundaries while identifying the areas considered to be protected
- A topology was built and validated containing the rules that there must not be overlapping polygons and that there must not be gaps between polygons (though the latter rule was used only as a check against a failure in earlier processing steps)

Manual Processing

Following the completion of the automated processing, we manually reviewed the urban areas parcel data to remove remaining topological problems and fill in land use data for the many unclassified polygons that remain. Unclassified polygons were due to no attributes having been entered for those locations by the counties or CoreLogic/DataQuick.

In general this was done in the following order:

- Repair any remaining topological problems identified in the validated topology.
- In most cases, these were easy to resolve through the sorting and removal of parcels with identical sets of attribute data.
- Sort the parcels by Land use Code (ascending) and acreage (descending), to identify all parcels with unclassified parcels larger than 5 acres in size.
- Working down this sorted list of parcels, zoom to, and review the contents of each parcel that is unclassified and larger than 5 acres in size, using NAIP imagery or Google maps to observe the land.
- Update the UF_Code field to contain the correct classification code (1: Multi-Family Residential, 2: Single Family Residential, 3: Commercial/Industrial/Institutional, 4: Open Space, 5: Water/Other, 6: Transportation).
- When zoomed in to a location also review any other unclassified parcels in the surrounding area with the goal of attributing them.

Each of the land use codes had some specific details regarding land uses assigned to them. Some commonly encountered ones were:

- Railroad infrastructure is category 3 (Commercial/Industrial/Institutional)
- Parking lots are category 4 (Open Space)

Following the completion of polygon coding, we conducted a final review of the coding and topology prior to forwarding the dataset on for analysis.
Because the minimum mapping unit was 5 acres, some parcels in each county's urban area were not classified, ranging from 0-3.19% of the urban area, mean = 0.39% and median = 0.23% (Table 6-2).

Table 6-2. Unclassified land use types by county. Three counties, shown as rows in grey, do not have incorporated urban areas according to the census data.

COUNTY	Area "Unclassified" (acres)	Total area (acres)	Percent "Unclassified"
ALAMEDA	135.0	174,960.9	0.08%
ALPINE			
AMADOR	0.0	4,933.8	0.00%
BUTTE	712.7	54,115.4	1.32%
CALAVARAS	0.0	6,637.4	0.00%
COLUSA	10.8	3,358.6	0.32%
CONTRA COSTA	211.0	196,644.9	0.11%
DEL NORTE	0.1	7,640.6	0.00%
EL DORADO	259.0	48,424.9	0.53%
FRESNO	4,375.0	136,945.2	3.19%
GLENN	2.1	5,408.5	0.04%
HUMBOLDT	15.1	29,108.7	0.05%
IMPERIAL	32.3	49,321.3	0.07%
INYO	3.7	2,739.5	0.13%
KERN	369.3	141,401.1	0.26%
KINGS	44.8	25,230.2	0.18%
LAKE	44.8	17,232.2	0.26%
LASSEN	3.2	3,378.4	0.10%
LOS ANGELES	12,909.6	916,177.4	1.41%
MADERA	147.9	25,352.3	0.58%
MARIN	78.1	54,713.7	0.14%
MARIPOSA			
MENDOCINO	79.5	18,768.7	0.42%
MERCED	5.9	44,853.3	0.01%
MODOC	0.4	1,223.5	0.04%
MONO	2.0	2,127.0	0.09%
MONTEREY	341.3	68,199.1	0.50%
NAPA	0.0	26,305.0	0.00%
NEVADA	238.0	30,577.9	0.78%
ORANGE	2,538.9	339,918.8	0.75%
PLACER	202.7	91,286.7	0.22%
PLUMAS	5.5	2,355.8	0.23%
RIVERSIDE	2,007.0	456,929.9	0.44%
SACRAMENTO	98.7	213,189.9	0.05%
SAN BENITO	16.7	7,324.2	0.23%

SAN BERNADINO	548.1	403,731.3	0.14%
SAN DIEGO	3,019.3	489,854.4	0.62%
SAN FRANCISCO	298.8	29,958.0	1.00%
SAN JOAQUIN	156.7	101,225.8	0.15%
SAN LUIS OBISPO	505.7	62,726.1	0.81%
SAN MATEO	790.3	90,880.5	0.87%
SANTA BARBARA	411.6	67,857.5	0.61%
SANTA CLARA	2,844.9	211,970.6	1.34%
SANTA CRUZ	126.5	50,745.4	0.25%
SHASTA	224.7	49,842.6	0.45%
SIERRA	0.0	4.5	0.00%
SISKIYOU	36.3	7,881.6	0.46%
SOLANO	69.1	73,643.4	0.09%
SONOMA	2.1	92,504.8	0.00%
STANISLAUS	224.1	76,756.3	0.29%
SUTTER	44.2	15,808.3	0.28%
TEHAMA	21.7	10,568.1	0.21%
TRINITY			
TULARE	264.4	71,885.2	0.37%
TUOLUMNE	33.3	20,108.4	0.17%
VENTURA	589.1	142,455.8	0.41%
YOLO	3.5	30,487.0	0.01%
YUBA	40.2	11,933.3	0.34%

Appendix 2: Evaluation of the EarthDefine accuracy in mapping urban tree canopy in California

The accuracy evaluation of EarthDefine's tree canopy data was conducted at three different scales. EarthDefine researchers performed evaluations of the EarthDefine tree canopy map to assess the accuracy of the tree canopy data of entire project area using 1,500 random sample points. UCD-USFS researchers completed the accuracy assessment at climate region scale using the same sample points, ground truth/reference canopy cover, and canopy cover mapping data provided by EarthDefine. In addition, the third accuracy assessment was completed by UCD, USFS, and CalFire researchers in Sacramento County to evaluate tree canopy by land use classes. The ground truth/reference tree canopy cover data were collected based on analysis of 2012 NAIP imagery by UCD, USFS, and CalFire researchers.

The EarthDefine research found that the overall mapping accuracy was 95%. The producer's accuracy for tree canopy cover was 80% while the user's accuracy for tree canopy cover was 87%. At climate region level, the user's accuracy for tree canopy cover varied from 81% to 96% and producer's accuracy varied from 67% to 87%. At land use level at Sacramento county region, UCD, USFS, and CalFire researchers found that the EarthDefine data had a 91% overall mapping accuracy. However, for tree canopy cover by land use classes, the producer's accuracy ranged from 57% to 69% while user's accuracy ranged from 75% to 89%.

Evaluation of the EarthDefine Canopy Cover Mapping Accuracy of Entire Study Area

The EarthDefine researchers assessment used a random point generator to select 1,500 points, specifying only that no two points were within 100 meters of each other, to minimize the effects of spatial autocorrelation in the data. For each generated point, the underlying EarthDefine data value was extracted and stored as 'trees' or 'other.' This value was then checked against the actual ground cover using 2012 California NAIP orthoimagery data, with Bing or Google imagery used if ground cover was ambiguous in NAIP. The tree canopy mapping accuracy was evaluated for entire study area and at climate region levels. Actual and classified tree canopy were compared to estimate the overall accuracy (Table 6-3).

Table 6-3. Tree canopy cover mapping accuracy at entire study area.

		Reference Data			
		Trees	**Other**	**Total**	**User Accuracy**
Classified Data	**Trees**	197	29	226	87.2%
	Other	49	1,225	1,274	96.2%
	Total	246	1,254	1,500	
	Producer Accuracy	80.1%	97.7%		
	Total correctly Classified	1,422			
	Overall Accuracy	94.8%			

Evaluation of the EarthDefine Canopy Cover Mapping Accuracy at Climate Region Level

The GIS climate region layer was overlay with ArcGIS shape file provided by EarthDefine. This shape file includes 1,500 samples' location, ground truth/reference canopy cover, and canopy cover from their mapping products. At climate region level, for regions with 39 or more sample points, tree canopy cover map user's accuracy varied from 81% to 96% while producer's accuracy varied from 67% to 87% (Table 6-4). Two large climate regions, the Interior West and Southwest Desert, had low number of trees within their urban areas, and therefore accuracy numbers reflected in this scan of the data are not statistically valid, but are based on only five and two tree samples, respectively.

Table 6-4. Accuracy for identifying tree canopy pixel ranges in climate zones.

Climate region	**Urban area (UA) km^2**	**%UA**	**Total Sample**	**Total Tree Sample**	**User's Accuracy %**	**Producer's Accuracy %**
Inland Valleys	6,231	29%	426	87	87%	87%
Northern California Coast	3,846	18%	252	50	96%	87%
Southern California Coast	5,163	24%	355	43	81%	73%
Inland Empire	4,744	22%	350	39	85%	67%
Interior West	365	2%	35	5	80%	80%
Southwest Desert	1,189	6%	82	2	50%	50%

The third evaluation, presented below was completed by UCD, USFS, and CalFire researchers. This evaluation focused on an area for which our group has more background experience and data.

Assessment of the Accuracy at Land Use Level - Sacramento Case Study

The study area covers the 2010 Census defined urban areas within the County of Sacramento. Sacramento is the largest city in the central valley of California. In this inland valley region, the environment is characterized by a Mediterranean climate. It is hot and dry during the summer and cool and wet in winter. Nearly all precipitation falls during the winter months. Fewer urban trees in this urban area derive from natural regeneration. The study area covers a large span in urban development, type of land uses, and population compositions. Downtown Sacramento is the central business district of the cities in Sacramento region that has development history back to the 18th century (Sacramento Archives and Museum Collection Center, 2006). New areas developed in the mid-2000s have balanced residential, business, and industrial land use. Tree canopy cover in this area ranges from 4.5% in the new development area to 25.1% in the old downtown area (Xiao et al., 2009).

Data sets

The 2013 EarthDefine canopy data, 2012 NAIP imagery, 2010 US Census data, land uses, and other GIS data layers such as jurisdiction boundary were used in this study.

The 2010 US Census data used in this study includes census block group, census urban and urban community boundaries. The census data were used to define urban boundaries for this study. Land use data were created from Sacramento County’s 2013 parcel data (Digital Map Products, 2013). The six land use types were used in this study: Low Density Residential (Residential Low), High Density Residential (Residential High), Commercial/Industrial/Institutional, Open Space, Transportation, and Other. Land use classes in the parcel data were assigned to this simple classification based on each parcel’s land use description (Table 6-5).

Table 6-5. Land use of Sacramento County.

Land use		Area km2	%
Urban	Commercial/Industrial/Institutional	257.3	10.0%
	Open Space	27.9	1.1%
	Multi-family Residential	99.1	3.9%
	Single Family Residential	326.0	12.7%
	Transportation Corridor	130.1	5.1%
	Water	21.3	0.8%
	Total	861.8	33.5%
Rural		1,712.3	66.5%
Total		2,574.1	100.0%

Sample design, Sampling scheme and sample size

A robust accuracy assessment requires sufficient number of samples to ensure adequate precision. For assessing the accuracy of the tree canopy cover, a stratified random sampling scheme was used to locate sample locations. Sample stratification was based on canopy cover of each land use class. All sample plots were located inside the project study area.

A binomial distribution model was used to calculate the number of samples needed for each type of land use. The formula for calculating sample size based on the binomial distribution theory is:

$$N_i = \mathrm{p}_i(1 - \mathrm{p}_i)(\frac{\mathrm{Z}}{\mathrm{C}})^2$$

Where N_i is the number of samples required for land use type *i*; Z is the Z-score for standard normal distribution at given confidence level; p_i is the expected percentage picking a choice (i.e., tree canopy coverage) of land use category *i*; and C is the margin of error. The sample size was conservatively estimated using a 95% confidence level and margin of error of 10%. A previous tree canopy cover study within the study area indicated that tree canopy cover varies with land use types (Xiao et al., 2009). Canopy cover and land use data from the previous 2009 Sacramento regional urban forest study were used to estimate the sample numbers for each land use type due to data availability at the early time of this project. A maximum sample number of each land use class was used. The sample number ranges from 64 to 95. The average sample size is 82 samples per land use class (Table 6-6).

Sample unit

For each sample site, the sample unit is a square plot which covers 90 by 90 NAIP pixels or 8,100 pixels. At this sample unit size, tree canopy cover mapping error induced by minimum mapping units was eliminated. The minimum distance among samples was set at greater than 60 NAIP pixels. The coordinates of randomly generated samples were moved to the central x-y location of the associated NAIP pixel.

Table 6-6. Canopy coverage and sample number by land use class.

Land Use Class	Canopy coverage				Sample number			
	Min	Max	Mean	Range	Min	Max	Mean	Range
Agricultural	3.8%	43.6%	8.0%	39.8%	14	94	28	80
Comm/Ind	0.4%	21.8%	10.1%	21.4%	2	66	35	64
High Density Res	0.2%	38.8%	21.5%	38.6%	1	91	65	90
Institutional	1.0%	29.5%	15.9%	28.5%	4	80	51	76
Low Density Res	3.0%	43.8%	25.6%	40.8%	11	95	73	83
Open Space	9.4%	54.6%	27.8%	45.2%	33	95	77	63
Transportation	1.0%	20.9%	11.7%	20.0%	4	64	40	60

Data extraction

Reference tree cover data

Reference tree canopy cover data was collected from 2012 NAIP imagery based on the sampling scheme and a semi-auto tree canopy classification method (McPherson et al., 2012). A square outline of this group of 8,100 NAIP pixels was created based on sample plots' central x-y coordinates. A segmentation of each sample unit was conducted based on NAIP imagery using Ecognition software. NDVI was used to screen out each non-vegetated polygon. Vegetation and non-vegetation was added to each polygon's attribution table based on their average NDVI value. Each tree cover polygon was visually verified from the NAIP imagery.

EarthDefine tree canopy cover data

The raster based EarthDefine tree canopy cover data was vectorized. Tree canopy cover was extracted from this vector format tree canopy cover data layer based on the boundary of the sample plots (i.e., 90 by 90 pixels central by the random sample's x-y coordinates).

Data analysis

In the final data analysis, land use data layer derived from 2013 parcel data were used. Tree canopy of each land use type was calculated based on overlaying the land use GIS layer with reference tree canopy cover layer, and overlay with the EarthDefine tree canopy data layer.
An error matrix method was used to evaluate the tree canopy cover mapping accuracy. An error matrix is also referred to as a confusion matrix or contingency table. It has been widely used for evaluating the effectiveness of a discrete classification of remotely-sensed data. An error matrix, a two dimensional matrix derived from a comparison of reference and classified map plots, is a means of reporting site-specific error (Campbell, 1987). Typically, the columns of the matrix represent the reference data by category and rows represent the classification by category.

Result and discussion

The tree canopy cover of the study area was estimated to be 18% based on reference canopy data and was 15% from the EarthDefine's tree canopy data (Table 6-7). EarthDefine's tree canopy data was slightly underestimated tree canopy cover of the study region. One reason may be due to the minimum mapping unit (0.005 acre or 20.2 m^2, http://www.earthdefine.com/spatialcover_treecanopy/) used in the image classification. At this minimum mapping unit scale, small single trees could be missed from tree mapping.

Normalizing the tree canopy cover difference of the two data sets to total land area for each land use type, the smallest tree canopy cover estimation error was on the “Open Space” land use. This may be because most trees in this land use category have been planted close to each other. The largest tree canopy cover estimation error was on the Transportation Corridor land use. This is may be due to the nature of the definition for the “Transportation Corridor” land use which covers all roads surfaces. The majority of trees in “Transportation Corridor” land use category are isolated trees.

Table 6-7. Tree canopy cover by land use class.

Land Use	**Land Area (m^2)**	**UTC (m^2)**		**UTC (%)**		$\frac{Ref-ED}{Land\ Area}$**x100***
		Ref	**ED**	**Ref**	**ED**	
Commercial/Industrial/ Institutional	648,000.0	99,748.0	77,757.8	15.4	12.0	3.39
Multi-family Residential	737,100.0	160,161.0	128,958.8	21.7	17.5	4.23
Single Family Residential	769,500.0	175,344.7	151,764.4	22.8	19.7	3.06
Open Space	769,500.0	90,707.0	69,003.1	11.8	9.0	2.82
Transportation Corridor	518,400.0	113,600.0	90,918.6	21.9	17.5	4.38
Water	348,300.0	48,262.0	37,197.5	13.9	10.7	3.18
Total	3,790,800.0	687,822.7	555,600.2	18.1	14.7	3.49
*: Ref = reference UTC (ground truth see 2.3.3 *Reference tree cover data* of this report) ED = EarthDefine’s image classification UTC						

The error matrix was created based on the Reference tree cover data and EarthDefine Image Classification tree canopy cover data. The error matrix shows the reference data verses the image classification for tree canopy (Table 6-8). The user’s accuracy and Producer’s accuracy are shown on Table 6-9. The EarthDefine tree canopy cover data had an overall 91% mapping accuracy. However, for tree canopy cover by land use class, the producer’s accuracy ranged from 57% to 69% among different land uses while user’s accuracy ranged from 75% to 89%. The high overall mapping accuracy (i.e., 91%) was caused by the correctly mapping the majority nontree canopy land cover (i.e., 82%). Thus, when evaluating urban tree canopy mapping accuracy, excluding nontree covered land would result more realistic mapping accuracy for the urban tree canopy cover.

Table 6-8. Tree canopy mapping error matrix.

	Reference land cover (m^2)				
EarthDefine Image Classification	**Land Use**		**Tree**	**NonTree**	**Total**
	Commercial/Industrial/Institutional	**Tree**	69,019.3	8,738.5	77,757.8
		NonTree	30,728.7	539,513.5	570,242.
		Total	99,748.0	548,252.0	648,000.0
	Multi-family Residential	**Tree**	108,456.9	20,501.8	128,958.8
		NonTree	51,704.1	556,437.2	608,141.2
		Total	160,161.0	576,939.0	737,100.0
	Single Family Residential	**Tree**	121,099.5	30,664.9	151,764.4
		NonTree	54,245.2	563,490.4	617,735.6
		Total	175,344.7	594,155.3	769,500.0
	Open Space	**Tree**	51,899.4	17,103.7	69,003.1
		NonTree	38,807.7	661,689.3	700,496.9
		Total	90,707.0	678,793.00	769,500.0
	Transportation Corridor	**Tree**	75,396.9	15,521.8	90,918.6
		NonTree	38,203.2	389,278.2	427,481.4
		Total	113,600.0	404,800.0	518,400.0
	Water	**Tree**	31,852.7	5,344.9	37,197.5
		NonTree	16,409.3	294,693.2	311,102.5
		Total	48,262.0	300,038.0	348,300.0

Table 6-9. Land use class mapping accuracy

Land Use	**Producer's Accuracy**			**User's Accuracy**	
	Tree	**NonTree**		**Tree**	**NonTree**
Commercial/Industrial/Institutional	69.2%	98.4%		88.8%	94.6%
Multi-family Residential	67.7%	96.4%		84.1%	91.5%
Single Family Residential	69.1%	94.8%		79.8%	91.2%
Open Space	57.2%	97.5%		75.2%	94.5%
Transportation Corridor	66.4%	96.2%		82.9%	91.1%
Water	66.0%	98.2%		85.6%	94.7%
Overall accuracy	91.3%				

Additional information on image processing, classification and analysis are available in McPherson, Simpson, Xiao, & Wu (2011); Xiao, Wu, Simpson, & McPherson (2009).

Definition of terms

Error matrix: The error matrix (also called confusion matrix, correlation matrix, or covariance matrix) summarizes the relationship between two datasets. In land cover mapping, these two data sets often a classification map and a reference data set.

Overall accuracy: Overall accuracy or total accuracy is the percentage of total agreement between two data sets. It is calculated as the ratio of total number of correctly classified pixel or area to the total number of pixels or area of the test area. The overall accuracy is an average value which does not reveal if error was evenly distributed between classes or if some classes were really bad and some really good.

User's accuracy: User's accuracy corresponds to error of commission (inclusion). From the perspective of the user of the classified map, it tells the user how accurate is the map or for a given class, how many of the pixels on the map are actually what they say they are? User's accuracy is calculated as the ratio of the number correctly identified in a given map class to the number claimed to be in that map class.

Producer's accuracy: Producer's accuracy corresponds to error of omission (exclusion). From the perspective of the maker of the classified map, how accurate is the map or for a given class in reference plots, how many of the pixels on the map are labeled correctly? Producer's accuracy is calculated as the ratio of the number correctly identified in reference plots of a given class to the number actually in that reference class.

Table 6-10. Example of error matrix.

		Classification Data		Row marginal	Producer's Accuracy
		Class 1	Class 2		
Reference Data	Class 1	n_{11}	n_{12}	$n_{11}+n_{12}$	$n_{11}/(n_{11}+n_{12})$
	Class 2	n_{21}	n_{22}	$n_{21}+n_{22}$	$n_{22}/(n_{21}+n_{22})$
Column marginal		$n_{11}+n_{21}$	$n_{12}+n_{22}$	$n=n_{11}+n_{12}+n_{21}+n_{22}$	
User's accuracy		$n_{11}/(n_{11}+n_{21})$	$n_{22}/(n_{12}+n_{22})$		
Overall accuracy					$(n_{11}+n_{22})/n$

Appendix 3: Detailed methods for the development of transfer functions

In this study, transfer functions are defined as field plot-based measures of CO_2 equivalent per hectare UTC (t ha^{-1} tree canopy cover) that are aggregated and applied to a climate zone by land use class. The area of UTC can include areas with no trees but that do have tree canopy. We express CO_2 fluxes in terms of UTC because previous research found that this approach provided higher accuracy, greater precision and improved spatial detail compared to CO_2 fluxes derived by land use class alone and applied as density values (e.g., t ha^{-1} residential land) (Strohbach & Haase, 2012). The UTC-based approach eliminated variation in UTC within land use classes, an important source of error. Because field plot sampling did not fully capture the extent of UTC for each land use class, land use based CO_2 storage estimates had large standard errors in areas where UTC was highly heterogeneous, such as town centers.

To derive UTC-based transfer functions, CO_2 storage, sequestration and avoided emission values are calculated for trees in each UFORE and FIA plot and divided by the plot's UTC. Plot data are aggregated by land use class for each climate zone and descriptive statistics are applied to determine sample means and standard errors. Different values reflect different stand structures and dynamics that influence C. For instance, the CO_2 storage transfer function for a hectare of UTC in an old residential neighborhood will be relatively high when the stand consists of closely spaced, mature oaks (*Quercus sp.*) and a lush understory. In contrast, the transfer function for a hectare of UTC in a new residential area will be lower when the stand is characterized by juvenile pear (*Pyrus sp.*) trees with a sparse understory.

The transfer function for each land use class is transferred to the UTC delineated within the corresponding land use. Using GIS capabilities, CO_2 fluxes are mapped and values are summed based on the amount of UTC in each land use class. The maps provide spatially explicit information on the distribution of urban forest CO_2 fluxes for planning and management purposes. Hence, transfer functions aggregate plot data by geographic units, such as UTC and land use class, and transfer the resulting values to map the spatial distribution of CO_2 fluxes across communities within each climate zone.

Within each climate zone, transfer functions were calculated for each land use (J_k) were applied to the total UTC for that land use and results were summed.

$$\text{Total } CO_2 = \sum_k J_k \times \text{Total UTC}^{(k)}$$

Urban-based biomass equations were developed from street and park trees measured in California (Pillsbury et. al., 1998) and Colorado cities (Lefsky and McHale, 2008). The rationale for nearly exclusive use of these equations is that trees in open-grown conditions partition carbon differently than closely spaced trees in forest stands because they do not compete as directly with other trees. There is evidence that they partition relatively more carbon in branches and foliage, and less carbon to the bole compared to forest trees. Also, urban tree growth can be enhanced by periodic irrigation and care, as well as elevated levels of carbon and nitrogen deposition (Jo and McPherson, 1995; Nowak and Crane, 2002).

The two types of allometric biomass equations were used to yield aboveground volume and dry weight of a tree. The methodology to convert green volume into biomass and eventually to stored

CO_2 is well established (Jenkins et al., 2003a, 2003b; Markwardt and Wilson, 1935; Simpson, 1993) and entailed calculating total dry weight biomass, then standing carbon and sequestered CO_2 equivalents. The conversion from carbon to CO_2 equivalent uses the following equation: Carbon * 3.67 = CO_2. Converting the fresh weight of green volume into dry weight required use of species specific dry weight density conversion factors. The amount of belowground biomass in roots of urban trees is not well researched. This study assumed that root biomass was 28% of total tree biomass (Cairns et al., 1997; Husch et al., 1982; Wenger, 1984). Wood volume (dry weight) was converted to C by multiplying by the constant 0.50 (Lieth et al., 1975).

The amount of CO_2 sequestered in year *x* was calculated as the amount stored in year *x+1* minus the amount stored in year *x*. To project tree size at year *x*+1 we used growth curves developed from samples of about 700 street and park trees representing the 20 to 22 predominant species in each climate zone's reference cities (Peper et al., 2001a, 2001b).

Species matching
Each tree in the sample plots was matched to one of the 20 to 22 species that were intensively studied in each climates zone's reference city. Correctly matching species from the sample to their corresponding reference city species insured that the appropriate allometric and growth equations were applied to calculate biomass and annual sequestration rates. Trees in plots were assigned to corresponding species in their climate zone's reference city. If that species was absent they were matched to corresponding species from any of the four other California climate zones. For non-matching species, each sampled species was classified with four descriptors (Urban Forest Ecosystems Institute, 1995-2012).

- tree type: broadleaf, conifer, palm
- life form: evergreen, deciduous
- mature tree size: large, medium, small
- growth rate: very fast, fast, medium fast, medium, slow medium, slow, very slow

The 20 to 22 species in each of the California reference cities were similarly classified. Each non-match from the samples was matched with the best fitting reference city species according to the four descriptors. If several species matched, the assignment was made based on taxonomic criteria (same genus) or expert knowledge about the species' architecture.

The 1,890 trees in the FIA survey and the 1,913 trees in the UFORE survey were used in calculations of biomass, carbon stored, carbon sequestered, and emissions avoided.

Biomass, Standing and Sequestered Carbon

In order to facilitate calculating biomass and carbon sequestered across datasets containing several thousand trees, as well as to enable subsequent development of a web-based calculation tool, the biomass and growth tools were converted from Excel spreadsheets to a set of functions written in Python with the data tables being stored in an SQLite database. Four main data tables were included in this database: a species code table, a table giving the equation types and coefficients for the biomass, a table giving equation types and coefficients relating growth by age to the size of the tree, and a table giving the minimum and maximum tree sizes and corresponding ages to bound the range over which the equations are applicable.

Inputs to both calculations were the tree species, the climate zone, the tree dbh, and the tree height. Trees with sizes that were outside the minimum or maximum size range were respectively set to their minimum or maximum size value for their species and climate zone. The biomass calculator contains functions for 14 different equation types, with the functions parameterized at each function call through a lookup into the biomass coefficient table. The carbon sequestration calculator uses functions for 12 different equation types relating tree size to age. The steps in this calculation were the following: 1) Determine age of the tree given the tree size (dbh and height). 2) Subtract 1 from this age to set up the calculations in the previous year. 3) Use the current dbh and height to calculate the biomass and CO_2 equivalent for the current year. 4) Calculate the dbh and height of the tree in the previous year. 5) Calculate the biomass and CO_2 equivalents for the previous year. 6) Subtract (5) from (3) to determine carbon sequestered over the year. Because the functional form of the growth equations predicts dbh or height from tree age, step (2) poses a challenge because it asks for the inverse relationship. In the previous generation of these tools, this inverse relationship was handled using a set of lookups into precomputed growth tables. In this Python version of the calculator, the inverse computation was made using numerical root solving techniques. Two different root solvers from the SciPy library were used in this calculation (fsolve and brentq), the choice of which being dependent on the equation type. By avoiding using precomputed growth tables, the calculator can easily be updated, for instance by changing the equation coefficients in the database.

Correct performance of the calculator function code was ensured by validating the output against a test dataset drawn from the precomputed growth tables used in the previous generation of the toolset. A collection of 256 instances of combinations of tree species, climate zone, dbh, and height was used as this test dataset. These 256 instances were chosen to span a wide range of species, equation types, and tree ages. For each instance, values of tree biomass and sequestered CO_2 were calculated and compared with the results from the test dataset. This validation process was enormously helpful in debugging the calculator code, in particular ensuring correct behavior at the endpoints of minimum and maximum ages. By the time the code was deemed ready for production use, the only cases that failed the validation were a few examples (about 2% of the total cases) where the calculated result diverged somewhat (on the order of 25%) from the test result as the tree size approached a minimum. Lacking a strong guarantee of the correctness of results in the test dataset, it is possible this divergence was due to numerical inaccuracies in the previously calculated test results rather than the new Python code.

The field plot-based measures of CO_2 equivalent per hectare UTC (t ha^{-1} tree canopy cover) are aggregated and applied to a climate zone by land use class. The area of UTC can include areas with no trees but that do have tree canopy. We express CO_2 fluxes in terms of UTC because previous research found that this approach provided higher accuracy, greater precision and improved spatial detail compared to CO_2 fluxes derived by land use class alone and applied as density values (e.g., t ha^{-1} residential land) (Strohbach and Haase, 2012). The UTC-based approach eliminated variation in UTC within land use classes, an important source of error. Because field plot sampling did not fully capture the extent of UTC for each land use class, land use based CO_2 storage estimates had large standard errors in areas where UTC was highly heterogeneous, such as town centers.

Calculation of Avoided Emissions and Energy Savings

Avoided emissions from power plants from effects of each sampled tree on building energy use were calculated based on data from the CUFR Tree Carbon Calculator (CTCC) (McPherson et al., 2008). The CTCC, a free Excel spreadsheet application, was produced by U.S. Forest Service researchers. It uses information on climate zone, species, and size to calculate CO_2 stored, sequestered CO_2, and avoided emissions. Since the application only accepts inputs for one tree at a time, a script was written to automate these calculations. To determine effects of tree shade on building energy performance (i.e., shade effect), over 800 simulations were conducted for each of the California reference cities using different combinations of tree sizes, locations, and building vintages (Simpson, 2002). The model also incorporates effects of a tree on wind speed and air temperature through cooling from evapotranspiration (i.e., climate effect). If a sampled tree was located within 18 meters of a conditioned residential building, information on its distance and compass bearing relative to a building, building vintage (its age, which influences energy use) and types of heating and cooling equipment were collected and used as inputs to calculate annual heating and cooling energy effects.

Three prototype buildings were used in the simulations to represent pre-1950, 1950-1980, and post-1980 construction practices (Ritschard et al., 1992). Building footprints were modeled as square, which was found to be reflective of average impacts for large building populations (Simpson, 2002).

Buildings were simulated with 1.5-ft. overhangs. Blinds had a visual density of 37%, and were assumed closed when the air conditioner is operating. Summer and winter thermostat settings were 78° F and 68° F during the day, respectively, and 60° F at night. Unit energy effects (UEE) were adjusted to account for saturation of central air conditioners, room air conditioners, and evaporative coolers and overlapping shade from multiple trees. Shade from multiple trees on the same building may overlap, resulting in less building shade from an added tree than would result if there were no existing trees. Simpson (2002) estimated that the fractional reduction in average cooling and heating energy use per tree was approximately 6% and 5% percent per tree, respectively, for each tree added after the first. Simpson (1998) also found an average of 2.5 to 3.4 existing trees per residence in Sacramento. A multiple tree shade reduction factor (SRF) of 85% was used here for the largest shade tree in a plot, based on dbh. This is equivalent to approximately three existing shade trees per residence. The second largest tree in the plot that shaded the building was assigned an SRF of 80%. This 5% reduction was given to each subsequent shade tree, such that the fifth plot tree received a 65% SRF to account for diminished effects of increased overlapping shade.

In addition to localized shade effects assumed to accrue only to plot trees within 60-ft. of buildings; lowered air temperatures and wind speeds from neighborhood tree cover (i.e., climate effects) produce a net decrease in demand for summer cooling and winter heating. Reduced wind speeds by themselves may increase or decrease cooling demand, depending on the circumstances. To estimate climate effects on energy use, air temperature and wind speed reductions as a function of neighborhood canopy cover were estimated from published values following McPherson and Simpson (1999), then used as input for building energy use simulations described earlier. Peak summer air temperatures were assumed reduced by 0.4 °F for each 10% increase in canopy cover. Wind speed reductions were based on the canopy cover resulting from the addition of the particular tree being simulated to that of the building plus other trees. A lot size of 10,000 ft^2 was assumed.

Unit energy effects (UEEs) from shade for multi-family residences (MFRs) were calculated from single-family residential UEEs adjusted by potential shade factor (PSFs) to account for reduced shade resulting from common walls and multi-story construction. Average PSFs were estimated from ratios of exposed wall or roof (ceiling) surface area to total surface area, where total surface area includes common walls and ceilings between attached units in addition to exposed surfaces (Simpson, 1998). A PSF=1 indicates that all exterior walls and roof are exposed and could be shaded by a tree, while PSF=0 indicates that no shading is possible (i.e., the common wall between duplex units). Potential shade factors were estimated separately for walls and roofs for both single- and multi-story structures. For this study, the PSF for multi-family residential (MFR) buildings was 57.5%, the average between values previously reported for MFR 2-4 units (74%) and MFR 5+ units (41%) (Maco et al., 2005) (Table 6-11).

Table 6-11. Potential Shade (PSF, %) and Climate Factors (PCF, %) applied to account for different effects of trees on energy use for buildings in a variety of land uses.

Land Use	PSF	PCF
Single-Family Residential	100	100
Multi-Family Residential	57.5	80
Commercial/Industrial/Institutional	20	32.5
Transportation	15	20
Open Space	0	0
Water/Other	0	0

Unit energy effects were also adjusted for climate effects to account for the reduced sensitivity of multi-family buildings with common walls to outdoor temperature changes with respect to single-family detached residences. The potential climate factor (PCF) was 1.0 for single-family residential buildings. Because PCFs were unavailable for multi-family structures, a multi-family PCF value of 80% was selected (less than single-family detached PCF of 1.0 and greater than small commercial PCF of 40%; see next section).

Unit energy effects for commercial/industrial/institutional land uses due to the presence of trees were determined in a manner similar to that used for multi-family land uses. Potential shade and climate factors of 20% and 32.5% were assumed, respectively. These values were based on reductions previously reported for small and large commercial/industrial buildings (Maco et al. 2005). Akbari and others (1992) observed that commercial buildings are less sensitive to outdoor temperatures than houses. Also, change in UEEs due to shade tend to increase with conditioned floor area for typical residential structures. As building surface area increases so does the area shaded. This occurs up to a certain point because the projected crown area of a mature tree (approximately 700 to 3,500 ft^2) is often larger than the building surface areas being shaded. Consequently, more area is shaded with increased surface area. However, for larger buildings, a point is reached at which no additional area is shaded as surface area increases. Average potential shade and climate factors for trees near structures in Transportation land uses were estimated to be 15% and 20%, respectively. However, data relating trees in the Transportation land uses to building space conditioning were not readily available, so there is substantial uncertainty for these factors. Trees in Open Space and Water land uses were seldom located near conditioned structures and no energy impacts were ascribed to them.

Associated power plant emissions reductions were based on the CO_2 emission factors for each utility reported by the Climate Action Reserve (CAR, 2008). Electricity emissions factors differ regionally because of utility-specific differences in the mix of fuels used to generate electricity. In cases where a tree shaded more than one building, effects were summed. Avoided emissions were totaled for trees in each plot.

Heating and cooling transfer functions were reduced based on the type and saturation of air conditioning or heating equipment by land use and climate zone (Table 6-12). Single and multi-family residential saturations were obtained from the 2009 California Residential Appliance Saturation Survey (https://websafe.kemainc.com/RASS2009). Equipment factors of 33% and 25% were assigned to homes with evaporative coolers and room air conditioners, respectively. These factors were combined with equipment saturations to account for reduced energy use and savings relative to simulations for homes with central air conditioning. Transfer functions were multiplied by the heating and cooling adjustment factors to reduce tree effects because not all buildings have central air conditioning and natural gas heating, which is assumed with the values derived from the CTCC. Lacking data on equipment types and saturations for buildings near trees in commercial/industrial/institutional land uses, reduction values for multi-family residential buildings were applied. Reduction values for single-family residential were applied to transportation land uses because local streets are included.

Table 6-12. Reduction values applied to transfer functions for avoided energy effects of trees.

Climate Zone (CEC Forecast Zone)				
Inland Valleys (3)	SFR	MFR	C/I/I	TRANSP.
Cooling				
CAC	65.20%	43.70%		
Room AC	20.40%	24.60%		
Evap. Cooler	10.20%	19.40%		
Heat Pump	7.90%	12.90%		
Adjustment	82.38%	69.57%	69.57%	82.38%
Heating				
Natural Gas	62.20%	48.80%	48.80%	62.20%
North Coast (5)	SFR	MFR	C/I/I	TRANSP.
Cooling				
CAC	9.50%	6.70%		
Room AC	5.90%	6.10%		
Evap. Cooler	0.40%	5.10%		
Heat Pump	1.10%	2.90%		
Adjustment	12.65%	12.89%	12.89%	12.65%
Heating				
Natural Gas	66.50%	36.20%	36.20%	66.50%
Interior West (9)	SFR	MFR	C/I/I	TRANSP.
CAC	50.30%	39.50%		
Room AC	28.40%	26.00%		
Evap. Cooler	2.70%	11.70%		
Heat Pump	2.70%	9.10%		
Adjustment	63.05%	60.11%	60.11%	63.05%
Heating				
Natural Gas	58.60%	47.40%	47.40%	58.60%
SW Desert (10)	SFR	MFR	C/I/I	TRANSP.
CAC	65.00%	45.90%		
Room AC	16.70%	28.70%		
Evap. Cooler	11.00%	35.20%		
Heat Pump	5.70%	4.10%		
Adjustment	78.96%	68.27%	68.27%	78.96%
Heating				
Natural Gas	72.60%	69.60%	69.60%	72.60%
South Coast (11)	SFR	MFR	C/I/I	TRANSP.
CAC	23.00%	9.60%		
Room AC	17.00%	40.80%		
Evap. Cooler	0.30%	2.60%		
Heat Pump	1.60%	3.40%		

Adjustment	30.29%	27.11%	27.11%	30.29%
Heating				
Natural Gas	47.90%	5.20%	5.20%	47.90%
Inland Empire (12)	SFR	MFR	C/I/I	TRANSP.
CAC	70.70%	53.70%		
Room AC	21.30%	35.50%		
Evap. Cooler	3.30%	10.70%		
Heat Pump	4.60%	24.80%		
Adjustment	83.15%	92.89%	92.89%	83.15%
Heating				
Natural Gas	77.40%	78.50%	78.50%	77.40%

Appendix 4: Transfer function table including other benefits

The development and use of the calculations for biomass, and CO_2 related benefits rely on a set of spreadsheets, databases and R code that were submitted as additional digital files with this report.

- Appendix4_Transfer_functions_summaries

This table has the transfer functions for biomass, CO_2 stored, sequestered and avoided emissions as well as energy savings, CO_2 reductions, air quality improvement, stormwater runoff reductions, asset value, and associated cost savings.

- Appendix4_rollup_slim.sqlite

This database includes the plot data used in the creation of the transfer functions.

- Appendix4_tf_rollup_01282015.R

This R file includes the code used to calculate the transfer functions.

Appendix 5: Transfer function development for co-benefits

Rainfall Interception

Intercepted rainfall can evaporate from the tree crown, thereby reducing stormwater runoff. A numerical interception model accounted for the amount of annual rainfall intercepted by trees, as well as throughfall and stem flow (Xiao et al., 2000). The volume of water stored in tree crowns was calculated from tree crown leaf and stem surface areas and water depth on these surfaces. Hourly meteorological and rainfall data from local weather stations were used for a year when total rainfall in that year was close to the average annual amount.

The rainfall interception benefit was priced by estimating costs of controlling stormwater runoff. Water quality and/or flood control costs were calculated per unit volume of runoff controlled and this price was multiplied by the amount of rainfall intercepted annually. More information on the methods used to model rainfall interception is available in each of the six regional Tree Guidelines documents.

Property Values, Aesthetics and Other Benefits

Many benefits attributed to urban trees are difficult to price (e.g., increased property values, beautification, privacy, wildlife habitat, sense of place, well-being). However, the value of some of these benefits can be captured in the differences in sales prices of properties that are associated with trees. Anderson and Cordell (1988) found that each large front-yard tree was associated with a 0.88% increase in sales price. Previous analyses showed that differences in residential property values among cities and associated tree benefits were best modeled by applying the 0.88% sales price increase to the city's median home sales price. Hence, in the I-Tree Streets analysis property value (A) benefits ($/tree/year) reflect differences in the contribution to residential sales prices of a large front yard tree and annual changes in leaf area (LA) as trees grow in each city. These relationships are expressed for a single street tree as:

$A = L * P$

Where L is the annual increase in tree LA and P is the adjusted price ($\$/m^2$ LA)

$P = (T \text{ x } C) / M$

where

T = Large tree contribution to home sales price = 0.88% x median sales price

C = Tree location factor that depreciates the benefit for trees in non-residential sites

M = Large tree leaf area (250 m^2).

Median residential sales prices were obtained for each city with a tree inventory for January-April, 2014 from the website: http://www.trulia.com/real_estate/. Values for parameters listed above were obtained from the six Tree Guidelines documents, one for each climate zone.

Appendix 6: CalEnviroScreen and California Air Resources Board information

CalEnviroScreen Data Layer
Data layer Input: CalEnviroScreen 2.0
http://oehha.ca.gov/ej/ces2.html

Processing steps:
- Clip to the Urban Area regions
- Use the field "PercentileRange" to assign a rank value of Low (0-45%), Medium (46-75%) and High (76-100%)
- Convert to raster (30 meter cell size, snap to nlcd2011_cart)
- Used "rank" as value
- Zonal Statistics as Table tool, using the union layer as the zones (union id field)
    - Take the mean of the rank numbers for each zone
- Join resulting table back to the polygon Communities/Urban Area/County union layer with additional pollution fields (comm_union_CES_pollution) and calculate fields for CES_mean
- Calculate CES_rank using the following ranges: 1.0-1.5 Low; 1.6-2.0 Medium; 2.1-3 High.

Pollution Data Layer
Data layer Input: CalEnviroScreen 2.0
(http://oehha.ca.gov/ej/ces2.html)

Processing steps:
- Convert to raster (30 meter cell size, snap to nlcd2011_cart)
- Used Ozone (raw numbers) as value
- Eliminate the 0's using Set Null tool
- Extract by Mask tool using the Communities/Urban Area/County union layer (unionid)
- Zonal Statistics as Table tool, using the union layer as the zones (union id field)
    - Take the mean of the ozone numbers for each zone
- Join resulting table back to the polygon Communities/Urban Area/County union layer with additional pollution fields (comm_union_CES_pollution) and calculate fields for ozone
- Repeat the process for PM 2.5

For PM 10
- Began with ARB Excel table
    - Import into Microsoft Access and create new table by selecting the maximum value of the years present for each site
    - Import the maximum table into ArcMap
    - Create x,y event layer using the latitude/longitude fields
    - Export layer to a shapefile

- Project shapefile to NAD83 Teale Albers
- Clip projected file by the urban area boundary
- Average the urban area point values for PM10 for each county to come up with one average PM10 value by County using Summary Statistics

Once each metric (Ozone, PM 2.5 and PM 10) had a final rank of 1, 2 and 3, the three ranks were averaged for each county. If the average rank was 1.0-1.5, the final rank was Low. If the average was 1.6-2.0, the final rank was Medium. And if the average was 2.1-3, the final rank was High.

The analysis related to the development of a pollution rank layer for the urban areas of California, as well as the ranking of areas by the CalEnviroscreen overall score and were submitted as additional digital files with this report.

- Appendix6_UCD_PM10_24hr_2010_2013
- Appendix6_CES20UpdateOct2014

The California Communities Environmental Health Screen Tool, Version 2.0 (CalEnviroScreen 2.0) Guidance and Screening Tool can be found here:
http://oehha.ca.gov/ej/pdf/CES20FinalReportUpdateOct2014.pdf

Appendix 7: Tree Canopy, Biomass and CO_2 Inventory by Community, Urban Area and County

The summary data provided in Chapter 3 were analyzed using a separate spreadsheet containing biomass and CO_2-related benefits by different geographies. This table was submitted as an additional digital file with this report.

- Appendix7_County_UTC_Benefits_all

This table has separate worksheets for benefits summarized by: urban area, county and climate zone.

Appendix 8: Urban Area Trends

The summary data presented in Chapter 3, Part 3. Trends in Urban Forests, rely on a set of spreadsheets containing the complete dataset for population change, impervious surface, public open space, tree canopy and land use within the urban areas in California. These tables were submitted as additional digital files with this report.

- Appendix8_Population_Change

This table includes population figures for urban areas in 2000 and 2010, by county and by urban area.

- Appendix8_Impervious_CPAD_UTC

This table has impervious surface, open space from CPAD data and tree canopy, by urban area, and county.

- Appendix8_Land_Use

This table includes land use area within the six land use classes, by union id (all) and urban area.