Technical appendix to Managing Open Space in Support of Net Zero: Carbon Sequestration Opportunities and Tradeoffs in the Alameda Watershed

SFEI February 24, 2023

Table of contents

1. Vegetation carbon quantification 2
2. Soil carbon quantification 5
3. 2020 wildfire carbon losses 11
4. Assessment of carbon management potential 13
    - 4.1. Rangeland compost 13
        - Carbon and GHG analyses 13
        - Footprint mapping 15
    - 4.2. Riparian forest restoration 15
        - Carbon and GHG analyses 15
        - Footprint mapping 18
    - 4.3. Silvopasture 19
        - Carbon and GHG analyses 19
        - Footprint mapping 21
    - 4.4. Cattle exclusion 21
        - Carbon and GHG analyses 21
        - Footprint mapping 24
    - 4.5. Native grassland restoration 24
        - Carbon and GHG analyses 24
        - Footprint mapping 24
    - 4.6. Open space conservation 25
        - Carbon and GHG analyses 25
        - Footprint mapping 25
5. References 26

1. Vegetation carbon quantification

The amount of carbon stored on the landscape was estimated for all locations in a 30 meter grid within the SFPUC's Alameda Creek Watershed landholdings. Carbon storage estimates combined values for woody and herbaceous aboveground vegetation, roots, dead and decaying plant matter, organic soil horizons, and mineral soils to 1 m depth. Carbon storage was mapped across the watershed and summarized for six broad ecosystem type categories: grassland, coastal scrub, chaparral, oak savanna, oak woodland, and riparian forest. Developed areas and aquatic habitats were excluded from the analysis.

Ecosystem type was defined for each 30 x 30 m grid cell by aggregating vegetation cover classes originally from the LANDFIRE program's 2010 Existing Vegetation Type (EVT) layer and initially aggregated according to the classification system in Gonzalez et al. (2015) (Table A1). We determined that the 30 m grid scale did not sufficiently capture areas of oak savanna, where tree spacing is greater than the grid scale. (Within areas of oak savanna, grid cells containing trees were often classified as woodland, and grid cells with no trees were often classified as grassland or shrubland.) For this reason, we burned in additional areas mapped as oak savanna by Jones and Stokes (2003) to define the extent of oak savanna for this analysis. Accordingly, the extents of ecosystem types in Table A1 differ from the final ecosystem type areas reported in this study and used in carbon and GHG calculations.

Table A1. Vegetation composition of the Alameda Watershed, based on LANDFIRE data (as aggregated by Gonzalez et al. (2015). The more exhaustive vegetation classes correspond to the LANDFIRE-based classification system used in Gonzalez et al. (2015). The ecosystem types identified in the first column were used to quantify and summarize carbon storage across the watershed, and to characterize opportunities for carbon management activities.

Ecosystem Type			Vegetation Class from Gonzalez et al. (2015), crosswalked from LANDFIRE Existing Vegetation Type	Acres	% Area
Chaparral			California Mesic Chaparral	2,550	6.6
			Northern and Central California Dry-Mesic Chaparral	1,511	3.9
			Shrubland	34	0.1
			Southern California Dry-Mesic Chaparral	1,071	2.8
Coastal Scrub			Southern California Coastal	2,242	5.8

			Scrub		
Grassland			Grassland	13,278	34.6
			Mediterranean California Sparsely Vegetated Systems	56	0.1
Oak Savanna			California Lower Montane Blue Oak-Foothill Pine Woodland and Savanna	478	1.2
			Deciduous sparse tree canopy	19	0.05
			Mixed evergreen-deciduous sparse tree canopy	72	0.2
			Southern California Oak Woodland and Savanna	2,206	5.8
Oak Woodland			California Montane Jeffrey Pine (-Ponderosa Pine) Woodland	1	0.003
			California Montane Woodland and Chaparral	1	0.003
			Central and Southern California Mixed Evergreen Woodland	8,122	21.2
			Evergreen open tree canopy	921	2.4
			Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	0.21	0.0013
			Mediterranean California Mixed Oak Woodland	476	1.2
Riparian Forest			California Montane Riparian Systems	657	1.7
Open water, barren, or developed			Open water, barren, or developed	4,667	12.2
Total			Total	38,363	

For grid cells with a tree-dominated canopy, defined in this study as grid cells classified according to Table A1 as oak savanna, oak woodland, or riparian forest, carbon stored aboveground in standing trees was estimated from LANDFIRE data according to Gonzalez et al. (2015). Gonzalez et al. (2015) used carbon stock measurements from Forest Inventory Analysis plots (FIA database version 5.1, November 23, 2011) to develop a set of equations specific to California that relate LANDFIRE EVT, canopy height, and canopy cover to aboveground carbon stocks in standing trees. These transfer equations were applied to 2010 LANDFIRE data layers, using a ratio of 0.47 to convert from vegetation biomass to carbon (McGroddy et al., 2004). Other carbon pools in tree-dominated sites were estimated from the US Forest Service's Fuel Characteristic Classification System (FCCS) fuelbeds (Prichard et al., 2019; Reeves et al., 2009; Riccardi et al., 2007). For each 30 x 30 m grid cell, FCCS fuelbeds predict modeled biomass values for low-stature vegetation and dead organic matter pools. FCCS fuelbeds were developed for wildfire modeling, but also offer reasonable estimates of biomass stocks for the purpose of carbon accounting (Saah et al., 2016). FCCS values were used to estimate carbon storage in woody and herbaceous understory vegetation; litter, lichen and moss; downed dead wood; duff; and basal accumulations around tree trunks, using a conversion ratio of 0.47 tons of carbon per tons of vegetation dry biomass (McGroddy et al., 2004).

For coastal scrub and chaparral habitats, Gonzalez et al. (2015) values were used as estimates of carbon in the shrub canopy. Tree carbon was assumed to be zero, and FCCS values were used for all other aboveground carbon pools.

For grasslands aboveground herbaceous biomass was estimated from residual dry matter (RDM) measurements from the SFPUC's Alameda Watershed RDM monitoring program, which measured RDM at 100 sites across the watershed's grazing leases in 2018 (ACRCD and LD Ford, 2018a) The layout of RDM plots was not designed to provide a random sample across the watershed or individual grazing leases. For this reason, we did not attempt to estimate spatial variability in herbaceous biomass across or within grazing leases. Instead, we calculated a simple average of all RDM plots (mean = 1.54 ± 0.57 MT C/acre, range = 0.29–1.18 MT C/acre). Given that the layout of RDM plots was not designed for statistical inference, this average RDM value should be viewed as an approximation. Additionally, RDM measurements excluded summer annuals, so estimates may be biased toward lower carbon storage. (We note, however, that per-acre carbon storage in herbaceous vegetation is 1-2 orders of magnitude lower than tree or soil carbon storage, so such sources of error are likely to have only negligible effects on overall carbon stock estimates. Tree carbon in grassland sites was assumed to be zero, and FCCS values were used for all other carbon pools.

Carbon stored in the roots of live vegetation was calculated for all ecosystem types using root-to-shoot ratios reported in the published literature for three ecosystem type categories: grassland, shrubland (applied to coastal scrub and chaparral), and woodland/savanna/forest(applied to oak savanna, oak woodland, and riparian woodland). Carbon stored in canopy, shrub, and herbaceous vegetation was summed and multiplied by the corresponding mean root-to-shoot ratio to produce root carbon estimates. Table A2 summarizes root:shoot values derived from the literature.

Table A2. Summary of root:shoot ratios from the published literature used in this analysis

Ecosystem type category	Mean Root:Shoot Ratio	Root:Shoot Ratio Range	Notes
Shrubland	0.532	0.14-0.9	mean and range from Billings, 1985 and Kummerow et al., 1977 (San Diego chaparral)
Woodland/savanna/ forest	0.456	0.35-0.99	value is from Mokany et al., 2006 with biomass < 75 MT/ha; range is from Namm, 2012 (tanoak) and Millikin and Bledsoe, 1999 (Blue Oak)
Grassland	0.9	0.3-1.5	low values from Ryals and Silver, 2013; higher values from Jackson et al., 1989 and Henry et al., 2006 Note this is the value reported for invasive annuals—much lower than the Mokany et al (2006) value of ~4 for temperate grasslands.

2. Soil carbon quantification

To estimate carbon storage in the watershed's soils, soil carbon stocks were synthesized from published measurements and additional samples collected from the Alameda Watershed. Literature values were limited to California, including both grasslands and woody ecosystems. Many of these data have been synthesized previously in Silver et al. (2010). This study built upon this prior synthesis, adding new published studies and 16 additional soil profiles collected from the Alameda Watershed in 2021 (Table A3). Alameda Watershed samples were collected from 4 paired grassland and woodland transects south of the San Antonio Reservoir, two from a ridgeline and two from a valley floor near a seasonal creek (data shown in Table A4). In order to quantify carbon stocks, studies included in the synthesis were limited to those that reported either soil carbon stock (mass of carbon per soil volume or area) or carbon content (% C) and bulk density (BD). Where BD and %C were reported, those values were used to calculate per-area carbon stocks.

Additional samples were collected from two sites at the former Sunol Valley Golf Course in June 2021 and analyzed for total carbon (%) and organic carbon (%). These data were not included in the synthesis, but are provided in Table A5 below.

Table A3. Published studies included in the soil carbon synthesis

Reference	Number of profiles

Fierer et al., 2005	1
Herman et al., 2003	4
Dahlgren et al., 1997	4
Berhe et al., 2008	4
Zavaleta and Kettley, 2006	2
Koteen et al., 2011	4
Camping et al., 2002	2
Jackson et al., 1988	1
Chou et al., 2008	1
Baisden et al., 2002	5
Gessler et al., 2000	1
Suddick et al., 2013	2
Caspi et al., 2018	6
Caspi et al., 2019	16
Ryals et al., 2014	2
Fissore et al., 2017	1
Williams et al., 2011	4
Lin et al., 2019	4
Dybala et al., 2019	1
Matzek et al., 2016	1
Bird et al., 2011	1
Sanderman and Amundson, 2008	2
Schaeffer et al., 2017	1

Table A4. Soil carbon data from Alameda Watershed sites south of the San Antonio Reservoir. Samples were collected on 5/18-19, 2021 using a multi-stage AMS corer and processed for bulk density and total carbon at the University of Missouri Soil Health Assessment Center.

Profile ID	Sample ID	Top depth (cm)	Bottom depth	Carbon stock (kg

			(cm)	m^{-2})
Channel Grass 01	CG01-1	0.00	26.67	3.186526488
Channel Grass 02	CG02-1	0.00	26.67	4.341675137
Channel Grass 03	CG03-1	0.00	29.85	3.911804971
Channel Grass 04	CG04-1	0.00	29.21	4.152407481
Channel Grass 05	CG05-1	0.00	29.21	2.917042965
Channel Grass 05	CG05-2	29.21	50.80	1.731066125
Channel Grass 05	CG05-3	50.80	85.34	0.930762889
Channel Tree 05	CT05-1	0.00	18.42	2.155236847
Hill Grass 01	HG01-1	0.00	32.00	4.317074927
Hill Grass 01	HG01-2	32.00	52.07	2.013391766
Hill Grass 02	HG02-1	0.00	31.75	4.232400272
Hill Grass 02	HG02-2	31.75	46.99	2.345849923
Hill Grass 03	HG03-1	0.00	29.85	4.039490062
Hill Grass 03	HG03-2	29.85	57.15	2.038292275
Hill Grass 03	HG03-3	57.15	83.82	1.202419276
Hill Grass 04	HG04-1	0.00	27.94	4.566235849
Hill Grass 05	HG05-1	0.00	31.75	4.408266953
Hill Grass 05	HG05-2	31.75	40.64	1.073825433
Hill Tree 01	HT01-1	0.00	31.50	7.401295262
Hill Tree 01	HT01-2	31.50	60.96	3.745986199
Hill Tree 02	HT02-1	0.00	30.48	3.941914195
Hill Tree 02	HT02-2	30.48	63.50	1.693613983
Hill Tree 02	HT02-3	63.50	91.44	1.362127944
Hill Tree 03	HT03-1	0.00	34.29	5.953586486
Hill Tree 03	HT03-2	34.29	48.26	3.245182781
Hill Tree 04	HT04-1	0.00	24.13	4.863018379

Hill Tree 04	HT04-2	24.13	62.23	2.126067243
Hill Tree 05	HT05-1	0.00	26.67	3.268785533

Table A5. Soil carbon data from samples collected at the former Sunol Valley Golf Course on June 30, 2021. Samples were processed for TOC and TC at the UC Davis Analytical Lab.

Profile ID	Sample ID	Top depth (cm)	Bottom depth (cm)	Total organic carbon (%)	Total carbon (%)
Golf Course 1	GC1A	0	11	1.605	1.595
Golf Course 1	GC1B	11	19.5	1.24	1.27
Golf Course 2	CG2A	0	3.75	4.86	4.91
Golf Course 3	GC3A	0	3.75	3.39	3.71
Golf Course 4	GC4A	0	3.75	3.5	3.63
Golf Course 5	GC5A	0	3.75	2.92	2.86
Golf Course 6	GC6A	0	4	3.28	3.33
2 Golf Course 1	2GC1A	0	3.75	4.77	4.82
2 Golf Course 2	2GC2A	0	3.5	7.6	7.5
2 Golf Course 3	2GC3A	0	3.75	3.275	3.29
2 Golf Course 4	2GC4A	0	3.75	4	4.03
2 Golf Course 5	2GC5A	0	3.75	3.72	3.79
3 Golf Course 1	3GC1A	0	3.5	6.4	6.25
3 Golf Course 2	3GC2A	0	3.75	3.18	3.24
3 Golf Course 3	3GC3A	0	4	6.03	5.8
3 Golf Course 4	3GC4A	0	3.75	7.74	7.57
3 Golf Course 5	3GC5A	0	3.5	6.695	6.79

Measurements used in the synthesis were grouped into profiles, defined in this study as sets of samples collected across different depths from the same location). For each profile, the cumulative soil carbon stock was calculated to each sampled depth. A regression between soil carbon stock vs. depth across the entire dataset was fit to a Michaelis-Menten curve (Figure A1 and Table A6; $y = 241.72\,x / (126.21 + x)$).

The model fit was used to estimate the model-predicted carbon stock at each sampling depth and at 10, 20, 50, and 100 cm. With each profile (set of vertically-associated measurements), measured and model-estimated carbon stocks were used to estimate carbon stock at 4 target depths: 10, 20, 50, and 100 cm according to:

$$C_{est,x} = \frac{C_{meas}}{C_{pred}} \times C_{pred,x}$$

Where $C_{est,x}$ is the estimated carbon stock at the target depth, C_{meas} is the calculated carbon stock at the sampled depth closest (for a given profile) to the target depth, C_{pred} is the model-predicted carbon stock at that sampled depth, and $C_{pred,x}$ is the model-predicted carbon stock at the target depth. Samples from Berhe et al. (2008) were deemed outliers and excluded from the sample set for the purpose of carbon stock estimation.

Figure A1. Relationship between soil sampling depth and areal carbon density for measurements included in the soil carbon synthesis. Black points indicate values from the literature, from sites outside the Alameda Watershed. Blue points represent measurements from grassland and woodland sites in the Alameda Watershed, south of the San Antonio Reservoir. The calculated regression equation was used to estimate carbon storage to 1 m depth for each measurement.

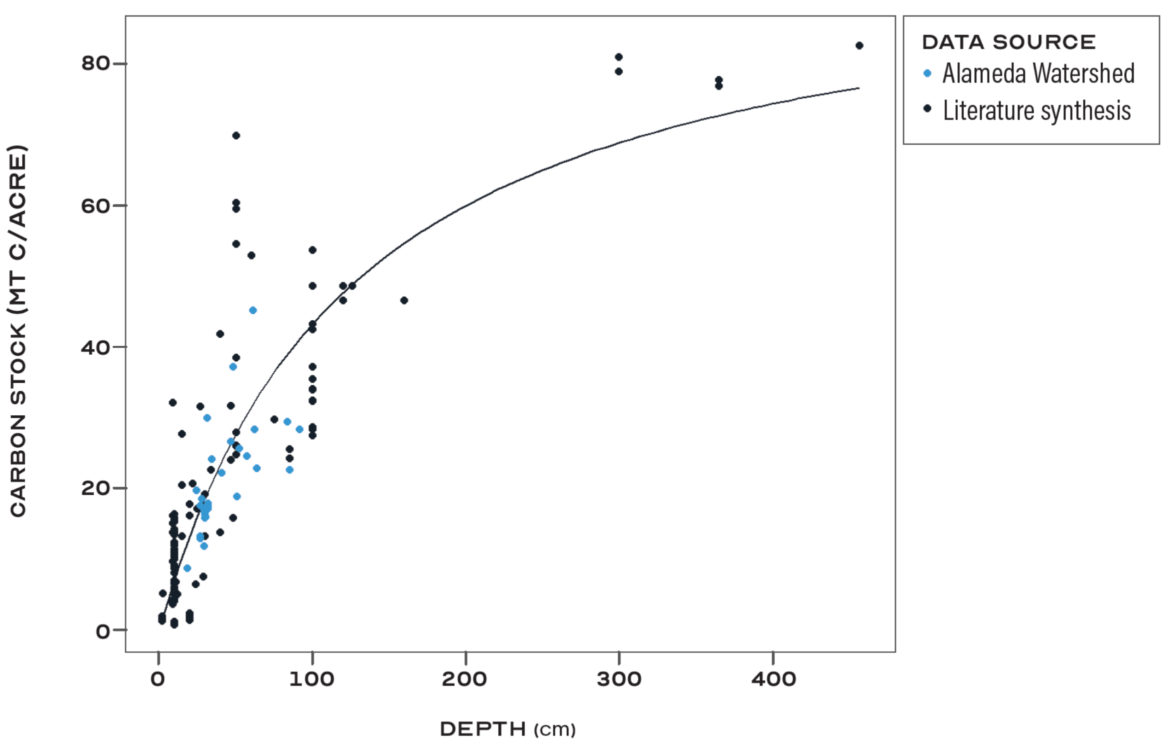

Table A6. Summary of Michaelis-Menten fit (shown in Figure xx).

```
Formula: C_cumulative_Mg_ha ~ Vm * bottom_depth_cm/(K + bottom_depth_cm)

Parameters:
   Estimate Std. Error t value Pr(>|t|)
Vm   241.72      22.09  10.942  < 2e-16 ***
K    126.21      20.11   6.277 4.67e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 24.11 on 131 degrees of freedom
```

For a depth of 100 cm, an ANOVA was used to test whether open grassland soils differed significantly from soils collected under a woody canopy (Table A7). We found that sites with a woody canopy had significantly higher carbon storage than grassland sites ($p = 0.0115$), with mean 1-m carbon stocks of 64.06 +/- 36.08 MT C/acre in shrubland and woodland, compared with 46.01 +/- 26.68 MT C/acre in open grassland.

Table A7. Summary of ANOVA testing whether 1m carbon stocks from the soil carbon synthesis differ between grassland and sites with a woody canopy

```
            Df Sum Sq Mean Sq F value Pr(>F)
woody        1  38844   38844     6.7 0.0115 *
Residuals   79 458026    5798
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The soil carbon stock estimate for woody-canopy sites was applied to sites on the Alameda Watershed classified as coastal scrub, chaparral, oak savanna, oak woodland, or riparian forest. The grassland soil carbon stock estimate was applied to sites classified as grassland. This approach provides rough estimates of carbon storage in soil organic matter, but is not able to capture spatial variation within the watershed beyond the estimated relationship between soil carbon storage and the presence of woody cover.

3. 2020 wildfire carbon losses

The SCU Lightning Complex fires burned in the Diablo Range from mid August through the beginning of October 2020. The area burned in these fires included portions of the Alameda Watershed covering 10,370 acres. Carbon losses in the Alameda Watershed due to these fires were estimated using the First Order Fire Effects Model (FOFEM). FOFEM was developed by the Missoula Fire Sciences Laboratory at the US Forest Service's Rocky Mountain Research Station to predict tree mortality, fuel consumption, smoke production, and soil heating from wildfire or prescribed burns (https://www.firelab.org/project/fofem-fire-effects-model), and is the model used by the California Air Resources Board (CARB) to track fire-related greenhouse gas (GHG) emissions (CARB, 2022). To estimate fire-related carbon losses from the Alameda Watershed, we ran FOFEM for each cell in a thirty-meter grid covering the landscape. Input fuel load parameters were derived primarily from FCCS fuelbeds. Table A8 describes the full set of parameters used in the model. So that fire-related carbon losses could be compared directly with watershed-wide carbon estimates, pre-fire biomass in each fuel category was determined from the same source data as the watershed-wide carbon stocks reported in chapter 3 of the report (and described above in the vegetation carbon quantification section).

Table A8. FOFEM model inputs used to estimate carbon losses from the Alameda Watershed during the SCU Lightning Complex Fires.

Parameter	**Source/value**
Litter Biomass	FCCS
Biomass of One-Hour Fuels	FCCS
Biomass of Ten-Hour Fuels	FCCS
Ten Hour Fuel Moisture	Based on data from Remote Automatic Weather Stations (RAWS), a network of automated weather stations run by the US Forest Service and Bureau of Land Management. An average was taken of ten-hour fuel moisture at three stations in or near the SFPUC's landholdings: Poverty, Rose Peak, and Calaveras Road. The average calculation Included all data for the duration of the fire, from August 18 through October 1, 2020. This singular average value was applied to all cells.
Biomass of Hundred Hour Fuels	FCCS
Biomass of Thousand-Hour Fuels	FCCS

Thousand Hour Fuel Moisture	As with ten hour fuel moisture, calculated using RAWS data.
Thousand Hour Fuels Percent Rotten	FCCS
Thousand Hour Fuel Size Class Distribution	LEFT
Duff Biomass	FCCS
Duff Moisture	Extracted from the Moisture Regime Defaults lookup table in the FOFEM User Guide. Ten hour fuel moisture, as calculated using RAWS data, was used as the lookup value.
Duff Depth	FCCS
Biomass of Herbaceous Vegetation	An average of residual dry matter measurements was used to quantify the biomass of herbaceous vegetation in grasslands, as mapped for current carbon estimates (see chapter 3 of the main report). Values provided by FCCS were used for all other land cover classes.
Shrub Biomass	Estimates of shrub biomass from Gonzalez et al. (2015) were used for Coastal Scrub and Chaparral land cover types, as mapped for current carbon estimates (see chapter 3 of the main report). FCCS values were used for all other vegetation classes.
Foliage Biomass	Derived from Gonzalez et al. (2015) woody biomass values and allometric equations from the literature. The ratio of foliage biomass to total biomass was calculated for an oak with an assumed total biomass of 500kg. Diameter at breast height for an oak of this size was calculated using allometric equation coefficients from Brown et al. (2004). Using coefficients from Chojnacky et al. (2014), foliage biomass was then calculated using the diameter output. The resulting ratio of foliage to total biomass for a 500kg oak was applied to Gonzalez et al. (2015) woody biomass values in woodland and savanna habitats. Chaparral, grassland, and coastal scrub foliage biomass values were assumed to be zero.
Branch Biomass	Branch biomass was calculated as the remaining biomass after accounting for foliage, root, bark, and stem biomass in woody vegetation. As with foliage biomass, values were derived by coupling Gonzalez et al. (2015) woody biomass values with allometric equations from the literature. Coefficients from Jenkins et al. (2003) were applied to the diameter of a 500kg oak to derive root, bark, and stem biomass values. Foliage biomass was derived as described above. The ratio of these values to total biomass for a 500kg oak was applied to total woody biomass values from Gonzalez et al (2015). Branch biomass

	was then calculated as the remainder after accounting for these four carbon pools. Chaparral, grassland, and coastal scrub branch biomass values were assumed to be zero.
Percent Crown Burn	Percent crown burn was estimated based on each cell's relativized difference in normalized burn ratio (RdNBR), a metric of burn severity based on remotely sensed near infrared and shortwave infrared radiation before and after the fire. Pre- and post-fire NBR maps were provided by Chris Potter and Jeremy Kirkendall at NASA (https://landsat.visibleearth.nasa.gov/view.php?id=147374). After translating NBR values to RdNBR, RdNBR values were classified into unburned, low, medium, and high burn classes based on the classification scheme outlined for Initial RdNBR assessments in Lyderson et al. (2016). Each class was then assigned the corresponding median crown consumption value from Figure 7 in Lyderson et al. (2016). Percent crown burn for non-treed ecosystems (i.e. grassland, coastal scrub, and chaparral) was assumed to be zero.
Region	PacificWest
Cover Group	FCCS
Season	Summer
Fuel Category	Natural

An important caveat for interpreting FOFEM outputs is that the model performs best under typical fire conditions, rather than high wind events like those that occurred during the SCU Lightning Complex Fires (Klaus Scott, pers. comm.). Outputs therefore represent an approximation of carbon losses on the landscape, and may underestimate actual burn severity.

4. Assessment of carbon management potential

For each of the six carbon management strategies evaluated, methods used to evaluate potential carbon sequestration and GHG benefits are described below under *Carbon and GHG analyses*. Additionally, maps were provided of opportunity areas within which each carbon management practice may be appropriate. These maps, based on ecosystem type and other landscape characteristics, should be viewed as a starting point for considering where a given strategy may be appropriate. Additional site considerations should be taken into account such as vegetation community, native wildlife habitat needs, and physical landscape characteristics that influence a strategy's feasibility and ecological effects. The *Footprint mapping* sections below describe the geoprocessing workflows used to derive each opportunity map.

4.1. Rangeland compost

Carbon and GHG analyses

The California Natural and Working Lands Carbon and Greenhouse Gas Model (CALAND) was used to model the potential effects of compost amendments on carbon stocks and fluxes within the Alameda Watershed (DiVittorio et al., 2021). CALAND simulates the effects of various land management practices on carbon dynamics across all lands in the state. It was developed for the California Natural Resources Agency by scientists at the Lawrence Berkeley National Laboratory. CALAND is an empirically based model that uses historical carbon stock and flux data, paired with remotely sensed estimates of land cover change, to quantify annual carbon stocks and fluxes. CALAND analyses of compost on rangeland are based on observations reported in Ryals et al. (2013), in which compost was applied to a depth of 0.5 inches. CALAND assumes applied material has a C:N ratio of 22. The CALAND model incorporates estimates of land cover change over time, and the per-acre calculation accounts for these changing areas of land cover classes.

For a given CALAND analysis, land management practices can be applied to 940 unique land categories derived from a combination of spatial regions, ownership class, and land cover type. The SFPUC's lands within the Alameda Watershed fall within the Central Coast region and local government ownership class. CALAND compost analyses for this study were applied to the full 98,039 acres of grassland owned by local government agencies in the Central Coast region. Results were then downscaled to estimate the per-acre effect of compost applications

The effect of compost applications to grassland carbon balance was modeled at thirty- and ten-year repeat application intervals (Table A9). Scenarios were run under historical climate conditions. CALAND offers the option to run analyses with a high-emissions future climate scenario equivalent to the IPCC RCP 8.5 scenario. Because the effect of future climate conditions predicted by CALAND are inconsistent modeling by Mayer and Silver (2022), however, we chose in this study to model compost applications under historical climate conditions only.

Compost scenarios were modeled for a timeframe of 2010 to 2100, with management practices first implemented in 2025. For low frequency compost scenarios, compost was reapplied in 2055 and 2085. For medium-frequency compost scenarios. Compost was reapplied in ten-year intervals through 2095. For all analyses, CALAND provides a mean estimate and an uncertainty range derived from running the model three times for each scenario: once for mean values of initial carbon density and fluxes, once for a lower bound of low initial carbon density and high carbon fluxes, and a final time for an upper bound with high initial carbon density and low carbon fluxes.

Table A9. Compost application scenario used in CALAND rangeland compost modeling

Activity	Application frequency	Compost application rate (inches)	C:N	Carbon application rate (MT ac-1)	Climate
Compost on grassland	30 years	0.5	22	14.27 Mg ha-1	historic
Compost on grassland	10 years	0.5	22	14.27 Mg ha-1	historic

To estimate net GHG benefits, life-cycle GHG emissions from compost production and transportation reported in DeLonge et al (2013) were subtracted from carbon gains in units of CO_2e. Compost production and transportation emissions were assumed to occur at discrete intervals every 10 or 30 years, depending on the reapplication frequency. Results of carbon accumulation and GHG modeling analyses are summarized in Table A10.

Table A10. Results of compost application modeling, based on CALAND and life-cycle GHG emissions from DeLonge et al. (2013). Parentheses indicate the range of values reported by the CALAND uncertainty module.

Application frequency	Mean annual C accumulation (MT C acre-1 yr-1)	Life cycle GHG emissions per application (MT CO_2e ha^{-1})	Average annual life cycle GHG emissions (MT CO_2e ha^{-1} yr^{-1})	Mean annual net GHG benefit (MT CO_2e acre^{-1} yr^{-1})
30 years	0.053 (0.022-0.084)	3.7	0.05	0.17 (0.061-0.29)
10 years	0.20 (0.086-0.32)	3.7	0.15	0.69 (0.25-1.1)

Footprint mapping

Grasslands and savannas were selected from the coarse vegetation map as the basis for the compost amendment opportunity map. The decommissioned Sunol Valley Golf Course was manually traced based on aerial imagery and burned into the vegetation raster. Areas on slopes steeper than 30% were removed from the map. Slope was calculated using the 3m National Elevation Dataset and resampling to a 30m resolution (https://gdg.sc.egov.usda.gov/Catalog/ProductDescription/NED.html). Areas classified as serpentine by Jones & Stokes vegetation mapping (2003), were likewise removed. Remaining areas were then classified according to slope categories of 0-8%, 8-20%, and 20-30%.

4.2. Riparian forest restoration

Carbon and GHG analyses

To evaluate carbon sequestration in reforested riparian areas, we used the Carbon in Riparian Ecosystems Estimator for California (CREEC; Matzek et al., 2018). For specified regions, prior land uses, and revegetation type, CREEC provides annual estimates of carbon accumulation in trees (aboveground and roots), downed dead wood, forest floor accumulations, understory vegetation, and soil organic matter. CREEC predictions are based on a synthesis of data from riparian sites in California (Matzek et al., 2018).

CREEC was run for the coast ranges and foothills location, assuming low or non-mechanical site preparation with grazing as the current land use. The CREEC estimator provides carbon accumulation values for either natural regeneration or planted communities. For planted communities, CREEC takes input values for a planting palette according to percentage by species or plants per acre. To run CREEC for the Alameda Watershed, we used both natural regeneration and planting palettes from prior riparian restoration sites in the watershed (Gold Fish Pond, San Antonio Creek, and Sheep Camp Creek). These planting palettes corresponded to two categories within CREEC for planted communities, which we designated willow riparian and oak/sycamore riparian.

Table A11. Carbon accumulation predictions for natural regeneration from CREEC

Age (years)	**Tree carbon (MT C ha^{-1})**	**Downed dead carbon (MT C ha^{-1})**	**Forest floor carbon (MT C ha^{-1})**	**Understory carbon (MT C ha^{-1})**	**Soil carbon (MT C ha^{-1})**	**Total (MT C ha^{-1})**
0	0	0	0	0	0	0
5	5.43	0.35	3.74	4.51	0.51	14.53
10	22.12	1.39	6.96	4.28	0.92	35.66
15	40.51	2.49	9.76	4.18	1.26	58.2
20	55.27	3.34	12.22	4.14	1.54	76.5
25	65.6	3.91	14.4	4.11	1.77	89.79
30	72.35	4.28	16.34	4.1	1.96	99.02
35	76.6	4.5	18.08	4.09	2.11	105.37
40	79.21	4.63	19.65	4.08	2.23	109.81
45	80.8	4.71	21.07	4.08	2.34	113
50	81.76	4.76	22.37	4.08	2.42	115.38

60	82.68	4.8	24.64	4.08	2.55	118.75
70	83.02	4.81	26.57	4.08	2.63	121.1
80	83.13	4.82	28.23	4.08	2.69	122.94
90	83.18	4.82	29.66	4.08	2.72	124.46
100	83.19	4.82	30.93	4.08	2.75	125.76

Table A12. Carbon accumulation predictions for planted willow riparian from CREEC

Age (years)	**Tree carbon (MT C ha^{-1})**	**Downed dead carbon (MT C ha^{-1})**	**Forest floor carbon (MT C ha^{-1})**	**Understory carbon (MT C ha^{-1})**	**Soil carbon (MT C ha^{-1})**	**Total (MT C ha^{-1})**
0	0	0	0	0	0	0
5	8.09	0.52	3.74	4.44	0.51	17.3
10	23.64	1.47	6.96	4.27	0.92	37.26
15	34.03	2.08	9.76	4.21	1.26	51.35
20	39.3	2.38	12.22	4.19	1.54	59.63
25	41.71	2.51	14.4	4.18	1.77	64.57
30	42.78	2.57	16.34	4.18	1.96	67.82
35	43.25	2.59	18.08	4.18	2.11	70.2
40	43.45	2.6	19.65	4.17	2.23	72.11
45	43.53	2.61	21.07	4.17	2.34	73.72
50	43.57	2.61	22.37	4.17	2.42	75.14
60	43.59	2.61	24.64	4.17	2.55	77.56
70	43.6	2.61	26.57	4.17	2.63	79.58
80	43.6	2.61	28.23	4.17	2.69	81.3
90	43.6	2.61	29.66	4.17	2.72	82.77
100	43.6	2.61	30.93	4.17	2.75	84.06

Table A13. Carbon accumulation predictions for planted oak/sycamore riparian from CREEC

Age (years)	**Tree carbon (MT C ha^{-1})**	**Downed dead carbon (MT C ha^{-1})**	**Forest floor carbon (MT C ha^{-1})**	**Understory carbon (MT C ha^{-1})**	**Soil carbon (MT C ha^{-1})**	**Total (MT C ha^{-1})**
0	0	0	0	0	0	0

5	5.87	0.38	3.74	4.49	0.51	14.99
10	23.93	1.5	6.96	4.26	0.92	37.57
15	43.82	2.68	9.76	4.17	1.26	61.69
20	59.79	3.58	12.22	4.12	1.54	81.25
25	70.96	4.19	14.4	4.1	1.77	95.42
30	78.27	4.57	16.34	4.09	1.96	105.21
35	82.86	4.8	18.08	4.08	2.11	111.92
40	85.68	4.94	19.65	4.07	2.23	116.58
45	87.4	5.02	21.07	4.07	2.34	119.9
50	88.44	5.06	22.37	4.07	2.42	122.37
60	89.44	5.11	24.64	4.07	2.55	125.8
70	89.8	5.12	26.57	4.07	2.63	128.19
80	89.93	5.13	28.23	4.07	2.69	130.04
90	89.97	5.13	29.66	4.07	2.72	131.56
100	89.99	5.13	30.93	4.07	2.75	132.86

CREEC results for total ecosystem carbon accumulation (Tables A11, A12, and A13) were converted to units of CO_2e to estimate GHG benefits of riparian restoration. This conversion assumes that GHG emissions due to restoration activities are minimal.

Footprint mapping

To identify areas potentially suitable for riparian restoration, we evaluated the vegetation composition within defined buffers around the watershed’s channel network. We used the Bay Area Aquatic Resources Inventory (BAARI) version 2.1 to depict the stream network of the Alameda Watershed.

To establish woody riparian buffer widths for the riparian opportunity space map, we used existing and historic riparian vegetation as benchmarks. The Jones and Stokes vegetation classes we used for establishing woody riparian buffer widths were: Coast Live Oak Riparian Forest, Sycamore Alluvial Woodland, Valley Oak Woodland, White Alder Riparian Forest, Willow Riparian Forest, and occasionally Blue Oak Woodland and Mixed Evergreen Forest/Oak Woodland. Historical habitats such as Sycamore Alluvial Woodland, Mixed Willow Riparian Scrub, Mixed Riparian Forest, and Sparsely Vegetated Braided Channel were used in conjunction with Jones and Stokes data (Jones & Stokes, 2003). Lastly, LANDFIRE 2016 existing vegetation types helped to verify our decisions.

Buffer widths were assessed separately for each of the eight Strahler stream order channel types in the study area. We excluded first order headwater channels from our riparian analysis because differentiating riparian vegetation from general forest for the majority of headwater streams wasn't possible. Second through fifth order streams' riparian vegetation was consistently captured by a 30 m buffer. The buffers for sixth order streams varied depending on location in the study area; we selected a 30 m buffer for the southern portion of Alameda Creek, but in the northeast portion of the study area, along San Antonio Creek, we found a 50m buffer. Seventh order stream buffer widths were primarily 75 m, but along the main stem of Alameda Creek, as it approaches its confluence with Coyote Creek, we found a 100 m buffer to be appropriate. Finally, we selected a 100 m buffer for the short section of eighth order stream, Coyote Creek. We applied a custom buffer around the narrow, southeast inlet of Calaveras Reservoir.

As with other carbon management strategies, this map is meant to provide a starting point for identifying opportunities on the landscape. Actual opportunities for carbon sequestration via riparian woodland restoration are likely not ubiquitous throughout the buffer area we established. For instance, in the southern portion of the study area, riparian woodland tends to grow on northeast-facing slopes, whereas grassland grows on the southwest-facing slopes. Therefore, favorable riparian habitat areas may be wider on one side of the river than the other. This is also the case in valley bottoms, where river meanders create uneven riparian buffer widths.

Our assessment of these riparian buffers will be useful for gaining a broad understanding of existing and potential riparian woodland habitat. However, many factors go into determining suitable restoration locations, and a detailed review may be necessary on a case-by-case basis when identifying suitable riparian woodland areas throughout the drainage network. Our buffer can be used as a guide in those efforts.

4.3. Silvopasture

Carbon and GHG analyses

To estimate carbon sequestration in standing biomass for individual trees, we used the i-Tree Planting calculator, which provides CO_2 sequestration values for individual tree plantings, with results specific to species and location. i-Tree Planting is designed for urban settings, where tree growth and biomass densities are typical of trees growing outside a forest setting. i-Tree was run for *Quercus lobata* in Sunol, CA, assuming an initial DBH of 1 inch, no buildings within 60 feet, and no mortality over the analysis period. To develop the carbon accumulation curve, i-Tree was run for 10, 20, 30, 40, 50, 60, 70, 80, 90, and 99 years, and results for CO_2 sequestration were converted to units of carbon. Additional carbon accumulated in downed dead wood was calculated using the constant factor of $0.062 \times$ standing tree carbon reported in

Matzek et al. (2018) for oak-dominated sites. Results of this analysis are summarized in Table A14.

Table A14. Modeled carbon accumulation in *Quercus lobata* grown in Sunol

Tree age (years)	**Individual tree carbon stock (kg C tree^{-1})**	**Individual tree downed dead carbon (kg C tree^{-1})**	**Biomass carbon, 10% canopy cover (MT C/acre)**	**Biomass carbon, 30% canopy cover (MT C/acre)**	**Biomass carbon, 60% canopy cover (MT C/acre)**
10	124	8	0.13	0.40	0.80
20	446	28	0.48	1.44	2.88
30	966	60	1.04	3.12	6.23
40	1685	104	1.81	5.43	10.87
50	2539	157	2.73	8.19	16.37
60	3234	201	3.48	10.43	20.86
70	3745	232	4.03	12.08	24.16
80	4108	255	4.41	13.24	26.49
90	4359	270	4.69	14.06	28.11
99	4517	280	4.85	14.56	29.13

With individual tree-level carbon sequestration rates (annual average carbon accumulation over 50 years), we used the relationship between tree cover and tree density (number of trees per ha) derived from six representative stands in the South Santa Clara Valley Historical Ecology Study (Figure A2; Chapter 6 in Grossinger et al., 2008) to estimate the number of trees in a sparse savanna ecosystem (10% cover), dense savanna ecosystem (30% cover), and low-density oak woodland (60% cover). This regression (Fig. A2) predicted stand densities of 1.01 and 3.04 trees/acre in representative valley oak savannas with 10% or 30% cover, and 6.07 trees/acre for low-density oak woodland with 60% cover. Stand densities were used to estimate per-acre carbon sequestration for 10%, 30%, and 60% cover.

Figure A2. Regression between tree density and canopy cover %, from the South Santa Clara Valley Historical Ecology Study (Chapter 6 in Grossinger et al., 2008)

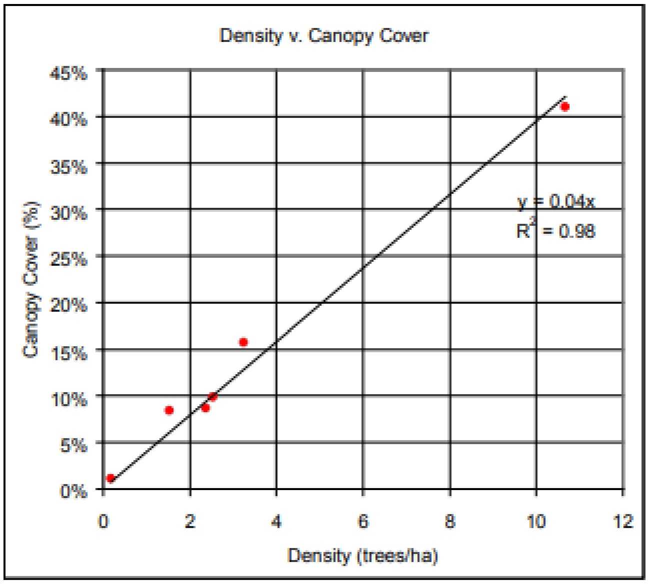

Figure 6.1. Density versus canopy cover for six representative stands using a linear regression with a fixed intercept.

Footprint mapping

All grassland areas are highlighted as opportunity areas for silvopasture.

4.4. Cattle exclusion

Carbon and GHG analyses

Potential carbon sequestration due to cattle exclusion was estimated from observations by Russell and McBride (2003) from six sites in the East Bay and Callaway and Davis (1993) from Gaviota State Park. Russel and McBride (2003) used aerial imagery to identify transitions between grassland, shrubland, and woodland/forest ecosystem types over 4-6 decades following cattle exclusion or reduction in grazing pressure. Callaway and Davis (2003) documented ecosystem type transitions between 1947 and 1989 following cattle exclusion.

We used data from Russell and McBride (2003) with Alameda Watershed carbon stocks to estimate equivalent carbon storage changes if the Alameda Watershed underwent similar transitions (Table A15). For each of the six sites studied, we calculated the percent cover at the beginning and end of the study period for three ecosystem type categories: grassland, shrubland, or woodland/savanna/forest. Where finer-scale vegetation types were reported (e.g., mixed evergreen, redwood, or eucalyptus), these were grouped into the aggregate woodland/savanna/forest category. The mean vegetation carbon stock for each of these categories (the mean from the Alameda Watershed calculated in this assessment) was used with these ecosystem type mosaics to estimate mean ecosystem carbon storage for each site and time point. Changes in ecosystem carbon stocks over time were used to estimate a rate of change in carbon storage per acre for each site due to the grazing reduction. To estimate increases in soil carbon due to the expansion of woody vegetation, a mean annual soil carbon accumulation rate of 0.3 MT C/acre-yr was applied to the fraction of the landscape transitioning from grassland to shrubland or woodland/savanna/forest, based on observations under coyote brush from Zavaleta and Kettley (2006).

Table A15. Vegetation transitions and carbon stock changes following cattle exclusion, based on vegetation changes reported in Russell and McBride (2003) following a reduction in grazing pressure, ecosystem type carbon stocks from the Alameda Watershed, and soil carbon accumulation with coyote brush encroachment from Zavaleta and Kettley (2006).

Site	Change in grassland fraction	Change in shrubland fraction	Change in woodland/savanna/forest fraction	Time elapsed (years)	Increase in vegetation carbon (MT C/acre-yr)	Increase in soil carbon (MT C/acre-yr)
1	-0.35	0.12	0.191	58	0.120	0.0933
2	-0.08	0.319	-0.07	58	0.023	0.0747
3	-0.27	0.33	0.011	58	0.066	0.1023
4	-0.06	-0.22	0.27	39	0.152	0.015
5	-0.02	-0.05	0.099	41	0.062	0.0147
6	-0.279	0.25	0.019	45	0.070	0.0807

Callaway and Davis (1993) evaluated transition probabilities between grassland, coastal scrub, chaparral, and woodland in the presence of cattle and following the cessation of cattle grazing. With the existing distribution of ecosystem types present on the Alameda Watershed, we used these transition probabilities to evaluate the predicted 1-yr change in acres of each ecosystem type, (a) in the presence of cattle, and (b) with cattle excluded. The effect of cattle exclusion on the extent of each ecosystem type was calculated as the difference between (b) and (a). The change in extent of each ecosystem type was multiplied by its carbon density to estimate the 1-yr change in watershed-wide carbon storage due to the exclusion of cattle (Table A16). The soil carbon accumulation rate of 0.3 MT C/acre-yr from Zavaleta and Kettley (2006) was used to estimate annual soil carbon storage increases where the extent of woody vegetation increased.

Table A16. 1-year predicted ecosystem type transitions and changes in carbon storage due to exclusion of cattle from 100 acres matching the Alameda Watershed's ecosystem type composition. Transitions between ecosystem types are based on transition probabilities with cattle present and cattle excluded from Callaway and Davis (1993).

Ecosystem type	**Starting scenario acres**	**Change in acres with cattle**	**Change in acres without cattle**	**Change in acres due to cattle exclusion**	**Change in vegetation carbon due to cattle exclusion MT C**
grassland	38	-0.025626	-0.2375628	-0.2119368	-0.26
coastal scrub	5.413	0.0709246	0.2477335	0.1768089	1.08
chaparral	14.24	-0.0046134	-0.0049577	-0.0003443	-0.0047
oak savanna, oak woodland, and riparian forest	42.34	-0.0406852	-0.005213	0.0354722	1.12
All	99.993	0	0	0	1.94

Vegetation type transitions and corresponding carbon accumulation depend on the initial ecosystem type mosaic. Sites in Russell and McBride (2003) with a high initial grassland fraction tended to experience greater percentage increases in woody vegetation. Accordingly, if cattle were excluded from areas of grassland on the watershed, this may lead to a greater expected increase in carbon storage. For this reason, we also used Callaway and Davis (1993) transition rates to estimate expected changes in carbon storage if cattle were excluded from an area composed exclusively of grassland (Table A17).

Table A17. 1-year predicted ecosystem type transitions and changes in carbon storage due to exclusion of cattle from 100 acres of grassland. Transitions between ecosystem types are based on transition probabilities with cattle present and cattle excluded from Callaway and Davis (1993).

Ecosystem type	**Starting scenario acres**	**Change in acres with cattle**	**Change in acres without cattle**	**Change in acres due to cattle exclusion**	**Change in vegetation carbon due to cattle exclusion MT C**

grassland	100	-0.19	-0.72	-0.53	-0.64
coastal scrub	0	0.19	0.69	0.5	3.05
chaparral	0	0	0.02	0.02	0.27
oak savanna, oak woodland, and riparian forest	0	0	0.01	0.01	0.32
All	100	0	0	0	2.99

Footprint mapping

All non-woodland ecosystems (i.e., grassland, savanna, chaparral, and coastal scrub) within the grazing leases on SFPUC lands. Grazing leases were mapped using grazing unit shapefiles provided by the SFPUC.

4.5. Native grassland restoration

Carbon and GHG analyses

The Comet Planner tool used by the California Department of Food and Agriculture Healthy Soils Program estimates a carbon sequestration benefit of 0.34 metric tons CO_2 equivalent per acre per year for restoring degraded rangelands with limited plant cover in Alameda County, through reseeding with either native or non-native species (http://bfuels.nrel.colostate.edu/health#).

Footprint mapping

For native grassland restoration, we used LANDFIRE mapping to identify sites in the watershed classified as bare ground or sparsely vegetated. Generalized regions were identified within the watershed's grasslands where low to moderate levels of invasive species and/or high native plant cover were reported in recent invasive plant inventories (Nomad Ecology, 2020) and rangeland monitoring (ACRCD and LD Ford, 2018b)

4.6. Open space conservation

Carbon and GHG analyses

To estimate avoided carbon losses due to conservation of the Alameda Watershed as protected open space, we compared the watershed's current carbon storage to expected carbon storage or carbon losses if the watershed were converted to an urban-suburban matrix, vineyard, or annual cropland.

For urbanization, we used carbon densities reported in Beller et al. (2020) for the Santa Clara Valley to estimate carbon storage in trees if the Alameda Watershed were converted to a similar urban-suburban matrix. Because Beller et al. (2020) carbon estimates include tree carbon only, we estimated shrub carbon storage as 5% of tree carbon storage, based on observations from both arid and humid cities (McHale et al., 2017; Nowak, 1994). Dead wood and litter in urban sites was assumed to be removed from the site and chipped, a common practice for urban tree and landscape residue (Whittier et al., 1994). Avoided carbon losses were calculated as the difference between average vegetation carbon storage for each of the Alameda Watershed ecosystem types and estimated tree and shrub carbon storage for the urban-suburban matrix. The long-term effects of urban development on soil carbon have been observed to vary widely across cities (Pouyat et al., 2006), making it difficult to predict how urbanization would affect carbon storage in the Alameda Watershed's soils. For this reason, avoided carbon losses were calculated with respect to biomass only.

For conversion to annual cropland, we estimated soil carbon losses as a fraction of existing carbon. Global syntheses have found that ~20-40% of soil carbon is lost when forest is converted to annual cropland. For post-conversion vegetation carbon stocks in annual cropland, we assumed the IPCC (2006) carbon storage default value of 2 MT C/acre for temperate annual croplands.

In addition to avoided ecosystem carbon losses, we estimated avoided N_2O emissions from fertilization of annual croplands or vineyards, as well as other non-biogeochemical GHG emissions related to farm machinery, fertilizer production, etc. N_2O emission rates from tomato fields and vineyards reported in Verhoeven et al. (2017) were used as estimates for annual croplands and vineyards, respectively. We used life-cycle non-biogeochemical emissions from California agriculture from Venkat (2012). This life-cycle assessment (Venkat et al., 2012) reports GHG emissions estimates in CO_2e for nine different field, truck, and tree crops, under conventional and organic management. For this study, we used an average of non-biogeochemical emissions across the nine crops as a generalized estimate of non-biogeochemical emissions. N_2O emissions were converted to CO_2e using the 100-year global warming potential of 265 (Myhre et al., 2013).

Footprint mapping

The opportunity area for open space conservation was defined as all undeveloped land owned by the SFPUC in the Alameda Watershed

5. References

[ACRCD] Alameda County Resource Conservation District, [LD Ford] LD Ford, Rangeland Conservation Science, 2018a. San Francisco Public Utilities Commission Alameda Watershed 2018 Rangeland Monitoring Report - Residual Dry Matter. Prepared for the San Francisco Public Utilities Commission.

[ACRCD] Alameda County Resource Conservation District, [LD Ford] LD Ford, Rangeland Conservation Science, 2018b. San Francisco Public Utilities Commission Alameda Watershed 2018 Rangeland Monitoring Report - Spring Species Composition and Production, Alameda Watershed. Prepared for the San Francisco Public Utilities Commission.

Baisden, W.T., Amundson, R., Brenner, D.L., Cook, A.C., Kendall, C., Harden, J.W., 2002. A multiisotope C and N modeling analysis of soil organic matter turnover and transport as a function of soil depth in a California annual grassland soil chronosequence. Glob. Biogeochem. Cycles 16, 82-1-82–26. https://doi.org/10.1029/2001GB001823

Beller, E.E., Kelly, M., Larsen, L.G., 2020. From savanna to suburb: effects of 160 years of landscape change on carbon storage in Silicon Valley, California. Landsc. Urban Plan. 195, 103712. https://doi.org/10.1016/j.landurbplan.2019.103712

Berhe, A.A., Harden, J.W., Torn, M.S., Harte, J., 2008. Linking soil organic matter dynamics and erosion-induced terrestrial carbon sequestration at different landform positions. J. Geophys. Res. Biogeosciences 113. https://doi.org/10.1029/2008JG000751

Billings, W.D., 1985. The historical development of physiological plant ecology. Physiol. Ecol. North Am. Plant Communities 1–15.

Bird, J.A., Herman, D.J., Firestone, M.K., 2011. Rhizosphere priming of soil organic matter by bacterial groups in a grassland soil. Soil Biol. Biochem. 43, 718–725. https://doi.org/10.1016/j.soilbio.2010.08.010

Brown, S., Shoch, D., Pearson, T., Delaney, M., Franco, G., Surles, T., Therkelsen, R.L., 2004. Methods for measuring and monitoring forestry carbon projects in California.

Callaway, R.M., Davis, F.W., 1993. Vegetation dynamics, fire, and the physical environment in coastal central California. Ecology 74, 1567–1578. https://doi.org/10.2307/1940084

Camping, 2002. Proceedings of the Fifth Symposium on Oak Woodlands: Oaks in California's Changing Landscape, October 22-25, 2001, San Diego, California. U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station.

[CARB] California Air Resources Board, 2022. Wildfire Emission Estimates for 2021.

Caspi, T., Estrada, L., Dowling, A.V., Su, E., Leshchinskiy, M., Cavalcanti, A.R.O., Crane, E.J., Robins, C.R., Meyer, W.M., 2018. Carbon and nitrogen in the topsoils of Inceptisols and Mollisols under native sage scrub and non-native grasslands in southern California. Geoderma Reg. 14, e00172. https://doi.org/10.1016/j.geodrs.2018.e00172

Caspi, T., Hartz, L.A., Soto Villa, A.E., Loesberg, J.A., Robins, C.R., Meyer III, W.M., 2019. Impacts of invasive annuals on soil carbon and nitrogen storage in southern California depend on the identity of the invader. Ecol. Evol. 9, 4980–4993.

Chojnacky, D.C., Heath, L.S., Jenkins, J.C., 2014. Updated generalized biomass equations for North American tree species. For. Int. J. For. Res. 87, 129–151. https://doi.org/10.1093/forestry/cpt053

Chou, W.W., Silver, W.L., Jackson, R.D., Thompson, A.W., Allen-Diaz, B., 2008. The sensitivity of annual grassland carbon cycling to the quantity and timing of rainfall. Glob. Change Biol. 14, 1382–1394. https://doi.org/10.1111/j.1365-2486.2008.01572.x

Dahlgren, R.A., Singer, M.J., Huang, X., 1997. Oak tree and grazing impacts on soil properties and nutrients in a California oak woodland. Biogeochemistry 39, 45–64. https://doi.org/10.1023/A:1005812621312

DeLonge, M.S., Ryals, R., Silver, W.L., 2013. A lifecycle model to evaluate carbon sequestration potential and greenhouse gas dynamics of managed grasslands. Ecosystems 16, 962–979. https://doi.org/10.1007/s10021-013-9660-5

Di Vittorio, A.V., Simmonds, M.B., Nico, P., 2021. Quantifying the effects of multiple land management practices, land cover change, and wildfire on the California landscape carbon budget with an empirical model. PLOS ONE 16, e0251346. https://doi.org/10.1371/journal.pone.0251346

Dybala, K.E., Steger, K., Walsh, R.G., Smart, D.R., Gardali, T., Seavy, N.E., 2019. Optimizing carbon storage and biodiversity co-benefits in reforested riparian zones. J. Appl. Ecol. 56, 343–353. https://doi.org/10.1111/1365-2664.13272Fierer, N., Craine, J.M., McLauchlan, K., Schimel, J.P., 2005. Litter quality and the temperature sensitivity of decomposition. Ecology 86, 320–326.

Fissore, C., Dalzell, B.J., Berhe, A.A., Voegtle, M., Evans, M., Wu, A., 2017. Influence of topography on soil organic carbon dynamics in a Southern California grassland. CATENA 149, 140–149. https://doi.org/10.1016/j.catena.2016.09.016

Gessler, P.E., Chadwick, O.A., Chamran, F., Althouse, L., Holmes, K., 2000. Modeling Soil-Landscape and Ecosystem Properties Using Terrain Attributes. Soil Sci. Soc. Am. J. 64, 2046–2056. https://doi.org/10.2136/sssaj2000.6462046x

Gonzalez, P., Battles, J.J., Collins, B.M., Robards, T., Saah, D.S., 2015. Aboveground live carbon stock changes of California wildland ecosystems, 2001–2010. For. Ecol. Manag. 348, 68–77. https://doi.org/10.1016/j.foreco.2015.03.040

Grossinger, R.M., Beller, E.E., Salomon, M.N., Whipple, A.A., Askevold, R.A., Striplen, C.J., Brewster, E., Leidy, R.A., 2008. South Santa Clara Valley Historical Ecology Study, including Soap Lake, the Upper Pajaro River, and Llagas, Uvas-Carnadero, and Pacheco Creeks Leidy (Historical Ecology Program Report No. 558). San Francisco Estuary Institute, Oakland, CA.

Henry, H.A.L., Chiariello, N.R., Vitousek, P.M., Mooney, H.A., Field, C.B., 2006. Interactive Effects of Fire, Elevated Carbon Dioxide, Nitrogen Deposition, and precipitation on a California Annual Grassland. Ecosystems 9, 1066–1075. https://doi.org/10.1007/s10021-005-0077-7

Herman, D.J., Halverson, L.J., Firestone, M.K., 2003. Nitrogen dynamics in an annual grassland: oak canopy, climate, and microbial population effects. Ecol. Appl. 13, 593–604. https://doi.org/10.1890/1051-0761(2003)013[0593:NDIAAG]2.0.CO;2

Jackson, L.E., Schimel, J.P., Firestone, M.K., 1989. Short-term partitioning of ammonium and nitrate between plants and microbes in an annual grassland. Soil Biol. Biochem. 21, 409–415. https://doi.org/10.1016/0038-0717(89)90152-1

Jackson, L.E., Strauss, R.B., Firestone, M.K., Bartolome, J.W., 1988. Plant and soil nitrogen dynamics in California annual grassland. Plant Soil 110, 9–17. https://doi.org/10.1007/BF02143533

Jenkins, J.C., Chojnacky, D.C., Heath, L.S., Birdsey, R.A., 2003. National-Scale Biomass Estimators for United States Tree Species. For. Sci. 49, 12–35. https://doi.org/10.1093/forestscience/49.1.12

Jones & Stokes Associates, Inc. 2003. [Vegetation mapping SFPUC Alameda Watershed Habitat Conservation Plan -Biological Inventory Report.] Data provided by San Francisco Public Utilities Commission.

Koteen, L.E., Baldocchi, D.D., Harte, J., 2011. Invasion of non-native grasses causes a drop in soil

carbon storage in California grasslands. Environ. Res. Lett. 6, 044001. https://doi.org/10.1088/1748-9326/6/4/044001
Kummerow, J., Krause, D., Jow, W., 1977. Root systems of chaparral shrubs. Oecologia 29, 163–177. https://doi.org/10.1007/BF00345795
Lin, Y., Slessarev, E.W., Yehl, S.T., D'Antonio, C.M., King, J.Y., 2019. Long-term Nutrient Fertilization Increased Soil Carbon Storage in California Grasslands. Ecosystems 22, 754–766. https://doi.org/10.1007/s10021-018-0300-y
Lydersen, J.M., Collins, B.M., Miller, J.D., Fry, D.L., Stephens, S.L., 2016. Relating Fire-Caused Change in Forest Structure to Remotely Sensed Estimates of Fire Severity. Fire Ecol. 12, 99–116. https://doi.org/10.4996/fireecology.1203099
Matzek, V., Stella, J., Ropion, P., 2018. Development of a carbon calculator tool for riparian forest restoration. Appl. Veg. Sci. 21, 584–594. https://doi.org/10.1111/avsc.12400
Matzek, V., Warren, S., Fisher, C., 2016. Incomplete recovery of ecosystem processes after two decades of riparian forest restoration. Restor. Ecol. 24, 637–645. https://doi.org/10.1111/rec.12361
Mayer, A., Silver, W.L., 2022. The climate change mitigation potential of annual grasslands under future climates. Ecol. Appl. e2705.
McGroddy, M.E., Daufresne, T., Hedin, L.O., 2004. Scaling OF C:N:P stoichiometry in forests worldwide: implications of terrestrial Redfield-type ratios. Ecology 85, 2390–2401. https://doi.org/10.1890/03-0351
McHale, M., Hall, S., Majumdar, A., Grimm, N., 2017. Carbon lost and carbon gained: A study of vegetation and carbon tradeoffs among diverse land uses in the Phoenix, AZ. Ecol. Appl. Publ. Ecol. Soc. Am. 27. https://doi.org/10.1002/eap.1472
Millikin, C.S., Bledsoe, C.S., 1999. Biomass and distribution of fine and coarse roots from blue oak (*Quercus douglasii*) trees in the northern Sierra Nevada foothills of California. Plant Soil 214, 27–38. https://doi.org/10.1023/A:1004653932675
Mokany, K., Raison, R.J., Prokushkin, A.S., 2006. Critical analysis of root : shoot ratios in terrestrial biomes. Glob. Change Biol. 12, 84–96. https://doi.org/10.1111/j.1365-2486.2005.001043.x
Myhre, G., Shindell, D., Bréon, F.-M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J.-F., Lee, D., Mendoza, B., Nakajima, T., Robock, A., Stephens, G., Zhang, H., 2013. Anthropogenic and Natural Radiative Forcing., in: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (Eds.)]. Cambridge University Press, New York, NY, p. 82.
Namm, B.H., 2012. Root morphology and belowground carbon storage in tanoak (*Notholithocarpus densiflorus*) (Thesis). Humboldt State University.
Nomad Ecology, 2020. Invasive Plant Mapping Update and Management Recommendations, Alameda Watershed, Alameda and Santa Clara Counties, California. Prepared for the San Francisco Public Utilities Commission and Alameda County Resource Conservation District. Martinez, CA.
Nowak, D.J., 1994. Atmospheric carbon dioxide reduction by Chicago's urban forest. Chic. Urban For. Ecosyst. Results Chic. Urban For. Clim. Proj. 83–94.
Pouyat, R.V., Yesilonis, I.D., Nowak, D.J., 2006. Carbon storage by urban soils in the United States. J. Environ. Qual. 35, 1566. https://doi.org/10.2134/jeq2005.0215
Prichard, S.J., Andreu, A.G., Ottmar, R.D., Eberhardt, E., 2019. Fuel Characteristic Classification System (FCCS) Field Sampling and Fuelbed Development Guide (No. PNW-GTR-972). U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station,

Portland, OR. https://doi.org/10.2737/PNW-GTR-972
Reeves, M.C., Ryan, K.C., Rollins, M.G., Thompson, T.G., 2009. Spatial fuel data products of the LANDFIRE Project. Int. J. Wildland Fire 18, 250–267. https://doi.org/10.1071/WF08086
Riccardi, C.L., Ottmar, R.D., Sandberg, D.V., Andreu, A., Elman, E., Kopper, K., Long, J., 2007. The fuelbed: a key element of the Fuel Characteristic Classification System. Can. J. For. Res. 37, 2394–2412.
Russell, W.H., McBride, J.R., 2003. Landscape scale vegetation-type conversion and fire hazard in the San Francisco bay area open spaces. Landsc. Urban Plan. 64, 201–208. https://doi.org/10.1016/S0169-2046(02)00233-5
Ryals, R., Kaiser, M., Torn, M.S., Berhe, A.A., Silver, W.L., 2014. Impacts of organic matter amendments on carbon and nitrogen dynamics in grassland soils. Soil Biol. Biochem. 68, 52–61. https://doi.org/10.1016/j.soilbio.2013.09.011
Ryals, R., Silver, W.L., 2013. Effects of organic matter amendments on net primary productivity and greenhouse gas emissions in annual grasslands. Ecol. Appl. 23, 46–59. https://doi.org/10.1890/12-0620.1
Saah, D., Battles, J., Gunn, J., Buchholz, T., Schmidt, D., Roller, G., Romsos, S., 2016. Technical Improvements to the Greenhouse Gas (GHG) Inventory for California Forests and Other Lands. California Air Resources Board, Agreement#14-757.
Sanderman, J., Amundson, R., 2008. A comparative study of dissolved organic carbon transport and stabilization in California forest and grassland soils. Biogeochemistry 89, 309–327. https://doi.org/10.1007/s10533-008-9221-8
Schaeffer, S.M., Homyak, P.M., Boot, C.M., Roux-Michollet, D., Schimel, J.P., 2017. Soil carbon and nitrogen dynamics throughout the summer drought in a California annual grassland. Soil Biol. Biochem. 115, 54–62. https://doi.org/10.1016/j.soilbio.2017.08.009
Silver, W.L., Ryals, R., Eviner, V., 2010. Soil carbon pools in California's annual grassland ecosystems. Rangel. Ecol. Manag. 63, 128–136. https://doi.org/10.2111/REM-D-09-00106.1
Suddick, E., Ngugi, M., Paustian, K., Six, J., 2013. Monitoring soil carbon will prepare growers for a carbon trading system. Calif. Agric. 67, 162–171.
Williams, J.N., Hollander, A.D., O'Geen, A.T., Thrupp, L.A., Hanifin, R., Steenwerth, K., McGourty, G., Jackson, L.E., 2011. Assessment of carbon in woody plants and soil across a vineyard-woodland landscape. Carbon Balance Manag. 6, 11.
Zavaleta, E.S., Kettley, L.S., 2006. Ecosystem change along a woody invasion chronosequence in a California grassland. J. Arid Environ. 66, 290–306. https://doi.org/10.1016/j.jaridenv.2005.11.008