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Planning Studies for Compost Application to California Rangelands Using Landsat Satellite Imagery, Carbon Modeling, and Machine Learning

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Abstract

Previous field measurements in rangelands throughout California have shown that spreading a relatively thin layer of compost on the soil surface of grasslands can enhance water-holding capacity and provide stabilized, slow-release nutrients to support long-term belowground carbon capture and storage. Compost-treated grasslands have been shown to consistently absorb more CO_2 from the atmosphere into the plant and soil cover, more than that was being lost to microbial respiration for many years after a single organic matter application. The purpose of this new study was to optimize the long-term increase and restoration of soil carbon pools across the state of California, based on a combination of state-wide satellite image analysis, soil carbon modeling, and Machine Learning.

Keywords

California, Rangeland, Compost, Satellite Imagery, Soil Carbon Modeling, Machine Learning

1. Introduction

Agricultural production systems are major sources of greenhouse gas (GHG) fluxes from the land to the atmosphere and are currently responsible globally for 10 to 20 Gt CO_2 Eq in GHG emissions each year [1]. It is therefore imperative and urgent that farming and grazing practices be reimagined and scientifically proven to help reverse soil degradation, biodiversity loss, and GHG emissions.

Studies reviewed across different "regenerative" agriculture practices that aim chiefly to restore soil organic matter and nutrients, in comparison with conventional practices of tillage and chemical fertilizer use to maximize crop yields, have shown that belowground carbon pools can be increased by as much as 3 Mg C ha^{-1} yr^{-1} [2]. Grassland soils treated with a thin layer (around 1.3 cm thick) of composted organic matter have consistently measurable increases in plant production and net carbon uptake through the enhancement of available nitrogen (N) and water holding capacity [3].

In general, field-based evidence of compost's potential to alter the soil state is being increasingly recognized by scientists and policymakers for sequestering carbon belowground for decades and conserving water during drought periods [3]-[5]. In field studies on grazed grasslands of coastal California (Marin County) and the Central Valley (Yuba County), a single organic matter application of 14 Mg C ha^{-1} increased and maintained the carbon content of surface soils by between 1.8 and 2.6 Mg C ha^{-1}, sampled three years following compost application [6]. These same compost amendments increased both above- and below-ground plant production by 2.1 to 4.7 Mg C ha^{-1} (compared to uncomposted control plots) over the three-year study period. In a meta-analysis of other grassland management practices, Conant *et al.* [7] reported that improved grazing management alone could increase the sequestration of soil carbon in rangelands at a rate of only 0.3 Mg C ha^{-1} yr^{-1}. In summary, organic amendments, mulching, cover cropping, and reduced tillage have been shown to restore soil carbon pools and microbial health in farmlands more rapidly than rotational livestock plans [2] [8].

Ryals *et al.* [9] combined field data and the DAYCENT biogeochemical model to investigate the GHG mitigation potential of soil compost amendments at their same two grazed grassland sites in Marin and Yuba County, California. The DAYCENT model [10] was used to test 100+ years of ecosystem C responses to a range of compost qualities (carbon to nitrogen [C:N] ratios of 11, 20, or 30) and application rates (single addition of 14 Mg C ha^{-1} or 10 annual additions of 1.4 Mg C ha^{-1} yr^{-1}). Results showed that the compost mass decay through time followed a negative exponential decay curve. The proportion of compost-C remaining in the soil ecosystem after 10, 30, and 100 years was 68%, 22%, and 1.0%, respectively. All compost amendment scenarios led to net GHG sinks that the modeling showed to persist for several decades following organic matter addition, reflecting the ability of compost to act as a slow-release organic fertilizer. Compost amendments with lower C:N led to higher C sequestration rates over time. However, these soils also experienced greater N_2O GHG fluxes.

As context for the need to make the best use of food waste that cannot be redistributed for human consumption, the California organics recycling law (State Bill 1383) took effect in 2022 with the main goal of reducing GHG emissions by diverting 75% of organic waste from landfills by 2025. As of 2024, CalRecycle (calrecycle.ca.gov) reported that 75% of communities have implemented residential organics collection programs and nearly 100% reported expanding their commercial organics collection programs. Under what is known as "Article 12" of the state law, CalRecycle assigns an annual procurement target for each jurisdiction (city or county) in the state, who in turn must meet that target by purchasing compost and mulch to spread on local soils.

The purpose of this new study was to assist in planning at the state and local levels for future compost applications to selected California rangelands, so as to optimize the use of limited resources and maximize the long-term increase and restoration of soil carbon pools across the state. The methods applied in this study were based on a combination of state-wide satellite image analysis, soil carbon modeling, and Machine Learning. The soil carbon modeling methods presented in this study were identical to those described by Ryals *et al.* [9] using DAYCENT; however, our new predictions of the lifetime in rangeland soils of added carbon applied as compost have been extended to cover the entire state. The main objective of this study was to select the optimal property locations in California to apply future compost amendments, based on the best scientific data and criteria available for the CO_2 capture and long-term storage by rangeland soils.

In a recent literature review, Adugna [11] concluded that many field investigations have demonstrated that compost has an equalizing effect on annual and seasonal fluctuations regarding the water content and heat balance of soils. In a review of long-term experiments (3 - 60 years), Diacono and Montemurro [4] reported that regular addition of composted organic residues commonly increases soil physical conditions and fertility, mainly by improving aggregate stability and decreasing soil bulk density. Findings such as these support the principal hypotheses that we have brought to our new remote sensing studies of trends in rangeland productivity, namely that: 1) Years of relatively high rainfall increase average daily soil water content and extend the herbaceous growing season, compared to relatively low rainfall seasons and years, and 2) Compost application to grasslands increases soil water holding capacity to make more precipitation available to herbaceous plant cover, compared to grasslands not treated with compost additions to the soil.

2. Materials and Methods

2.1. Surface Soil Carbon Content

Veloz *et al.* [12] applied machine learning methods to map soil carbon pools for all California rangelands at a 270 m pixel size. Boosted regression as a machine learning algorithm was used in a classification tree model that iteratively adds new trees to the set, and at each step focuses on explaining the remaining unexplained variation from the set of previous trees. The final parameters for the algorithm were selected by balancing the ability of the model to explain the variation in the input data set (training values) while also being able to accurately predict the data set withheld from the training values (*i.e.*, the testing values).

Soil carbon concentrations were first measured from both 0 - 10 cm and 10 - 40 cm depths at 282 grassland sites across California from 2015 to 2021. Samples were collected in a standardized way and analyzed at the University of Idaho Analytical Lab via dry combustion. Bulk density measurements were also taken at each site and used to convert carbon concentrations to stocks on a fixed mass basis (Mg C ha^{-1}).

Input data sets to the Machine Learning model included:

- Elevation from the Shuttle Radar Topography Mission Digital Elevation Dataset, 30 m resolution.
- Climate data, including monthly average winter minimum temperature (Dec-Feb) and average summer maximum temperature (Jun-Aug), as well as annual precipitation, runoff, recharge, storage, and climactic water deficit, averaged over the years 2016 to 2021 from California's Basin Characterization Model v8, 270 m resolution [13].
- Nine measures of annual vegetative productivity derived from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) satellite Normalized Difference Vegetation Index (*NDVI*) data; averaged over the years 2016 to 2021, 250 m resolution [14].
- Fractional landcover of bare ground, litter, annual, annual herbaceous, shrub, and sagebrush as well as sagebrush and shrub height in 2016 from the National land Cover Dataset (NLCD) Rangeland Components dataset, 30 m resolution [14].
- Soil class, suborder, order, and drainage class; and the weighted average by horizon of pH, sand, silt, and clay; bulk density from the Soil Survey Geographic Database (SSURGO) Soil Survey Staff from 2022.

The best boosted regression model results for the 0 - 10 cm soil depth had a correlation coefficient (R^2) between the observed average soil carbon stocks and predicted soil carbon stocks of 0.72 (SE ± 0.022), whereas the best model results for the combined 0 - 40 cm soil depth had a correlation coefficient R^2 of 0.85 (SE ± 0.015).

2.2. Landsat Greenness Index of Live Vegetation Cover

Bi-weekly Landsat 8 Collection 2 images from the years 2022 to 2024 at 30-m pixel size, were used to calculate the normalized difference vegetation index (*NDVI*) of the near-infrared (*NIR*) and red spectral bands. *NDVI* provides consistent spatial and temporal profiles of herbaceous vegetation biomass according to the equation:

$$NDVI = \left(NIR - Red\right) / \left(NIR + Red\right)$$

Which resulted in values between −1.0 and +1.0 *NDVI* units. Negative *NDVI* values are indicative of water bodies, low values of *NDVI* (near 0.1) indicate barren land cover, and high values of *NDVI* (above 0.8) indicate dense green plant cover. *NDVI* has been shown to be an accurate index of herbaceous green cover in grasslands of California and can be converted with high accuracy into seasonal herbaceous biomass (g C m^{-2}) each year [15].

2.3. Soil Fertility Index

This study used a Soil Fertility Index (FI) map previously generated for the lower 48 United States by the U. S. Department of Agriculture (USDA) [16]. The FI uses family-level Soil Taxonomy information to rank soils from 0 (least fertile) to 19 (most fertile). To calculate the FI, the following variables were used to guide expert assessments of fertility among 12 main soil orders: 1) organic matter content, 2) cation exchange capacity—CEC, and 3) clay mineralogy, as well as USDA knowledge of general land uses in each of the soil orders.

2.4. Climate Normals for Average Precipitation and Temperature

This study used the 30-year normal maps previously generated from the PRISM project which were used to quantify average annual climate conditions across California over the most recent three full decades (1991 to 2020) at 4-km pixel resolution. Long-term average datasets are modeled from weather station records in PRISM using a digital elevation model (DEM) as the predictor grid [17].

2.5. CASA-Century Model for California Grasslands

The CASA (Carnegie-Ames-Stanford Approach) carbon cycle model [18] [19] predicts the monthly net primary production (NPP) flux of atmospheric CO_2 between plants and soils on a global scale using satellite image inputs from MODIS. CASA is the only global carbon model that has consistently used MODIS and Landsat products for land cover classes and green vegetation indices as monthly inputs to drive the prediction of NPP and soil CO_2 emissions in the terrestrial biosphere. It is the most well-integrated model of the global carbon and water cycles with high-level products from NASA satellite remote sensing missions. Moreover, the nominal 8-km grid cell resolution of the CASA model enables localized studies of ecosystem carbon and water fluxes of interest to public sector stakeholders working at nearly every organizational level. CASA NPP model calibration has been validated repeatedly, first globally by comparing predicted annual NPP to more than 1900 field measurements of NPP by Potter *et al.* [18]. More recently, Jay *et al.* [14] validated CASA NPP estimates using 17 Ameriflux tower flux sites located across North America.

The CASA soil model design is based closely on the DAYCENT model [10] and includes three-layer (M1 - M3) heat and moisture content computations: surface organic matter (SOM), topsoil (0.3 m), and subsoil to grassland rooting depth (1 m). These layers can differ in soil texture, moisture holding capacity, and carbon–nitrogen dynamics. Water balance in the soil is modeled as the difference between precipitation or volumetric percolation inputs, monthly estimates of evaporation, and the drainage output for each layer. First-order equations simulate exchanges of decomposing plant residue (metabolic and structural fractions) at the soil surface. CASA also simulates surface soil organic matter fractions that vary in age and chemical composition. Active (microbial biomass and labile substrates), Slow (chemically protected), and Passive (physically protected) fractions of the soil organic matter are represented in the model. Along with moisture availability and organic residue quality, estimated soil temperature in the M1 - 3 layers controls soil organic matter decomposition rates at the monthly time step.

Following the DAYCENT modeling approach reported by Ryals *et al.* [9] for the present study, compost amendments to rangelands across California were simulated starting with a single amendment of 14 Mg C ha^{-1} added to the CASA soil organic pools. Compost is a source of stabilized organic matter, more prone to be incorporated for years into soil than are additions of fresh manure, which rapidly mineralize [20]. Hence, for these CASA model runs, it was assumed that compost was nearly identical in protected chemical properties and stabilized microbial products to the CASA-Century model's Slow C pool, with residence times in a temperate zone soil profile typically ranging from 20 to 60 years [18]. Using monthly PRISM climate inputs, CASA was then run to simulate the lifetime decay function of a one-time compost application with C:N ratio of 20 - 30 (for close-to-zero N_2O emission risk) [9].

2.6. Landsat *NDVI* Trend Analysis

The linear trend (positive or negative) in bi-weekly *NDVI* values at every 30-m Landsat pixel location across all of California was calculated in Google Earth Engine from the wet seasons (October to May water year) of 2021 to 2024 as a greening regression slope coefficient, following the approach described by Potter and Alexander [21]. According to NOAA's National Centers for Environmental Information, 2021-22 was the driest water year ever recorded in the state (dating back to 1895), whereas 2022-23 recorded one of the four wettest seasons in the modern history of the state. This historic and abrupt trend upward in seasonal precipitation totals and available soil water in grasslands for annual growth provided a surrogate to test the central hypotheses outlined in this study: Future compost applications to grassland ecosystems will increase available soil water to herbaceous plants in the same manner that years of high annual precipitation makes added soil water available for elevated plant growth.

2.7. Statistics

Zonal statistics for simulated compost lifetime and *NDVI* trends were computed within the boundaries of California counties (**Figure 1**, with name labels), and eventually for selected river and creek drainage basins, using the geographic information systems application QGIS. The population mean, standard deviation, and maximum values were computed for the set of raster pixels that intersected each polygon-delineated layer.

3. Results

3.1. CASA Slow C Pool Size

The counties estimated by the CASA model with the highest average Slow C pool sizes (in excess of 70 Mg C ha^{-1}) were all located in northern California (**Figure**

1), from the Del Norte to Sonoma county lines (Table 1). Other counties located further south and with relatively high average Slow C pool sizes (in excess of 50 Mg C ha^{-1}) included Santa Cruz, Tuolumne, Tulare, and Santa Barbara. Counties with the highest geographic variability in Slow C pool sizes included Humboldt, Mendocino, Siskiyou, Tuolumne, Tulare, and Santa Barbara. Counties with the lowest Slow C pool sizes included Solano, Yolo, Contra Costa, San Diego, San Mateo, Stanislaus, San Joaquin, Merced, and Alameda. This ranking of counties with the highest average Slow C pool sizes represents the CASA model's synthesis of the combined effects of climate conditions that favor relatively high annual NPP and the soil types that favor high levels of long-term carbon sequestration in a chemically protected form.

Figure 1. California county map.

Table 1. Top 25 counties for soil Slow C pool size, sorted by mean values.

County	County Area (km^2)	Mean (Mg C ha^{-1})	Standard Deviation (Mg C ha^{-1})	Maximum (Mg C ha^{-1})
Del Norte	2,626	147	19	184
Humboldt	9,585	123	36	170
Mendocino	8,797	97	30	119
Trinity	8,141	88	18	136
Siskiyou	16,413	76	29	163
Shasta	10,110	75	17	111
Lake	3,545	73	22	106

Continued

Plumas	6,828	71	14	114
Sierra	2,626	71	18	101
Santa Cruz	1,050	71	15	84
Tuolumne	5,777	68	29	142
Sonoma	4,070	68	25	110
Nevada	2,495	67	26	103
Alpine	1,970	66	15	99
Napa	2,232	62	16	90
El Dorado	4,333	61	24	95
Calaveras	2,626	58	28	106
Tulare	12,343	57	41	156
Placer	4,070	56	26	105
Mariposa	3,939	54	29	107
Santa Barbara	7,747	54	36	129
Lassen	12,080	54	15	88
Glenn	3,414	53	29	94
Tehama	7,747	53	19	102
Marin	1,576	52	26	89

3.2. Compost Lifetime in the Soil

Statewide map results (**Figure 2**) from the CASA model show the number of years for practically 100% of the 14 Mg C ha^{-1} of applied compost tonnage to decompose (*i.e.*, its full lifetime in the soil), with the light green shades showing time periods in the 20 - 50 years range and the dark green shades in the 80 - 90 years range. For most Marin County grazed rangelands, CASA estimates of the compost lifetime were between 40 - 60 years, consistent with the Ryals *et al.* [9] DAYCENT model results for these coastal rangeland sites near Nicasio (at 38.06˚ N, 122.71˚ W). In comparison, grassland sites measured for soil carbon at the Sierra Foothill Research and Extension Center (SFREC) by Ryals *et al.* [9] in Yuba County (at 39.24˚ N, 121.30˚ W) were predicted by the CASA model to have a compost lifetime in the soil of over 100 years. This longer compost lifetime resulted mainly from a shorter growing season with lower annual mean temperatures and higher summer evapotranspiration in Yuba County, compared to Marin County.

The counties with large areas of rangeland (in excess of 90,000 ha) that were mapped using the CASA model with the shortest average lifetime of 14 Mg C ha^{-1} applied compost in the soil were ranked as Mendocino, Lake, Napa, Sonoma, and Santa Barbara (**Table 2**). Counties with notable rangeland acreage and with the longest average lifetime (greater than 85 years) of 14 Mg C ha^{-1} applied compost to the soil were San Benito, Stanislaus, Mariposa, Modoc, Alameda, San Joaquin, and Merced. This ranking of counties by compost lifetime in the soil represents the CASA model's estimation of the combined effects of climate conditions and soil types that favor the most rapid (to the slowest) decomposition rates of organic matter added as compost to rangeland soils. Areas of counties with the longest average lifetime represent those where compost applied to rangeland soil surfaces will persist for the longest period of time, largely as a result of climate conditions (drier annually and hotter in the summer) that are relatively unfavorable to rapid litter/soil carbon decay.

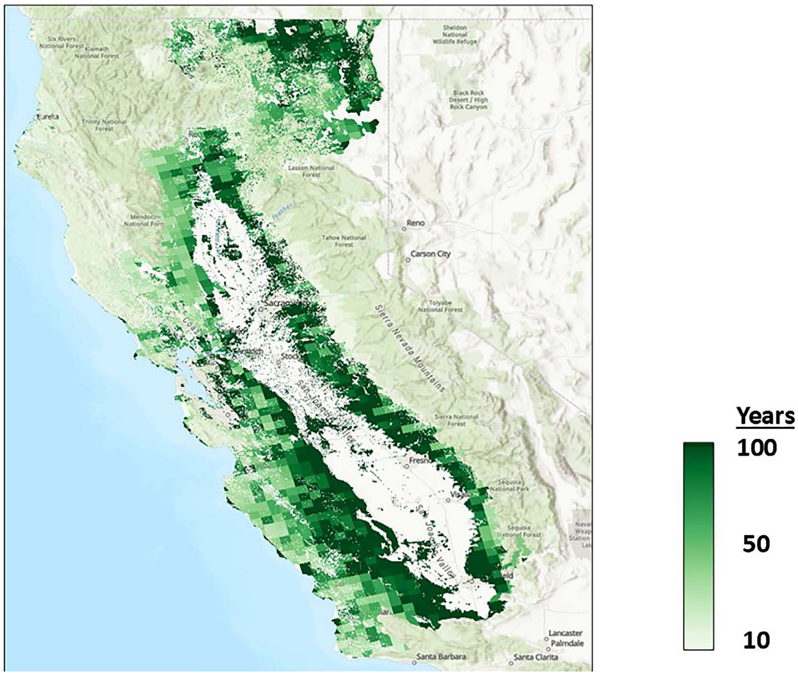

Figure 2. CASA model predictions for the number of years for all of a 14 Mg C ha^{-1} of applied compost tonnage to decompose.

Table 2. Counties with the shortest lifetime for the complete decay of 14 Mg C ha^{-1} applied compost to rangeland soil surfaces, sorted by mean values.

County	Rangeland Area (ha)	Mean (years)	Standard Deviation (years)
Del Norte	10,016	28	20
Mendocino	106,033	29	19
Humboldt	84,870	33	18
Santa Cruz	21,906	47	25
San Mateo	44,156	48	84
Lake	181,441	50	16
Napa	110,662	53	17
Sonoma	173,189	54	23
Marin	71,325	55	49
Santa Barbara	305,291	56	40
Plumas	13,924	57	8
Glenn	159,345	58	23
Shasta	322,262	60	15

Continued

Colusa	143,700	67	28
Monterey	714,048	70	25
Lassen	458,833	73	17
Siskiyou	297,753	74	19
Tehama	481,162	74	23
San Luis Obispo	733,986	76	31
Tulare	252,475	80	32
Calaveras	114,803	83	16
Santa Clara	186,150	85	60
Yolo	99,159	85	30

3.3. Change in *NDVI* from Dry to Wet Years

Statewide map results (Figure 3) from Landsat *NDVI* time series analysis show the strongest response of rangelands to the transition from an historically extreme dry year (2021-2022) to two wet years (2023 and 2024) occurred in the northern Sacramento Valley and the eastern side of the Central Valley south to around Fresno. Other regions that showed a strong greening trend with increasing rainfall were in the grasslands north and east of San Francico Bay, the southern Santa Clara Valley, and on the central coastal prairies from San Simeon to Morro Bay.

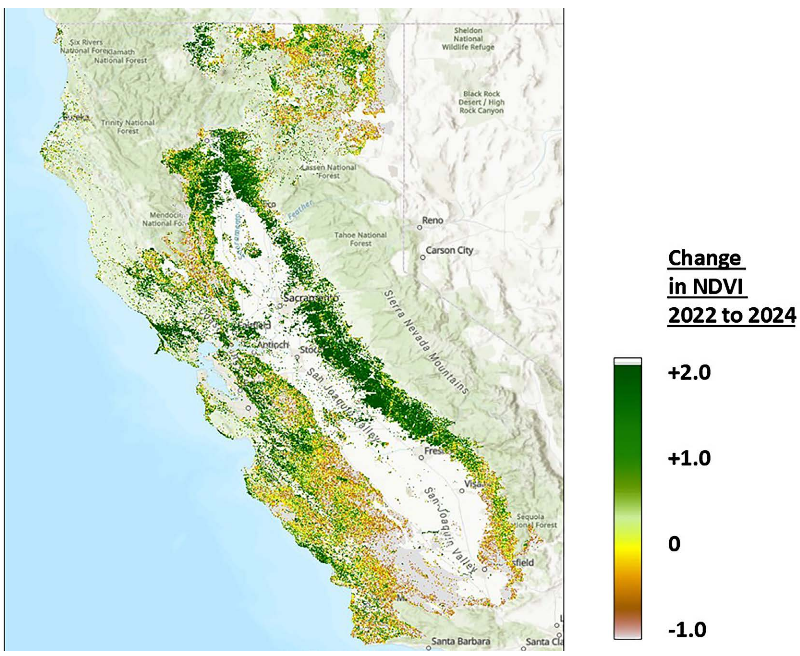

Figure 3. Landsat *NDVI* time series analysis results as the greening linear regression slope coefficient (monthly rate of change) over the wet seasons (October to May water year) of 2021 to 2024, showing positive trends in the darkest green shades and negative trends in brown shades.

The counties with the strongest positive response and among the lowest geographic variability in rangeland *NDVI* from extreme dry to wet years were ranked in Table 3 as Calaveras, Tuolumne, Marin, Sacramento, Amador, and Yuba. Counties with the highest geographic variability in response of rangeland *NDVI* from extreme dry to wet years (2022 to 2024) included San Joaquin, Sonoma, Plumas, Stanislaus, and Santa Cruz. Counties with the lowest response of rangeland *NDVI* from extreme dry to wet years included Monterey, Tulare, Santa Barbara, Glenn, Napa, and San Luis Obispo. This ranking of counties by rangeland *NDVI* response to varying yearly precipitation (most positive to most negative) reflects the soil types and potential grassland productivity that should also favor a positive of response of soil carbon sequestration following compost applications in rangelands across California.

Table 3. Counties ranked by positive response of rangeland *NDVI* from extreme dry to wet years (2022 to 2024).

County	Mean Change in *NDVI*	Standard Deviation
Calaveras	1.98	1.32
Tuolumne	1.89	1.24
Marin	1.86	1.89
Sacramento	1.82	1.74
Amador	1.74	1.30
Nevada	1.64	1.40
Placer	1.60	1.68
Yuba	1.52	1.59
Mariposa	1.50	1.04
El Dorado	1.46	1.29
Madera	1.39	1.21
Sonoma	1.36	1.77
Tehama	1.13	1.61
Butte	0.96	1.80
San Joaquin	0.91	1.90
Mendocino	0.90	1.26
Plumas	0.86	3.56
Contra Costa	0.81	1.57
Merced	0.76	1.66
Alameda	0.75	1.39
Sutter	0.75	1.98
Solano	0.69	2.68
San Francisco	0.67	1.40
Stanislaus	0.59	1.95

Continued

Santa Cruz	0.57	2.36
San Mateo	0.56	1.23
Santa Clara	0.54	1.80
Siskiyou	0.33	1.79
Del Norte	0.32	1.89
Humboldt	0.30	1.24
Yolo	0.18	2.02
San Benito	0.15	1.06

The coastal rangeland sites near Nicasio in Marin County studied by Ryals *et al.* [9] for soil carbon dynamics had a strong *NDVI* response to varying yearly precipitation, with a regression slope between +1.5 and +2.6 from 2022 and 2024, whereas grassland sites at the SFREC in Yuba County showed a very strong *NDVI* response with a regression slope of +2.9 from 2022 and 2024.

3.4. Surface Soil Carbon Pools

The counties with large areas of rangeland (in excess of 90,000 ha) that were mapped using Machine Learning methods by Veloz *et al.* [12] with high soil carbon content (percent by volume to 10 cm depth) were ranked as Siskiyou, Mendocino, Sonoma, Alameda, Shasta, Lassen, and Santa Clara (**Table 4**). Counties with notable rangeland acreage and low geographic variability in soil carbon content included Marin, Santa Cruz, Contra Costa, and Santa Clara. Counties with notable rangeland acreage and among the lowest soil carbon content included Stanislaus, San Joaquin, Glenn, San Luis Obispo, San Benito, and Merced, all at lower than 0.8 percent on average and commonly with a maximum surface soil carbon content no higher than 1.6 percent.

Table 4. Top counties for soil carbon content within the 0 - 10 cm surface layer, sorted by mean values.

County	Rangeland area (ha)	Mean (%)	Standard Deviation (%)	Maximum (%)
Del Norte	8,916	1.65	0.42	3.39
San Mateo	37,595	1.48	0.38	2.65
Humboldt	81,072	1.46	0.38	3.37
Plumas	12,583	1.45	0.40	3.05
Marin	61,936	1.35	0.25	2.46
Santa Cruz	21,032	1.17	0.25	2.31
Siskiyou	277,822	1.12	0.60	6.65
Mendocino	99,567	1.12	0.26	2.49
Sonoma	161,597	1.08	0.26	2.90
Alameda	95,266	1.07	0.18	2.08

Continued

Shasta	307,704	1.05	0.48	4.31
Lassen	448,546	1.03	0.30	3.77
Contra Costa	84,302	1.01	0.16	2.07
Santa Clara	184,546	1.00	0.17	2.01
Nevada	20,959	0.95	0.14	1.72
Napa	99,742	0.94	0.25	3.09
Santa Barbara	281,051	0.93	0.22	2.26
Solano	82,443	0.92	0.24	1.92
Modoc	664,323	0.91	0.31	4.02
Sutter	25,092	0.89	0.31	2.51
Butte	116,968	0.88	0.26	3.30
El Dorado	45,096	0.85	0.15	1.91
Yuba	52,816	0.84	0.19	2.31
Monterey	653,009	0.82	0.19	2.20
Lake	170,550	0.82	0.18	2.74
Tehama	469,257	0.81	0.29	3.79
Calaveras	109,663	0.80	0.14	1.85
Yolo	87,764	0.80	0.16	1.57
Colusa	140,223	0.80	0.16	1.64

3.5. Soil Fertility Index

Statewide mapping of the USDA Soil Fertility Index (**Figure 4**) relatively high values in the Modoc National Forest region, the northern Sacramento Valley, the southern Santa Clara Valley, and on the Central Coast prairies from Marin to Morro Bay. The counties with the highest Soil Fertility Index on average in California were ranked as San Benito, Kings, Ventura, Marin, Santa Cruz, and Monterey (**Table 5**). Counties with notable rangeland acreage and averaged among the lowest Soil Fertility Index included Merced, Sonoma, Siskiyou, Santa Barbara, Humboldt, and Santa Clara. Both the coastal rangeland sites in Marin County and in Yuba County studied by Ryals *et al.* [9] for soil carbon dynamics had high Soil Fertility Index values that ranged between 13 - 14 in the grasslands of these locations.

Table 5. Counties ranked by soil fertility index values, sorted by majority class values.

County	County Area (km^2)	Majority	Mean	Standard Deviation
San Benito	3,599	15	10	5.7
Kings	3,605	15	9	4.5
Ventura	4,807	15	10	4.3
Marin	1,532	14	10	5.1
Santa Cruz	1,156	14	13	3.4
Monterey	8,584	14	11	5.0

Continued

Lassen	12,227	12	11	4.3
Plumas	6,769	12	8	4.4
Glenn	3,437	12	9	3.9
Sutter	1,575	12	12	3.0
Placer	3,885	12	7	4.1
Yolo	2,644	12	10	3.5
Solano	2,357	12	10	4.0
San Joaquin	3,693	12	11	3.6
Contra Costa	2,080	12	10	5.0
Stanislaus	3,927	12	9	3.5
Alameda	2,126	12	9	5.3
Modoc	10,885	11	11	4.7
Colusa	2,996	11	11	3.3
Napa	2,048	11	9	4.3
San Luis Obispo	8,597	11	10	4.2
Mendocino	9,096	10	10	3.4
Sierra	2,490	10	9	3.7
Nevada	2,525	10	8	4.2
El Dorado	4,632	10	6	4.1
Calaveras	2,683	10	9	2.8
Fresno	15,565	10	7	4.6

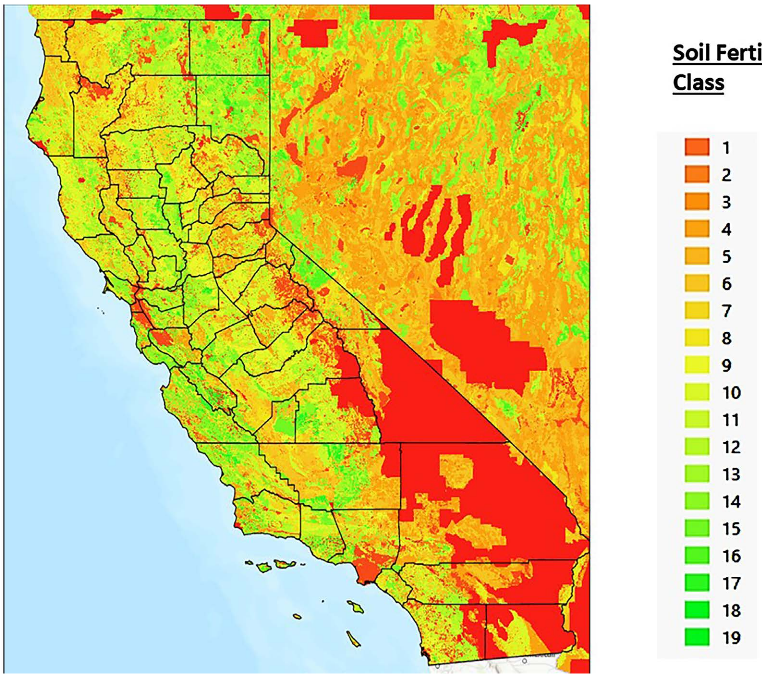

Figure 4. Map of the USDA Soil Fertility Index for California.

4. Discussion

In merging all of the mapping results from this study to identify optimal rangelands in California for future compost applications, we combined the: 1) high average *NDVI* response in rangelands to increased annual rainfall, 2) relatively low current soil carbon contents, and 3) relatively high soil fertility. From these selection criteria combined (in that order), the optimal counties for future compost applications were determined to be: Marin, San Benito, Calaveras, Tuolumne, San Joaquin, Stanislaus, Sacramento, Amador, Yuba, and Mendocino counties. Depending on site-specific soil fertility assessments, rangelands in Merced and Sonoma could also fall into the category of optimal locations for future compost application.

In the final selection of optimal property locations for future compost applications, topography must be considered as well, particularly the presence of steep slopes. As a general rule, hillsides with slopes in excess of 30% should be avoided to alleviate concerns over erosion of applied organic matter and nutrient runoff [22]. Mapping and filtering of steep slopes is a routine analysis function using digital elevation models (DEMs).

It should be noted that the CASA-simulated decay function for applied compost tonnage does not take into account the (roughly) 1 - 2 Mg C ha^{-1} yr^{-1} of additional soil carbon that commonly follows this level of compost application to rangelands [1]. A "state change" in the plant-soil growing system seems to occur with compost amendments. Data from field measurements indicate that these ecosystems have been transformed from a relatively low-nutrient, low-water holding capacity, and low-aeration status to elevated states of all these soil properties [2] [4]. If this enhanced grassland carbon capture effect of 1 - 2 Mg C ha^{-1} yr^{-1} lasts for at least 10 years after a one-time compost application, then one can add another two decades to the Slow C soil carbon lifetime of compost estimated in this modeling study.

Field-based evidence of compost's potential to alter the soil state is being increasingly recognized by scientists and policymakers for reducing GHG from waste sent to landfills, sequestering carbon belowground for decades, and conserving water during drought periods [4]-[6]. Well-documented changes in grassland ecosystems after compost application have been summarized in **Figure 5**. Soil nutrient levels, microbial activity, water holding capacity, drainage, and aeration are all improved rapidly after a thin layer of composted organic matter has been applied to the soil surface [3].

California State Bill (SB) 1383 is being implemented under "Article 12" as CalRecycle assigns annual procurement targets for compost and mulch for each jurisdiction (city or county) in the state. In the first year after SB 1383, organic waste diverted for recycling increased from 9.9 to 11.2 million tons. Nevertheless, rural counties with large open spaces and rangeland acreages will have different and diverse processes for determining how compost should be delivered to or picked-up by landowners and managers and applied to their soils. In one mode, growers and ranchers anywhere in the state can purchase compost on behalf of their jurisdiction to help meet Article 12 procurement targets. In other cases, non-profit organizations (NGOs) can help jurisdictions meet their SB 1383 procurement requirements by navigating the compost procurement process, meeting reporting requirements, and increasing farmers' and landscapers' purchasing power for compost. The Association of Compost Producers (ACP) has created a map of SB 1383-compliant composters in California (available online at http://www.healthysoil.org/compostproducermap) who are able to collaborate with jurisdictions and direct service providers (DSPs) to meet their compost procurement goals. Other NGOs (http://www.zerofoodprint.org/sb1383) offer lists of organic recycling facilities with complete local addresses and products for sale.

Two of the counties targeted from the results of this planning study as optimal for extensive future compost application on grasslands, namely Amador and Calaveras have less than two local organic waste recycling facilities listed by the ACP or by Zero Foodprint within their jurisdiction, whereas Mendocino and Yuba have only three such facilities. Promoting the expansion of local compost production facilities will be needed to accelerate the state's GHG reduction goals while building prosperous, equitable, and resilient communities [23]. CalRecycle issued permits for seven solid waste facilities from October 2022 to December 2023 that included new compost, in-vessel digestion, and transfer/processing facilities. Presently, the state has 210 operating organics processing facilities, including 169 composting facilities, 24 biomass operations, and 17 anaerobic digestion facilities (with 21 more under construction). CalRecycle estimates that nearly 100 new or expanded anaerobic digestion facilities must come online to help meet the organic waste processing demand, resulting in the diversion of about 15 million tons of organic waste and the production of roughly 5 million additional tons of compost per year by CalRecycle [24].

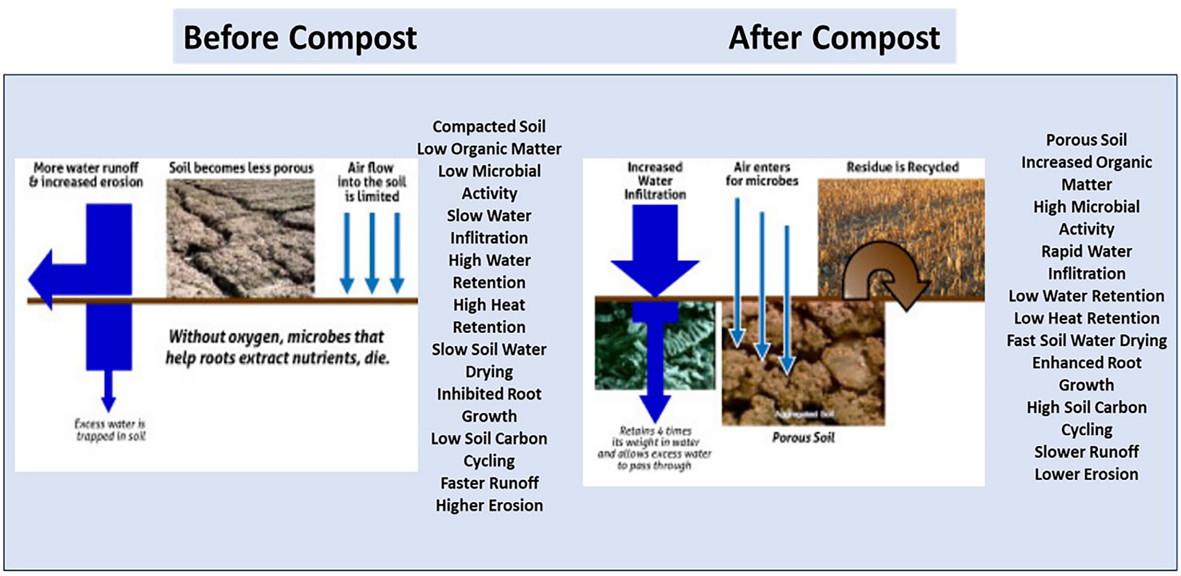

Figure 5. Changes in the grassland ecosystem after compost application.

5. Conclusions

Compost-treated grasslands soils have been shown to consistently absorb and store more CO_2 from the atmosphere than that will be lost to microbial respiration for decades after the organic matter application. We have used a combination of state-wide satellite image analysis, soil carbon modeling, and Machine Learning methods to select the optimal property locations in California to apply future compost amendments. Based on the best scientific data available to account for controls on carbon pools in soils, the counties that should be targeted first for future rangeland compost applications are Marin, San Benito, Calaveras, Tuolumne, San Joaquin, Stanislaus, Sacramento, Amador, Yuba, and Mendocino. Potential ranch locations for these organic amendment projects can be examined in detail and selected from the interactive geographic information system (GIS) created from our study results.

Acknowledgements

The statewide map results displayed as figures in this study, along with basemaps for roads, elevation, slope, soil types, and property ownership, will be made available in an open access, fully interactive GIS user portal. The initial ESRI ArcPro GIS project package is presently available for download at: https://casa2100.maps.arcgis.com/home/item.html?id=90649589dc8848c08b088b8ce1c85b19 under the name CASASystems_SoilC_CompostMaps.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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