A NOVEL APPROACH FOR ESTIMATING NONFOREST CARBON STOCKS IN SUPPORT OF FOREST PLAN REVISION

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INTRODUCTION

Globally, more carbon is stored in the soil than in any other terrestrial form (Brevik 2013; Woodall et al. 2015). Soil organic carbon (SOC) may contain more than three times the carbon found in the atmosphere and terrestrial vegetation combined (Qafoku 2014). Soil organic carbon is derived from soil organic matter (i.e., decomposition of living organisms) and is generally about 58 percent of soil organic matter by weight (Pribyl 2010). Storage of SOC is limited by soil physical and chemical composition as well as microbial and plant community types, all of which are determined by soil moisture and temperature (Emmet et al. 2004; Kardol et al. 2010).

Changes to vegetative community types can affect carbon storage both above-ground and below-ground. Shrublands have a greater percentage of SOC stored in the soil profile below 1 meter while grasslands usually have most SOC in the first meter of soil (Meyer 2012; USDA FS 2013). A shift from sagebrush shrublands to nonnative annual grasslands will eventually move carbon from deeper in the soil profile to the upper 20 cm (Qafoku 2014). An estimated 8 teragrams (Tg; 10¹² grams) of carbon have been lost due to shrubland conversion to annual grasses, particularly cheatgrass (*Bromus tectorum*), in the Great Basin since 2006 (Meyer 2012). Although most conversion has occurred on lands not managed by the USDA Forest Service (hereafter, Forest Service), the potential for future conversion on Forest Service lands exists. Conversely, increased woody encroachment offers the possibility of increased aboveground and belowground storage on the landscape. Rau and others (2011) found that woodland expansion increased SOC (0–15 cm soil depth) by 2.2 Mg C ha⁻¹.

The Forest Service seeks to understand the role of its lands in sequestering carbon to mitigate the effects of greenhouse gases and climate change (USDA FS 2015a). In this vein, it is important to define and differentiate two terms relating to carbon assessment and management commonly used in the Forest Service and elsewhere: carbon sequestration and stores. "Carbon sequestration" is the process of removing carbon from the atmosphere and depositing it in a reservoir. "Stores" refers to the quantity of carbon in a given reservoir. Management of carbon storage in rangeland landscapes may represent the most cost-effective method to reduce greenhouse gases (Mahdavi and Esmaili 2015). Rangelands cover greater than half of the Earth's land surface and contain between 10 and 30 percent of the SOC (Derner and Schuman 2007; Limbu et al. 2013). In rangelands, SOC may represent as much as 95 percent of the total terrestrial carbon pool (Meyer 2012). Even modest changes in rangeland carbon sequestration can influence the global carbon cycle and thus climate (Derner and Schuman 2007). Soil organic carbon also enhances retention of soil moisture and increases productivity.

The National Forest System (NFS) has identified the need to evaluate baseline carbon stocks for a given time period for two primary reasons. First, the NFS recognizes the importance of managing carbon. Second, national forests and grasslands are required to develop land management plans under the 2012 Forest Planning Rule, as mandated by the National Forest Management Act (USDA FS n.d.), and carbon stock estimates fulfill one requirement for forest plans. The Forest Service has interpreted baseline carbon stocks to include both aboveground and belowground carbon (USDA FS 2015b). Few methods or datasets are available for quantifying carbon stocks in rangelands. In recognition of this issue and NFS's need to evaluate carbon stocks, we provide an assessment of carbon stocks of rangelands for national forests in the Forest Service Intermountain Region (Region 4: southern and central Idaho, Utah, Nevada, western Wyoming, and east-central California) (fig. 1). Here, we present a novel methodology to rapidly estimate aboveground carbon in shrubs and describe an approach for estimating soil carbon. For estimates of aboveground standing carbon in shrubs, we processed vegetation structure and composition using the Rangeland Vegetation Simulator (RVS; Reeves 2016), which hosts a large array of allometric equations that link vegetation structure and composition to biomass. We used SOC estimates for surface (0–30 cm) and maximum depths (0–999 cm) from the Soil Survey Geographic Database (SSURGO) and Digital General Soil Map of the United States

(STATSGO2; hereafter referred to as STATSGO; <u>https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/</u> <u>survey/geo/?cid=nrcs142p2_053627</u>) products where available. Where these data were not available, we modeled SOC as a function of the normalized difference vegetation index and mean annual temperature to fill data gaps.



Figure 1—The study area. Areas in green in panel A indicate forest cover type (Blackard et al. 2008). Areas in tan in panel B indicate rangelands (Reeves and Mitchell 2011). Areas in tan in panel C represent the final carbon mask used to derive rangeland carbon estimates in Region 4. Areas in purple represent areas that Blackard et al. (2008) consider forest but Reeves and Mitchell (2011) consider rangeland. In these cases, we allowed the forest map to take precedence and no carbon estimates were derived for forested areas because the Forest Service's Forest Inventory and Analysis program already provides carbon estimates for the lands.

METHODS

Study Area

The study extent encompasses the Forest Service Intermountain Region (Region 4; fig. 1). We removed forest vegetation types based on a forest type map (Blackard et al. 2008). We retained classified rangelands and removed nonnatural types, such as agricultural lands, and urban areas (Reeves and Mitchell 2011). We identified approximately 3.7 million ha of rangeland in this region to include in the project.

Aboveground Carbon

To model aboveground carbon in shrub vegetation, we used vegetation structure and composition from LANDFIRE project data layers (LANDFIRE, n.d.b): Existing Vegetation Cover (EVC), Existing Vegetation Height (EVH), and Existing Vegetation Type (EVT). These data cover the entire region with no gaps or inconsistencies. The EVT product acts as a guide (in concert with other information) for species information and canopy architecture. These data are offered at 30-m × 30-m spatial resolution.

For each pixel, we determined estimates of cover, height, and canopy architecture. Because the LANDFIRE height product represents a range of height values, standing carbon was estimated for minimum, average, and maximum estimates, resulting in a range of potential standing carbon (table 1). For a given architecture of shrubs, we applied allometric relationships between cover, height, and species to calculate the following outputs: projected crown diameter, stems per hectare, and total aboveground biomass. Estimates of total aboveground biomass were then converted to carbon by multiplying by a carbon fraction of 0.5 (table 2). Species were estimated from the EVT product that represents U.S. Ecological Systems (Comer et al. 2003). To estimate species in each EVT, we analyzed the LANDFIRE Reference Database (LFRDB; LANDFIRE, n.d.a.) and identified the most common shrub species in each EVT (by counting the frequency of each shrub species across each plot in every instance of a given EVT). This process yielded the percentage of plots in an EVT where a given shrub species was found. We then were able to automatically and seamlessly process the entire extent of the Region 4 rangelands because we had developed the RVS, which is a program that calculates succession, fuels, annual production, and biomass for rangeland habitats.

	Minimum	Average	Maximum
Description of existing vegetation height class		(m)	
Shrub height 0 to 0.5	0.1	0.25	0.5
Shrub height 0.5 to 1.0	0.5	0.75	1
Shrub height 1.0 to 3.0	1	2	3
Shrub height >3.0	3	4	5

Table 1—The categories of shrub heights (stand averages) represented in the LANDFIRE Existing Vegetation Height product (LANDFIRE, n.d.b).

Table 2—Steps in estimating stems per acre and per stem biomass. The example stand is dominated by sagebrush (*Artemisia tridentata*), at 50 cm with 15-percent canopy cover. HT, PCH, and EVC are stand height, projected canopy on a horizontal plane, and stand cover, respectively. The final estimated standing carbon for the example stand (or pixel) would be 2,867 stems ac^{-1} (7,081 stems ha^{-1}) × 0.218 lbs ac^{-1} (0.244 kg ha^{-1}) of carbon, resulting in a final standing carbon estimate of 628 lbs ac^{-1} (706 kg ha^{-1}). Float indicates a type casting of the resulting number to a float so that decimal points can be retained. HT refers to shrub height estimated from the ground to the top of the shrub canopy. SQRT refers to the square root mathematical function.

Step	Output	Units	Equation	Result
Step 1	Projected crown area	log space	$0.8471 + (2.2953 \times (LOG_{10}(HT)))$	3.053
Step 2	Projected crown area	cm ²	Exp10(PCH)	21.168
Step 3	Projected crown area	in^2	Float(PCHcm ² × 0.15500031)	3.281
Step 4	Stems per acre possible	Stems ac ⁻¹ possible	Float((43560/(PCHin ² /144.0)))	1,911,807
Step 5	Stems per acre adjusted for cover	Stems ac ⁻¹	int(Float(Stems $ac^{-1} \times (EVC^* 0.01)))$	2,867
Step 6	Crown width	Crown width cm ²	$Float(2 \times (sqrt(PCHcm^2/3.14)))$	5.193
Step 7	Aboveground biomass	lbs ac ⁻¹	0 + (0.00102 + HT × crown width × crown width + 196) × 0.002205	0.435
Step 8	Aboveground carbon	lbs ac ⁻²	Biomass × 0.5	0.218

The LANDFIRE data used in this project represent the landscape circa 2008, and as a result, we needed to account for fires from after this time in the aboveground carbon analysis. Therefore, we made the following assumptions for dealing with fire effects on standing carbon in shrubs: All standing carbon is consumed within a burn perimeter identified by the Monitoring Trends in Burn Severity data layer (https://www.mtbs. gov/product-descriptions), and all shrubs are either nonsprouters, as in the case of nearly all *Artemisia* species, or they do not exhibit growth rates that would supply appreciable (or detectable) carbon since 2013. Using these assumptions, we set carbon values to zero at each pixel where a fire was estimated to have occurred since 2013.

Quantifying Temporal Variability of Shrub Cover

As mentioned, we used the version 1.1 EVC representing the landscape circa 2008. Shrub cover will obviously vary on an interannual basis, as will the various versions of EVC products (version 1.1, 1.2. 1.3, and 1.4). Likewise, the amount of biomass contained in shrubs across a national forest will vary in response to changes in shrub cover. As a result, we wanted to quantify the amount of variability of shrub cover through time to ensure that the biomass estimates from the 2008 landscape reasonably represent present-day conditions. To accomplish this objective, we quantified the mean and standard deviation using all versions of EVC available today. In this process, we used only shrub values (shrub pixels) that were within the Region 4 rangeland domain (Reeves and Mitchell 2011). In addition, all shrub pixels encountering fire (indicated from the MTBS data) were removed from the analysis. The amount of variability was then characterized as a percentage of the mean using equation 1:

 $Shrub_{Var} = (EVC_{srddev}/EVC_{mean}) \times 100, \tag{1}$

where Shrub_{Var} is the variability of shrub cover in the LANDFIRE EVC product, EVC_{mean} is the mean, and EVC_{stddev} is the standard deviation of shrub cover value from the EVC versions 1.1, 1.2. 1.3, and 1.4.

Soil Organic Carbon

Two existing data sources were available for estimating SOC: SSURGO and STATSGO (fig. 2). The SSURGO database is a much finer scale (1:24,000 versus 1:250,000) database than STATSGO. However, the SSURGO dataset is incomplete and provides less spatial coverage, especially in NFS lands (table 3). The SSURGO dataset provides 1.36 million ha of coverage while the STATSGO data covers about 3.54 million ha. The area of STATSGO coverage represents about 26 percent of the total national forest area in the region, whereas the SSURGO coverage in the 0- to 30-cm depth range represents only about 10 percent (table 3). Where no SSURGO data were available, the STATSGO data were used.

A provisional SSURGO dataset for Utah, not yet publicly available (Campbell 2016), supplemented SSURGO data to assist in filling some soil survey gaps (fig. 2). The provisional SSURGO data represent draft or interim data, but they still provide the best and most recent soil survey information available and provide much more detailed soil carbon information than STATSGO for these areas containing spatial gaps. These data are available only for the State of Utah and only the full soil depth. The dataset does not break out the 0-to 30-cm depth range. Henceforth they are referred to as the "Utah SSURGO."



Figure 2—Area that is not modeled in this report for any reason (gray area in panel A); SSURGO coverage and the areas where STATSGO has valid data but SSURGO does not (in black; panel B); areas where SSURGO data are valid when combined with the supplemental Utah data (panel C), but this coverage applies only to the 0- to 999-cm depth range because the supplemental data do not break out the 0- to 30-cm depth range.

Table 3—Areas of coverage by geospatial data for the Region 4 soil organic carbon assessment. The total area that can be modeled is rangeland only; agriculture, urban, water, and other land uses are excluded. The Utah SSURGO data are unofficial and cover only the full soil depth, not the 0- to 30-cm depth. The SSURGO and STATSGO data are official and contain the two soil depths. The modeled area is the area where the 0- to 30-cm depth was estimated from models rather than STATSGO data.

Forest	Estimated area of national forest	Total area that can be modeled	Utah SSURGO (0–999 cm depth) area	SSURGO area	STATSGO area	Modeled area (0–30 cm
			ha	a		
Uinta-Wasatch-Cache National Forest	1,179,333	280,720	822,420	172,130	276,721	108,590
Boise National Forest	1,023,025	179,803	N/A	122,252	159,292	57,551
Caribou-Targhee National Forest	1,245,942	341,063	3,431	259,976	320,582	81,087
Fishlake National Forest	723,993	140,290	711,144	3,839	138,990	136,451
Ashley National Forest	567,245	125,121	4,975	6,110	120,768	119,011
Humboldt-Toiyabe National Forest	2,714,700	1,256,071	N/A	532,859	1,250,416	723,211
Sawtooth National Forest	886,696	381,122	37,355	46,630	378,795	334,492
Salmon-Challis National Forest	1,779,874	357,765	N/A	1,324	356,098	356,441
Payette National Forest	974,617	36,791	N/A	109	36,849	36,682
Dixie National Forest	692,828	114,065	668,958	33,057	101,773	81,007
Bridger-Teton National Forest	1,403,364	362,678	N/A	168,766	295,139	193,912
Manti-La Sal National Forest	572,561	111,428	89,878	11,265	101,573	100,163
Total	13,755,304	3,686,915	2,338,162	1,358,318	3,536,997	2,328,597

For this project we assessed SOC at the 0- to 30-cm depth and the full soil depth. In the SSURGO and STATSGO datasets, SOC estimates were available by soil horizon, except in the Utah SSURGO. Where the Utah SSURGO data were used to fill gaps, it was necessary to model SOC at the 0-to 30-cm profile. Soil organic carbon was modeled as a function of normalized differenced vegetation index (NDVI) and mean annual temperature (MAT) in a similar manner as Ogrič and others (2019) and Patton and others (2019). The NDVI was derived as the annual maximum NDVI value from biweekly composites of the Moderate-Resolution Imaging Spectroradiometer (MODIS) at 250-m × 250-m spatial resolution, and the MAT was obtained from the PRISM (Parameter-elevation Regression on Independent Slopes Model) project (Daly et al. 2008). Mean annual temperature was computed from 1980 through 2016 while the MODIS data were evaluated from 2000 through 2016.

Statistical modeling was carried out in the R statistical programming environment (R Core Team 2016; glmnet package in R, Friedman et al. 2010). Soil organic carbon values were log-transformed prior to model fitting. Five potentially important predictors of SOC (MAT, NDVI, interannual variability of NDVI, elevation, and annual precipitation) were explored in models fit with lasso regularization and 10-fold cross validation (Friedman et al. 2010).

The final equation used to predict SOC at the 0- to 30-cm horizon depth was:

$$SOC_{020} = EXP^{[6.4660163 + [(-0.0472868) \times (MAT) + (0.0003712) \times (NDVI)]},$$
(2)

where SOC_{030} is modeled SOC over the 0- to 30-cm horizon depth in grams of carbon [C] m⁻², MAT is mean annual temperature, and NDVI is the annual maximum MODIS-derived NDVI value.

Data were also missing for the full depth. Thus, we developed estimates of SOC for the full depth, where needed, based on a relationship with SOC at 0 to 30 cm.

The linear relationship between SOC at the 0- to 30-cm horizon depth and the full depth was:

 $SOC_{0999} = 1.8282 \times (SOC_{030}) + 700.1,$ (3)

where SOC_{0999} is the estimated value of SOC through the entire horizon, and SOC_{030} is the modeled estimate of SOC. This relationship was developed using the SSURGO and Utah SSURGO data describing SOC at the 0- to 30-cm and 0- to 999-cm soil profiles.

Creating Seamless Layers of Soil Organic Carbon for Both Depths

We developed two different seamless depictions of SOC at the 0- to 30-cm depth. The first model is based solely on SSURGO data and modeled estimates without coarser resolution STATSGO data. We first selected SSURGO data and if SSURGO data were missing, then the modeled estimates of SOC from equation 2 were used to fill the remainder of the rangeland area in Region 4. In a similar manner, we created a second model that combined SSURGO, STATSGO and, where STATSGO data were not available, the modeled estimates from equation 2.

To understand the accuracy of our approach to estimate SOC for the 0- to 30-cm depth at the scale of national forests, we compared the observed SOC values with the predictions at each national forest. The observations were derived using whatever SOC values were available in the SSURGO dataset. The predicted values come from equation 2, scaled to each national forest and compared with the observed SOC density on each national forest. In similar manner, observations of SOC within the 0- to 999-cm depth were compared with estimates derived from equation 3. In deriving statistical metrics, no hold-out dataset is used because the reporting unit is national forests, of which there are only 12. In this case a hold-out dataset is one in which observed values of carbon are withheld from the modeling process and would be available for independent evaluation of accuracy of resulting models.

We also developed two different seamless depictions of SOC for the full soil depth profile. The first spatially explicit model does not include STATSGO estimates and was developed in three steps: We first selected Utah SSURGO data, followed by SSURGO data, and if neither SSURGO nor Utah SSURGO were available, then we applied the modeled estimates of SOC from equation 3 to fill the remainder of the rangeland area in Region 4. For the second spatially explicit model, we first selected Utah SSURGO data, followed by SSURGO nor Utah SSURGO were available, then SSURGO data, and if neither SSURGO nor Utah SSURGO data, followed by SSURGO data, and if neither SSURGO were available, then SSURGO data, followed by SSURGO were available, then SSURGO data, and if neither SSURGO nor Utah SSURGO were available, then STATSGO data were used.

These four models offer independent estimates of SOC at the 0- to 30-cm and 0- to 999-cm depth ranges. We then generated ensemble models from the means of these two modeled layers at each depth. The resolution of the STATSGO data commingles forest and rangeland areas into one estimate (see figure 3) and produces smaller SOC density estimates than SSURGO. We determined carbon values and the spatial variability of SOC for each national forest.



Figure 3—Predicted and observed soil organic carbon (SOC) at the 0- to 30-cm depth aggregated to each national forest in Region 4. The predicted values come from equation 2 while the observations are derived from SSURGO at the same locations. MAE is mean absolute error. The codes for each national forest are as follows: ANF, Ashley National Forest; BNF, Boise National Forest; BTNF, Bridger-Teton National Forest; CTNF, Caribou-Targhee National Forest; DNF, Dixie National Forest; FNF, Flathead National Forest; HTNF, Humbolt-Toiyabe National Forest; MLNF, Manti-LaSal National Forest; PNF, Payette National Forest; SCNF, Salmon-Challis National Forest; SNF, Sawtooth National Forest; and UWCNF, Uinta-Wasatch-Cache National Forest.

RESULTS

Aboveground Carbon

At the scale of results reported here (national forest) the shrub cover exhibits low variability through time (fig. 4). This outcome indicates that the version 1.1 EVC (landscape circa 2008) can be used to derive regional estimates of standing carbon in the shrubs. Total standing carbon within the rangeland domain of Region 4 for the maximum, average, and minimum shrub height categories was estimated to be 21.16, 17.41, and 13.99 Tg C, respectively. The Humboldt-Toiyabe National Forest (located throughout Nevada and east-central California), due to its large extent, had the greatest amount of standing carbon: an estimated average of 7.7 Tg C (table 4). Carbon densities at the tallest shrub height ranged from 1.38 Mg C ha⁻¹ (Bridger-Teton National Forest, located in western Wyoming) to 13.33 Mg C ha⁻¹ (Dixie National Forest, located in southern Utah). Carbon densities at the medium shrub height ranged from 1.19 Mg C ha⁻¹ (Bridger-Teton National Forest) to 12.45 Mg C ha⁻¹ (Dixie National Forest). Carbon densities at the smallest shrub height ranged from 0.61 Mg C ha⁻¹ (Bridger-Teton National Forest) to 11.75 Mg C ha⁻¹ (Dixie National Forest).

Forest	Total area that can be modeled	Maximum	Average	Minimum	Average standing carbon
	(ha)		-(Mg C ha ⁻¹)		(Tg C)
Uinta-Wasatch-Cache National Forest	280,720	6.48	5.06	3.63	1.42
Boise National Forest	179,803	3.89	2.67	1.61	0.48
Caribou-Targhee National Forest	341,063	3.08	2.35	1.52	0.80
Fishlake National Forest	140,290	10.55	9.62	8.91	1.35
Ashley National Forest	125,121	4.80	4.08	3.60	0.51
Humboldt-Toiyabe National Forest	1,256,071	7.48	6.16	5.26	7.74
Sawtooth National Forest	381,122	5.38	4.49	3.25	1.71
Salmon-Challis National Forest	357,765	3.19	2.10	1.03	0.75
Payette National Forest	36,791	2.72	1.90	1.09	0.07
Dixie National Forest	114,065	13.33	12.45	11.75	1.42
Bridger-Teton National Forest	362,678	1.38	1.19	0.61	0.43
Manti-La Sal National Forest	111,428	7.27	6.46	5.83	0.72

 Table 4—Standing carbon density of shrubs in the rangeland domain of Region 4.

Temporal Variability of Shrub Carbon

The temporal variability of shrub carbon depends on numerous factors. The carbon estimates are, by design, sensitive to shrub structure as indicated by the EVC and EVH products, especially EVC. We evaluated the effect of estimated changes in EVC between the various LANDFIRE product versions. Shrub cover varies by about 0.4 to 13 percentage points across the various LANDFIRE product releases (versions 1.1, 1.2. 1.3, and 1.4) (fig. 4). However, the amount of shrub cover estimated to occur within the NFS boundaries is very small in relation to the entire region (fig. 4A). The Sawtooth National Forest (located in southern Idaho and northern Utah), Salmon-Challis National Forest (east-central Idaho), and Boise National Forest (central Idaho) all exhibit variability in shrub cover greater than 8 percent.



В					
National Forest	Mean Change in Shrub Cove				
	(%)				
Uinta-Wasatch-Cache National Forest	0,38				
Boise National Forest	8.74				
Caribou-Targhee National Forest	4.41				
Fishlake National Forest	1.33				
Ashley National Forest	5.01				
Humboldt-Toiyabe National Forest	2.45				
Sawtooth National Forest	10.30				
Salmon-Challis National Forest	13.14				
Payette National Forest	5.28				
Dixie National Forest	2.48				
Bridger-Teton National Forest	5.49				
Manti-La Sal National Forest	0.60				

Figure 4—The interannual variation in shrub cover in Region 4 (panel A; note the overall lack of shrub-dominated vegetation cover within the national forest boundaries); the estimated variation of shrub cover as indicated by the versions (1.1, 1.2. 1.3, and 1.4) of the LANDFIRE Existing Vegetation Cover product (panel B).

Modeled Estimates of Soil Organic Carbon

The model of SOC in the 0- to 30-cm depth range described in equation 2 resulted in an adjusted R^2 for the final model of 0.82, indicating a good overall linear fit. Residual diagnostics did not indicate any further potential problems with this fit. Similarly, the modeled estimates of SOC in the full depth described in equation 3 had an adjusted R^2 of 0.85.

The resulting comparison of predicted (modeled) versus observed SOC indicated that the modeling process was reasonable at the scale it was applied. For the 0- to 30-cm depth, the R² is 0.71 with a bias of 275 g C m⁻² (2.75 mg C ha⁻¹), and mean absolute error of 649 g C m⁻² (6.49 mg C ha⁻¹). For the entire profile (0–999 cm), the R² is 0.86, with a bias of 160 g C m⁻² (1.6 Mg C ha⁻¹), and mean absolute error of 638 g C m⁻² (6.38 Mg C ha⁻¹) (figs. 3, 5). It is important to understand the relationship between SSURGO and STATSGO estimates of SOC because it can affect the interpretation of all the area where these data were used to estimate SOC across the landscape. Recall that where SSURGO data exist, they were preferentially used, but where they did not exist, the STATSGO data were used. Comparing SSURGO to STATSGO SOC data where the two data sources are spatially coincident reveals that on average, the SSURGO data produced estimates of SOC that were about 25 percent greater than where STATSGO was used to fill in missing values. Anywhere that SSURGO data are used more consistently in place of STATSGO, the SOC estimates will be relatively higher.



Figure 5—Predicted and observed soil organic carbon (SOC) at the 0- to 999-cm depth aggregated to each national forest in Region 4. The predicted values come from equation 3 while the observations are derived from SSURGO at the same locations. MAE is mean absolute error. The codes for each national forest are as follows: ANF, Ashley National Forest; BNF, Boise National Forest; BTNF, Bridger-Teton National Forest; CTNF, Caribou-Targhee National Forest; DNF, Dixie National Forest; FNF, Flathead National Forest; HTNF, Humbolt-Toiyabe National Forest; MLNF, Manti-LaSal National Forest; PNF, Payette National Forest; SCNF, Salmon-Challis National Forest; SNF, Sawtooth National Forest; and UWCNF, Uinta-Wasatch-Cache National Forest.

Soil Organic Carbon Estimates in the 0- to 30-cm Depth

For SOC in the 0- to 30-cm depth, carbon densities ranged from about 2 to 4.5 kg C m⁻² (20 to 45 Mg C ha⁻¹) (table 5). The Humboldt-Toiyabe National Forest, along with the Ashley National Forest (located in northeastern Utah and southwestern Wyoming), had the lowest carbon densities, around 2 kg C m⁻² (20 Mg C ha⁻¹). The Uinta-Wasatch-Cache National Forest (northern Utah, southeastern Idaho, and southwestern

Wyoming), Caribou-Targhee National Forest (southeastern Idaho, western Wyoming, and northern Utah), Sawtooth National Forest, and Boise National Forest had carbon densities above or very near 4 kg C m⁻² (39.5 to 40 Mg C ha⁻¹).

Table 5—Data describing soil organic carbon at the 0- to 30-cm depth. STD is standard deviation, sum is total estimated standing carbon, and CV is coefficient of variability. Model 1 does not include STATSGO estimates and was developed in three steps: First Utah SSURGO data were used, followed by SSURGO data, and if neither SSURGO nor Utah SSURGO were available, then modeled estimates from EQ. 2 were used to fill gaps. In Model 2, Utah SSURGO data were selected first, followed by SSURGO data, and if neither SSURGO were available, then STATSGO data were used.

Forest		Model 1			Model 2			Model ensemble			
	Total area that can be modeled	Mean	STD	Sum	Mean	STD	Sum	Mean	STD	Sum	CV
	(ha)	(kg C n	n ⁻²)	(Tg C)	(kg C n	1 ⁻²)	Tg C	(kg C m	- ⁻²)	(Tg C)	(%)
Uinta-Wasatch- Cache National Forest	280,720	4.83	2.48	13.57	3.66	2.41	10.18	4.25	0.83	11.87	0.20
Forest	179,803	3.98	1.37	7.15	3.92	1.44	6.33	3.95	0.04	6.74	0.01
Caribou-Targhee National Forest	341,063	4.78	2.17	16.30	4.29	2.08	13.85	4.53	0.35	15.07	0.08
Fishlake National Forest	140,290	3.22	1.81	4.52	2.31	2.02	3.20	2.77	0.65	3.86	0.24
Ashley National Forest	125,121	2.77	1.67	3.46	1.38	1.01	1.66	2.07	0.98	2.56	0.48
Humboldt-Toiyabe National Forest	1,256,071	2.60	1.66	32.69	1.78	1.10	22.41	2.19	0.58	27.55	0.26
Sawtooth National Forest	381,122	4.18	1.96	15.92	4.06	1.62	15.36	4.12	0.08	15.64	0.02
Salmon-Challis National Forest	357,765	3.15	1.20	11.26	2.46	0.99	8.74	2.80	0.49	10.00	0.17
Payette National Forest	36,791	4.17	1.22	1.53	2.84	1.16	1.04	3.50	0.94	1.29	0.27
Dixie National Forest	114,065	2.80	1.53	3.19	1.88	1.80	1.92	2.34	0.65	2.56	0.28

Soil Organic Carbon Estimates in the Full Depth

For SOC in the entire soil depth, carbon densities ranged from about 4 to 11 kg C m⁻² (40 to 110 Mg C ha⁻¹) and exhibited great variability (table 6). The Humboldt-Toiyabe National Forest and Ashley National Forest had the lowest carbon densities: 4.4 and about 4 kg m⁻², respectively. The Ashley National Forest had the greatest coefficient of variability (64 percent), indicating greater disagreement between the models in that national forest (table 6). The total SOC (SOC across all rangeland domain within the national forests) ranged from about 2.4 Tg C in the Payette National Forest (located in central western Idaho) to 55 Tg C in the Humboldt-Toiyabe National Forest. It is important to understand, however, that the estimates provided in table 6 represent the results of SOC estimated from two modeling approaches and their ensemble. As a result, the values of SOC estimated across the full soil depth in this study have a range of possible outcomes.

Table 6—Data describing soil organic carbon at the 0- 999 cm (full depth). STD is standard deviation, sum is total estimated standing carbon, and CV is coefficient of variability. Model 1 does not include STATSGO estimates and was developed in three steps: First Utah SSURGO data were used, followed by SSURGO data, and if neither SSURGO nor Utah SSURGO were available, then modeled estimates from EQ. 2 were used to fill gaps. In Model 2, Utah SSURGO data were selected first, followed by SSURGO data, and if neither SSURGO were available, then STATSGO have used.

Forest	Model 1				Model 2			Model ensemble			
	Area that can be modeled	Mean	STD	Sum	Mean	STD	Sum	Mean	STD	Sum	CV
	(ha)	(kg C n	n ⁻²)	(Tg C)	(kg C n	n ⁻²)	(Tg C)	(kg C n	1 ⁻²)	(Tg C)	(%)
Uinta-Wasatch- Cache National Forest	280,720	10.33	7.45	27.95	8.66	4.95	24.12	9.49	1.18	26.03	0.12
Boise National Forest	179,803	7.98	2.50	14.08	6.66	2.33	10.75	7.32	0.94	12.41	0.13
Caribou-Targhee National Forest	341,063	9.45	3.98	31.59	9.26	5.13	29.93	9.36	0.13	30.76	0.01
Fishlake National Forest	140,290	11.08	8.85	14.86	10.56	7.70	14.81	10.82	0.37	14.83	0.03
Ashley National Forest	125,121	5.79	3.05	6.98	2.17	1.63	2.62	3.98	2.56	4.80	0.64
Humboldt-Toiyabe National Forest	1,256,071	5.47	3.13	67.43	3.32	2.39	41.73	4.40	1.52	54.58	0.35
Sawtooth National Forest	381,122	8.40	3.68	31.42	8.30	3.38	31.40	8.35	0.08	31.41	0.01
Salmon-Challis National Forest	357,765	6.47	2.20	22.65	4.69	1.93	16.65	5.58	1.26	19.65	0.23
Payette National Forest	36,791	8.34	2.24	3.00	4.66	2.32	1.71	6.50	2.60	2.36	0.40
Dixie National Forest	114,065	8.62	6.48	9.43	8.18	6.27	9.33	8.40	0.31	9.38	0.04
Bridger-Teton National Forest	362,678	8.82	4.81	31.25	4.85	3.21	16.13	6.84	2.81	23.69	0.41
Manti-La Sal National Forest	111,428	9.46	5.38	10.04	5.14	5.87	5.44	7.30	3.05	7.74	0.42

DISCUSSION

We have developed a unique methodology to estimate carbon stocks in rangeland areas based on a combination of standing carbon in shrubs and SOC across landscapes. This work was conducted to directly support the Forest Plan Revision process in Region 4. The results offer insight into aboveground and belowground carbon stocks but require thoughtful consideration when interpreting these data. To illustrate, it is important to remember that there is a large difference between minimum and maximum estimates of standing carbon. For example, the Salmon-Challis National Forest exhibits a 68-percent difference between the maximum and minimum estimates of standing carbon densities. This large difference reflects a great diversity of shrub heights and species within the region, along with substantial heterogeneity through varying stand ages presumably caused by disturbance, principally fire. Our assumption that all carbon is consumed by fire is not quite realistic because not all carbon is consumed in a flaming front where shrubs are present. Other analyses can easily adopt our method and then use other consumption estimates as desired. For example, those from the Intergovernmental Panel on Climate Change Fifth Report (see IPCC 2014: chapter 2, tables 2.4, 2.5, and 2.6) provide fuel biomass consumption values for estimating proportion of biomass lost in fires. Differences between SSURGO and STATSGO produced considerable variability in background estimates as well. The methods developed by Cao and others (2019) and Domke and others (2017) could add improvements over the present work.

Although this project was developed for national forests in Region 4 to provide carbon stock estimates in support of Forest Plan Revision, the process developed can be applied to any spatial extent, such as national forests or ranger districts. It is well established that past management actions influence carbon stocks, but these management actions may not be reflected in the estimates of belowground carbon given a lack of land use history and up-to-date soil data in a spatially explicit manner. As a result, the data developed here are applicable to scales of ranger districts or national forests, or greater, but not for local interpretation (e.g., 10s of hectares). Our results are similar to those of other studies seeking to map SOC in rangelands. Vågen and Winowiecki (2013) report R² values of 0.65 in East Africa for predictions in the 0- to 30-cm depth range. In a study similar to ours, Gonzalez and others (2015) used LANDFIRE EVH data and other information to estimate changes in carbon stocks in California. In 2010, Gonzalez and others (2015) estimated shrub carbon stocks in California to be 66 +/- 53 Tg (95-percent confidence interval).

Just as past land management and disturbances influence carbon stocks, future land management decisions may enhance SOC (Thomey et al. 2014). Within Region 4, near-surface SOC (by mass) for most soils ranges from 0.5 percent for hotter and drier areas to 8 percent for the cooler and moist areas (Brady and Weil 1999). Due to SOC saturation under the limitation of warm, dry conditions, carbon storage will decrease under future warmer and drier climate. The greatest opportunity for improving carbon sequestration on rangeland is on degraded sites (Derner and Schuman 2007), especially where soil erosion may occur. Typical soil erosion rates under land use may be up to 1 mm per year while topsoil replenishes at a rate of less than 0.1 mm per year (Thurow and Taylor 1999).

Strategies to increase SOC generally involve activities that increase vegetative ground cover, which protects soil and promotes organic matter formation and retention. A 1-percent increase in organic matter can triple water holding capacity, equivalent to an additional 3 inches (7.6 cm) of rain per year (Steiner et al. 2015), which increases productivity and resistance to drought. Region 4 has potential to manage both aboveground and belowground carbon through vegetation management. More annual production occurs below the soil surface in grasslands because roots are a primary contributor of organic matter (Sims and Singh 1978). Management strategies include management for deep-rooted perennial herbaceous plants, drought-tolerant herbaceous plants, and diverse native plants. Limiting soil disturbance during vegetation management operations and limiting losses due to catastrophic fires, when carbon is consumed, also protect the soil resource. Management of aboveground carbon affects belowground carbon, and changes to belowground carbon affect water-holding

capacity and aboveground vegetation. At a forest planning scale, carbon estimates can be used to provide interpretations as to the vulnerability of ecosystems to changes in productivity, drought, and climate change. Indeed, SOC may be an early indicator that change in ecosystems is occurring. However, it should be noted that there appears to be greater variability in the SOC values in the 0- to 30-cm depth compared with the 0-to 999-cm depth. This difference may reflect the number of studies that look at the 0- to 30-cm depth compared with those looking at the full depth (0–999 cm). In addition, it is highly difficult to quantify SOC flux and under the best of circumstances, site-level estimates from models such as those developed in this report are associated with high levels of uncertainty. Moreover, the assessment of uncertainty is itself difficult when considering SOC flux on rangelands.

CONCLUSIONS AND MANAGEMENT IMPLICATIONS

Planners and managers are already using these data throughout Region 4. Initial funding for this effort yielded a cogent and novel process for evaluating SOC and standing carbon in shrubs. These data can be used to support Forest Plan Revisions and also yield the first-ever evaluations of standing carbon pools in shrubs where that information is needed. In addition, the process developed here can be easily scaled to smaller or larger areas as needed. It is important to remember, however, that this process will not work for evaluating carbon flux or sequestration rate. Instead, it offers a coarse estimate of SOC and standing carbon in shrubs. The data and modeling procedures developed here can be applied in other ways and in other NFS regions seeking baseline carbon estimates for rangelands.

It is important to consider potential sources of uncertainty. First, this is a cursory evaluation of carbon in rangelands of Region 4 and a careful analysis is needed to identify how disturbance affects these carbon estimates. Second, the uncertainty in the LANDFIRE EVC and EVH should be considered as main sources of uncertainty because our results depend directly on these data. Third, the uncertainty associated with the allometric relationships linking EVC, EVH, and EVT to biomass and carbon should be considered. Figure 4 offers evidence for this issue, showing how shrub cover is estimated to change on an interannual basis. Though changes are fairly small, they can affect the associated carbon stock estimates. Fourth, the errors in the SSURGO and STATSGO data sources will greatly influence our ability to model SOC. Finally, it is important to note that we did not address live belowground carbon pools, which could be substantial. Quantifying these pools represents a next logical step in future work.

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