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Deep soil organic carbon stocks in pastures do not reflect surface soil properties or land use

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Abstract

Optimizing soil organic carbon (SOC) sequestration in pasture systems requires understanding the carbon storage capacity across the entire soil profile. Though SOC concentrations typically decline with depth, the large volume of subsurface soil means it can constitute more than half of the total SOC pool. Therefore, it is important to consider deeper soil layers beyond those typically sampled (i.e., 0–30 cm). Here, we quantified the SOC stocks to 1 m on 12 Vermont (USA) pastures. This SOC stock averaged 12.9 kg C m^{-2} (range 8.8–19.2), which is consistent with both SOC storage in US grasslands and average stocks across Vermont, including forests. Environmental variables, including temperature, precipitation, and pH, were generally poor predictors of SOC stocks, though there was a positive relationship between clay content and surface SOC. We found that surface SOC stocks in these pastures were not a good predictor of deeper SOC stocks. Variability in SOC stocks, which increased with depth, may instead be influenced by untested factors. Depth to bedrock and accurate bulk density measurements substantially influence total SOC estimates and are important considerations for quantifying SOC. Our results suggest that the labor-intensive collection of deep soil cores is necessary to accurately quantify soil carbon. Pastures are tractable landscapes for managing soil carbon compared to forests, and intensive sampling provides a baseline for evaluating soil carbon sequestration in these systems.

Plain Language Summary

We studied how much soil carbon is stored in 12 pastures in Vermont. While most soil studies only sample the top 30 cm, we measured down to 1 m and found that deeper soils can hold more than half of the total soil carbon. On average, these pastures stored 12.9 kg of carbon m^{-2}, similar to other grasslands across the United States and forests in Vermont. We discovered that surface carbon levels did not predict how much carbon was deeper in the soil. Variability in the soil organic carbon increased

Abbreviations: BD, bulk density; CASH, Comprehensive Assessment of Soil Health; MAP, mean annual precipitation; MAT, mean annual temperature; NCSS, National Cooperative Soil Survey Soil Characterization Database; PTF, pedotransfer function; SOC, soil organic carbon.

in deeper soil. Factors like soil texture, depth to bedrock, inorganic carbon, and bulk density were more important. Our results show that to understand and manage carbon storage in pasture soils, we need to sample deeper layers, even though it requires more work.

1 | INTRODUCTION

Soil organic carbon (SOC) is the largest terrestrial carbon stock (Jobbágy & Jackson, 2000), and more than half of SOC resides below 30 cm (Chaopricha & Marín-Spiotta, 2014; Harrison et al., 2011; Jackson et al., 2017; Jobbágy & Jackson, 2000). However, researchers rarely sample below this depth due to the logistical challenges and costs of deep soil coring (Yost & Hartemink, 2020). Deep soil carbon can play an outsized role in climate mitigation because of its mass and persistence (Paustian et al., 2016) and can be influenced by management and land use (Hicks Pries et al., 2023; Rumpel & Kögel-Knabner, 2011). The potential to protect and increase persistent SOC may be best realized at depth (Angst et al., 2018) where SOC is more stable due to organo–mineral interactions (Lehmann et al., 2020), unsaturated mineral surfaces (Georgiou et al., 2022), and reduced exposure to microbial activity, oxygen, temperature fluctuations, and direct disturbances (Hicks Pries et al., 2023).

Grazing lands have substantial carbon sequestration potential worldwide (Follett & Reed, 2010; Lal, 2024). Pastures allocate proportionally more plant-derived carbon belowground than forests, which can contribute to deep SOC stocks (Jobbágy & Jackson, 2000). These belowground inputs may persist in the soil because they often decompose more slowly than aboveground inputs (Jackson et al., 2017). However, root inputs do not necessarily translate into greater SOC at depth. Increased rhizodeposition may stimulate microbial activity and induce positive priming (Tian et al., 2016), potentially accelerating SOC loss at depth. Complementary evidence suggests that deep SOC can remain stable in the absence of new carbon inputs like root exudates (Hicks Pries et al., 2018). In many temperate regions, pastures were converted from forests, but the contrasting roles of roots in SOC storage can make it difficult to predict how land use change will affect SOC storage at depth. A decrease in SOC through the soil profile has been documented following forests' conversion to agricultural land (Hauser et al., 2022), yet grazing lands generally store more SOC than annual cropping systems due to continuous plant cover and more established rooting systems for belowground carbon input (Shang et al., 2024).

Given our limited knowledge of SOC content at depth (Don et al., 2024), empirical measurements are critical for research design, management decisions, and climate mitigation considerations (Stockmann et al., 2013). SOC is notoriously variable across landscapes and is influenced by factors such as soil properties, landscape position, management, and depth (Heckman et al., 2022). Models, in general, have poor predictive capacity for carbon stocks and fluxes, particularly in deep soils (Todd-Brown et al., 2014). In pastures, high spatial variability in surface SOC content may be due to uneven distribution of manure from grazing animals (Franzluebbers, 1999). While forests have high variability in surface and deep (>60 cm) SOC (Eilers et al., 2012), how depths affect variability in pastures is unknown. Deep SOC variability may be due to factors influencing the downward redistribution of carbon through the soil such as roots. Quantifying SOC throughout the soil profile is essential because management, like tillage, can redistribute SOC to depth, reducing surface SOC while leaving total stock unchanged (Harrison et al., 2011). Establishing a baseline of carbon stocks across the profile will enable comparisons across land uses, provide estimates of carbon storage potential, and expand options for optimizing carbon sequestration efforts. Land managers can use information on the capacity for building persistent carbon stocks across the soil profile to support decision-making (Minasny et al., 2017). Increasing SOC content is most feasible in areas where soil is already being actively managed. Investigating SOC stocks in pastures is particularly important due to claims that rotational grazing or forage management can have a substantial influence on carbon stocks (Griscom et al., 2017).

Unfortunately, measuring deep carbon stocks is not a trivial endeavor. The labor involved in sampling soils, both in time and in physical effort, increases with depth and stone content. A particular challenge is measuring soil bulk density (BD), a necessary factor in the calculation of SOC stocks (Lang et al., 2025). Pedotransfer functions (PTFs) are one option used to predict BD from other soil properties like SOC concentrations, circumventing the need to take empirical BD measurements for every soil sample (Abdelbaki, 2018). Additionally, using shallow SOC data to predict deep SOC stocks could provide a cost-effective and time-efficient alternative to deep soil sampling (Garrett et al., 2024; Harrison et al., 2011). However, further research is needed to determine if shallow SOC can reliably reflect deep soil C stocks and if BD inferred from a PTF can be used to accurately estimate deep soil C stocks.

This study has four primary objectives. (1) To quantify a baseline for SOC stocks in northeastern US pastures to a depth of 1 m and compare these empirical measurements with SOC stock estimates from model predictions, global pasture data, and local forested ecosystems. We expect that the SOC stock in pastures will be lower than in forests due to soil disturbance and the loss of deep root inputs after forest clearing. (2) To evaluate how the variability of SOC stocks changes with depth. (3) To evaluate the potential predictors of deep SOC stocks, including easily measured factors such as climate, surface texture, pH, and soil health. (4) To evaluate potential methods for SOC stock estimation by (a) comparing stocks derived from measured BD to those derived from PTFs and (b) determining whether surface (0–15 cm) measurements can be effectively used to predict deeper organic carbon stocks (up to 1 m). We hypothesize that surface SOC stocks can predict subsurface carbon stocks as pastures are a more uniform land use than forests. We addressed these objectives using deep soil cores collected across actively grazed pastures in Vermont.

Core Ideas

- Pasture soil organic carbon (SOC) stock to 100 cm averaged 12.9 kg C m^{-2} (± 3, n = 12), similar to forest soils.
- Deep SOC (30–100 cm) was highly variable ~5 kg C m^{-2} (ranged 3–10) and contributed ~30%–50% of total SOC.
- Inorganic carbon, depth to bedrock, and accurate bulk density are key to quantifying SOC stock.
- Environmental variables and soil health were weak predictors of SOC stocks, particularly at depth.
- High spatial variability at depth means direct sampling is needed for precise estimates of soil carbon.

2 | METHODS

We quantified SOC stocks on pastures throughout Vermont. A total of 66 soil cores on 17 fields across 12 farms were collected between the summer of 2020 and fall of 2023 (Figure 1). The farm fields span a range of soil characteristics and climate conditions found in Vermont (Table 1). The region is dominated by Inceptisols and Spodosols (see Table S1 for specific soil series). Vermont has a humid continental climate where mean annual temperatures (MAT) range from 5.06˚C to 8.17˚C (mean 6.5˚C) and mean annual precipitation (MAP) ranges from 92.8 to 131 cm (mean 11.1 cm). One to three fields were selected for each farm, and then three

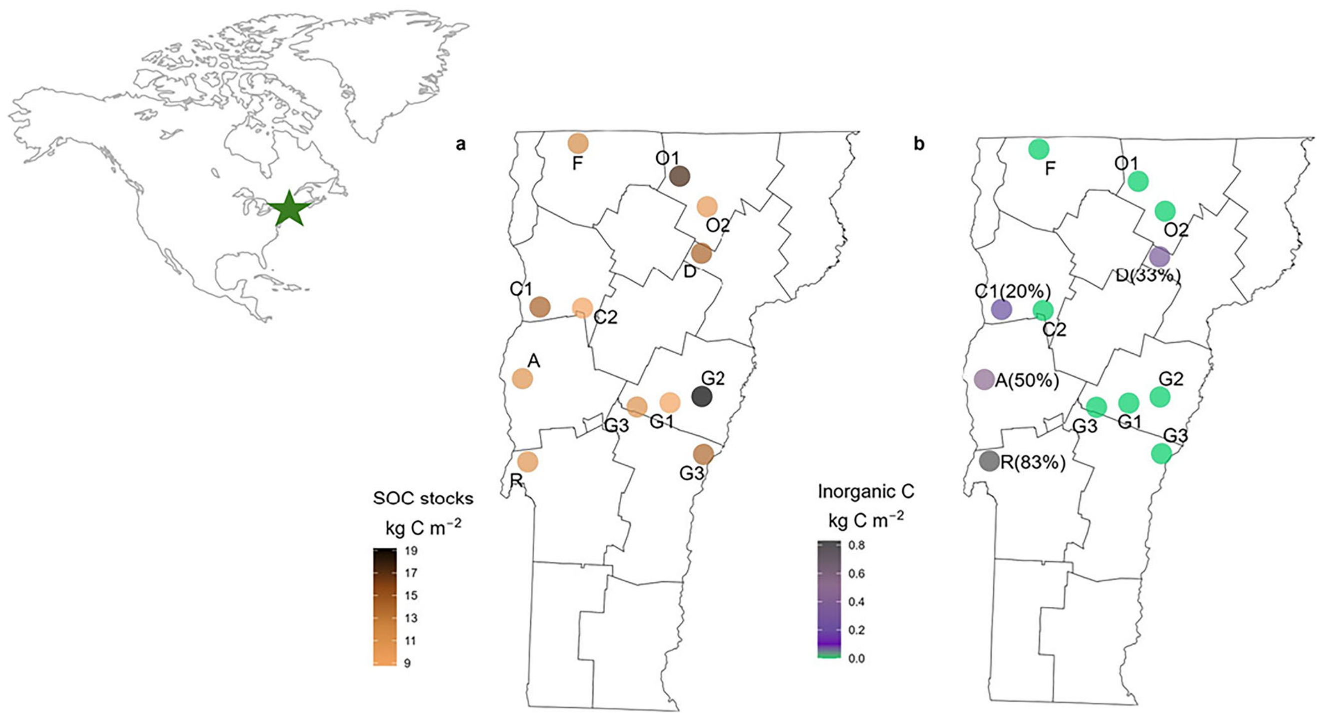

FIGURE 1 Approximate locations of 12 farms in Vermont (green star shows location of Vermont within North America) where we collected deep soil core samples. (a) Soil organic carbon stocks at each farm are represented by the brown color scale with darker colors showing greater SOC stocks to 100 cm and labels identifying the farms by county. (b) Labels indicate the farm ID and, for those farms where inorganic carbon was detected, the percentage of cores with inorganic carbon detected in parentheses. Locations where no inorganic carbon was detected are represented with green, while sites with inorganic carbon are represented by the purple color scale.

TABLE 1 Farms included in this study. Mean soil organic carbon (SOC) stock in all pastures to 100-cm depth was 12.9 kg C m^{-2} (± 3.1, n = 12 farms). Mean SOC stock using equivalent soil mass (ESM) up to 1032 kg m^{-2} of soil mass was 12.6 ± 3.21 (n = 12). Coefficient of variation (CV) reflects the variation in carbon stock between cores on each farm. ESM stock is the amount of SOC in the corresponding equivalent soil mass. Note that calculating stocks to 1032 kg m^{-2} ESM was not always possible due to incomplete data caused by the presence of ledge or just a lower bulk density due to rocks, so we also report the mean maximum ESM of the cores at each farm. Soil health index comes from the Comprehensive Assessment of Soil Health (CASH).

Farm ID	Cores (#)	County	SOC stock to 100 cm (kg C m^{-2} ± SD)	CV (%)	SOC stock to ESM (kg C m^{-2} ± SD)	ESM (kg soil m^{-2} ± SD)	MAT (˚C)	MAP (cm)	Soil texture	Grazing	Soil health index
A	4	Addison	10.7 ± 1.96	18.3	10.5 ± 1.06	957 ± 96	8.1	94	Clay loam	Dairy	72
O1	6	Orleans	17.5 ± 3.10	17.7	15.8 ± 2.15	1032 ± 0.25	5.5	131	Loam	Dairy	99
F	4	Franklin	11.7 ± 3.88	33.2	10.9 ± 2.41	1016 ± 31	7.2	107	Silt loam	Dairy	81
D	5*	Caledonia	14.2 ± 2.81	19.9	15.1 ± 3.23	840 ± 398	5.2	116	Loam	Beef	89
R	12	Rutland	10.6 ± 2.45	23.2	10.9 ± 2.11	923 ± 116	8.1	99	Silty clay loam	Beef	97
G1	4*	Orange	11.4 ± 4.89	42.9	15.3 ± 0.35	342 ± 372	5.4	108	Sandy loam	Beef	69
W	4	Windsor	13.9 ± 3.18	22.8	11.6 ± 2.33	1032 ± 0.68	6.6	107	Loam	Beef	81
C1	4	Chittenden	14.2 ± 3.22	22.7	13.9 ± 1.87	950 ± 117	7.8	99	Silty clay loam	Beef/sheep	81
O2	4	Orleans	10.1 ± 2.75	27.2	8.95 ± 2.06	1032 ± 0.34	5.1	125	Loam	Dairy	81
C2	4	Chittenden	8.77 ± 0.45	5.15	7.61 ± 0.69	820 ± 152	6.9	114	Loam	Dairy	54
G2	11	Orange	19.2 ± 2.95	15.4	18.8 ± 2.00	907 ± 105	5.6	118	Loam	Beef/dairy	97
G3	6*	Orange	12.3 ± 5.93	48.1	12.2 ± 2.40	439 ± 370	6.7	115	Loam	Sheep	43

Note: Symbol "*" denotes where ledge was encountered and carbon stocks were 0 below the depth of ledge.
Abbreviations: MAP, mean annual precipitation; MAT, mean annual temperature.

to four soil cores to 1-m depth were collected at randomized locations stratified across the field without regard to topography. Researchers roughly quartered the field and either used a randomly generated geographic information system point on a digital map (when available) or a frisbee thrown blindly into the quadrant in the field to locate each plot. Soil cores were taken in segments of ∼10 cm using a slide hammer corer for the first 30 cm (2′′ AMS, Inc.; 4.867 cm inner diameter) and the remaining with an auger (3′′ mud, AMS, Inc.; 7.62 cm inner diameter) with the exception of two more hammer core samples around 50–60 cm and 90–100 cm. Hammer core samples were used to calculate BD and carbon concentration, while auger samples were analyzed for carbon concentration only. Samples were kept cool in a cooler until brought back to the lab (within 8 h) where they were frozen at −20˚C until processing (for 6–8 months).

Subsamples were sieved (2 mm) to remove rocks and dried (105˚C for 48 h), then pulverized to homogenize. Ground subsamples were analyzed for carbon and nitrogen content using an ECS4010 elemental analyzer (Costech Analytical Technologies). To focus our analysis on organic carbon stocks, we also removed inorganic carbon from the subsamples prior to elemental analysis. We added 1N hydrochloric acid (HCl) to samples with pH > 7 to test for the presence of carbonates and found evidence of carbonates in 8% of total samples ($n = 45$ of 552 total); all those with evidence of carbonates had pH > 7.5. If we observed bubbles following the acid addition, we removed inorganic carbon from these samples using 6N HCl (Harris et al., 2001) and then re-analyzed them for C and N content.

For each pasture, researchers also collected soil using the Comprehensive Assessments of Soil Health (CASH) protocol for sample collection (Moebius-Clune et al., 2016). This protocol consists of collecting 10 subsamples of the top 15 cm of soil (organic litter removed from the surface) in a zigzag pattern across each field using a sharp trowel. The subsamples were composited and homogenized, then portioned for the standard CASH analysis from Cornell University Soil Health Lab. Soil health metrics and scores are derived from average indicator ratings of multiple biological, nutrient, and physical variables as compared to other previously analyzed samples in the CASH database. The CASH training manual (Moebius-Clune et al., 2016) describes each part of the CASH process, including rationale for including each metric with links to the standard operating procedures for processing and analyzing the samples. The metrics used in our analysis include active carbon, aggregate stability, pH, soil texture, and an overall soil health index. The overall soil health index (Table 1) is an integration of indicator scores derived from all metrics used in CASH and intended for interpretation and unit-less comparison among samples (Fine et al., 2017). Climate data for each field were derived from the Parameter-elevation Regressions on Independent Slopes Model using geographic coordinates and the data explorer. Data for MAT and MAP are averages of monthly climate normals for that location between 1991–2020 at 800 m resolution (PRISM Climate Group, Oregon State University, 2024).

2.1 | Carbon stocks

We calculated BD for samples taken with the hammer corer. Whole samples were weighed and then sieved (2 mm) to homogenize, then the removed rocks were weighed and measured for volume (Poeplau et al., 2017). Then a subsample was weighed wet and dried (105˚C for 48 h) to calculate gravimetric soil moisture. The BD in g cm^{-3} was calculated by dividing the moisture-corrected mass of the soil by volume of the core (Throop et al., 2012).

$$\mathrm{BD} = \left(M_{\mathrm{Dry}} - R\right) / \left(\pi \times r^2 \times (D_{\mathrm{L}} - D_{\mathrm{U}})\right)$$

where M_{Dry} is the dry mass of the total sample in g, R is the rock mass in g, r is the corer radius in cm, and D_{L} and D_{U} are the lower and upper depths of the interval, respectively, in cm. Because BD measurements were only obtained at locations in the profile where we used the hammer corer, we interpolated the BD across the depth profile using mass-preserving splines fit to our empirical measurements with the *mpspline2* package in R (Version 4.4.1; O'Brien, 2022). The same process was used to spline percent carbon data (Figure 2). The splines estimate average BD and percent carbon for standard depth intervals (0-5, 5–15, 15–30, 30–60, 60–100 cm) throughout the profile. The splines were fit separately for each core. Out of the 66 cores, we encountered bedrock ledge (rock beneath the soil) in seven, which prevented further sampling. For these cores, we assumed no SOC existed below the deepest collected soil, causing the splines to terminate early. To estimate soil carbon stocks (SC) in kg C m^{-2} for each depth interval within each core, the splined percent carbon data were multiplied by the splined BD data and by the length of the depth interval.

$$\mathrm{SC} = C/100 \times \mathrm{BD} \times \left(D_{\mathrm{L}} - D_{\mathrm{U}}\right) \times 10$$

where C is carbon in %, BD is bulk density in g cm^{-3}, and D_{L} and D_{U} are the lower and upper depths of the interval, respectively, in cm. The carbon in the equation can be total, organic, or inorganic depending on the stock being calculated.

We compared carbon stocks calculated using empirically measured BD against those estimated using a PTF for BD based on carbon concentration data. Abdelbaki (2018) evaluated the predictive capacity of 48 previously published PTFs. Of the eight high-performance functions, two matched our geographic scope and used percent organic carbon. These functions were as follows (Manrique & Jones, 1991;

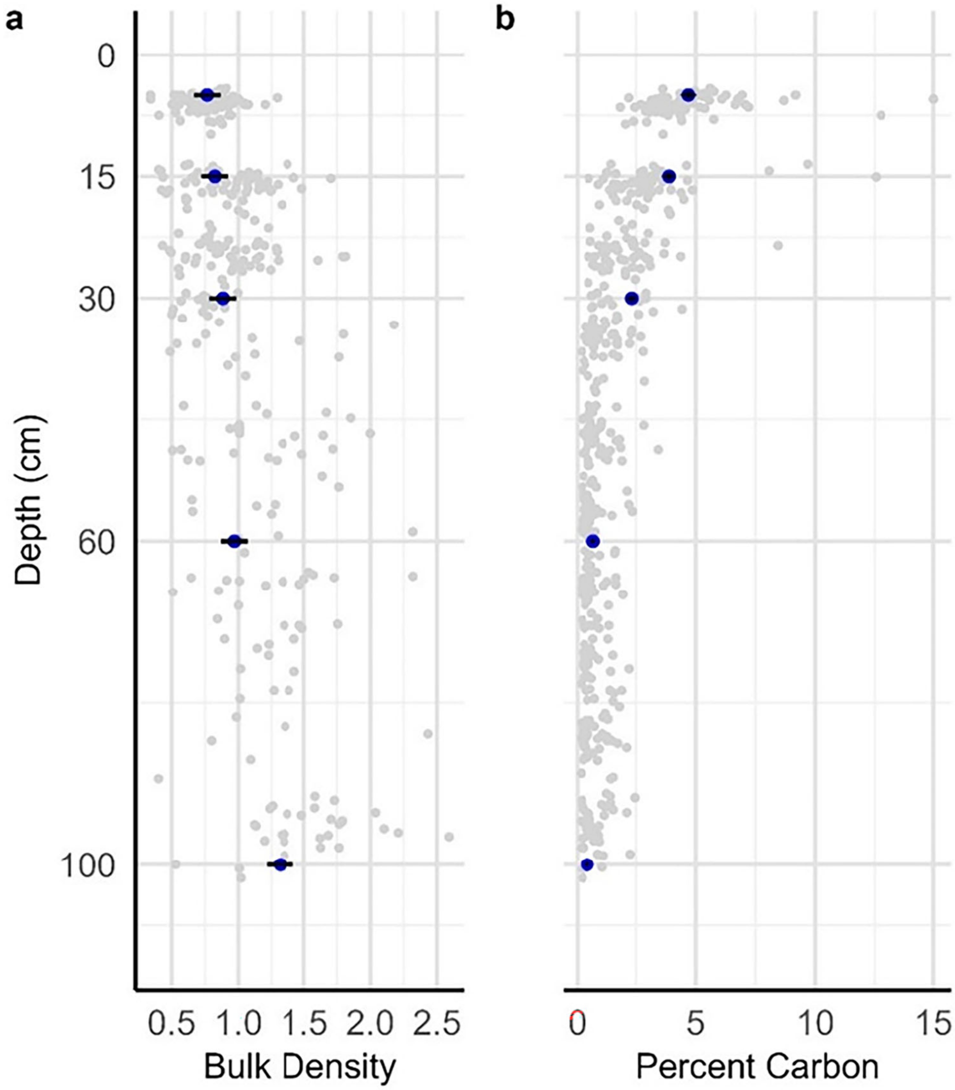

FIGURE 2 Bulk density (g soil cm^{-3}) and percent carbon by depth (lower depth interval) across all farms. Measured values are gray points, and the median of the splined values are blue points. Error bars show 95% confidence intervals for the splined medians, and most are too small to be seen.

Ruehlmann & Körschens, 2009):

$$\text{PTFa}: \ \text{BD} = 1.660 - 0.318(\text{OC})^{0.5}$$

$$\text{PTFb}: \ \text{BD} = (2.684 - 140.943 \times 0.006) \times e^{-0.006 \times \text{OC}}$$

where BD is the bulk density and OC is the measured organic carbon. We used these two functions to calculate BD before applying splines as described above, allowing us to compare the resulting stock estimates with those derived from empirical BD measurements.

In addition, we calculated SOC stocks using the equivalent soil mass (ESM) method (Wendt & Hauser, 2013; Von Haden et al., 2020). To enable comparison across cores, cumulative SOC profiles were interpolated onto a common set of equivalent mineral soil mass intervals derived from the median mass–depth relationship across all cores using 5-, 15-, 30-, 60-, and 100-cm depths. These depths corresponded to 34, 113, 237, 528, and 1032 kg m^{-2} ESMs. For each core, we determined mineral soil mass and SOC mass cumulatively using a monotonic cubic spline interpolation with method "monoH.FC" in the splinefun function in the *stats* package in R (Von Haden et al., 2020). We did not extrapolate beyond observed data. SOC stocks were expressed as incremental stocks across each ESM interval. Farm-level SOC stocks were then calculated by averaging each increment within farms (using only the cores that reached each interval boundary) and then summing those increment means across all intervals. For some farms, the full ESM (1032 kg m^{-2}) was not sampled due to the presence of ledge or rocks. Thus, when averaging stocks by intervals, the fixed-depth stock where ledge was hit is treated as a zero, while for ESM, the stock for the corresponding mass interval is treated as missing. For this study,

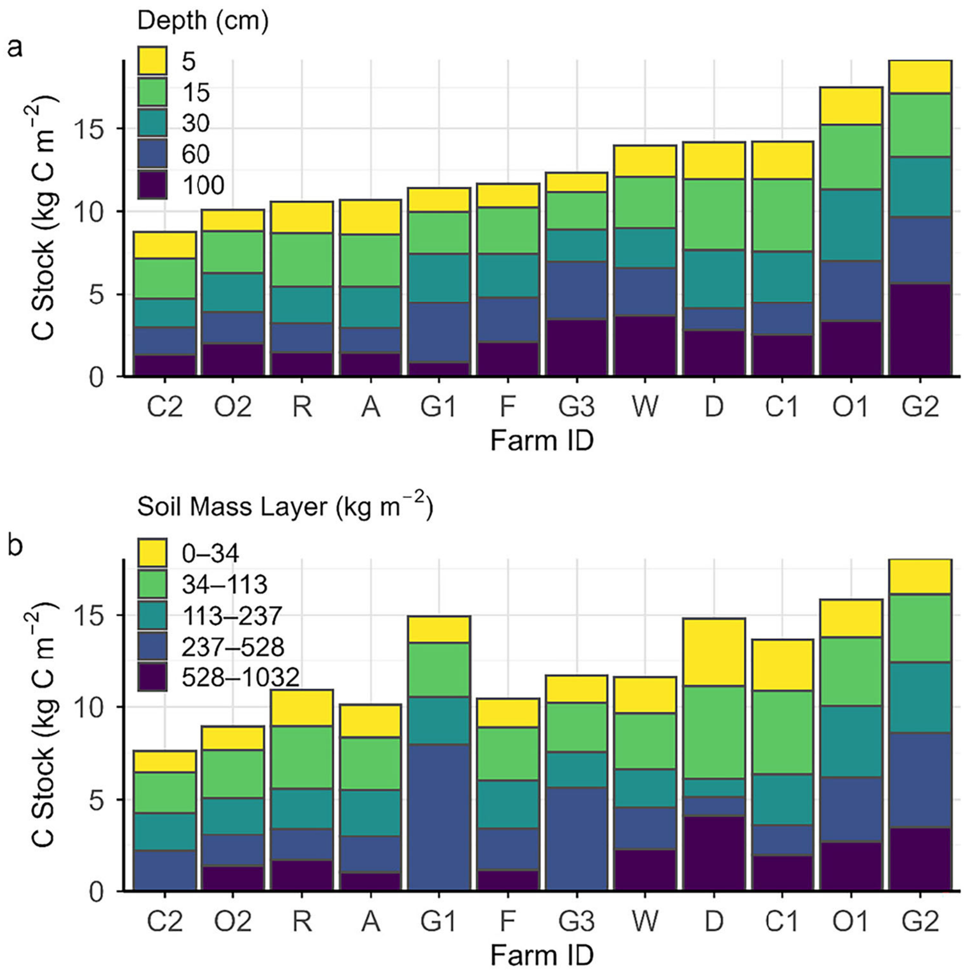

FIGURE 3 Mean soil organic carbon stocks across farm sites varied in overall magnitude and in proportion across (a) depth intervals and (b) equivalent soil mass (ESM) layers. Note that three of the farms hit ledge before the 528–1032 kg m^{-2} ESM intervals (C2, G1, and G3). We are thus not reporting stocks for those intervals to avoid extrapolation (Figure S1 shows fixed depths surface [0–30 cm] compared to deep [30–100 cm] SOC stocks).

we focus on the SOC stocks to a fixed depth to facilitate accurate comparisons to other ecosystems and published data but provide the stocks calculated using ESM for comparison (Table 1; Figure 3).

To provide benchmarks for regional and national comparison, we applied our spline and stock calculation methods to data in the National Cooperative Soil Survey Soil Characterization Database (NCSS). We extracted data from two categories: grasslands across the United States and all landscapes in Vermont (Rasmussen et al., 2018). We filtered the data to include samples to 100 cm, and pedons (cores) with organic carbon values at each depth and more than one BD value.

2.2 | Data analysis

We conducted statistical analysis and plotting in R (v. 2024.04.2; R Core Team, 2024). To visualize trends in BD and percent carbon trends across depths, we overlaid median splined values (for BD and percent carbon) on the raw data. We assessed the effect of depth on SOC stocks using a linear mixed-effects model with depth as a fixed effect and cores nested in farm as the random effects. To account for differences in depth interval thickness, SOC stock was normalized by the thickness of the sampled soil layer to create a carbon stock per centimeter. A linear mixed-effects model was then fitted to assess the depth effect on carbon stock per centimeter. To evaluate how the variability of SOC stocks changes with depth, we calculated the coefficient of variation (CV) for each depth at each farm and modeled it using depth as a fixed effect and farm as the random effect. Models were fit using the lme function in R (nlme package; Pinheiro et al., 2021), which used restricted maximum likelihood to fit the data.

We also evaluated the relationship between SOC stocks and environmental predictors using a mixed-model multiple regression, incorporating farm as a random effect and presence of ledge, percentage clay (0–15 cm), MAT, MAP, elevation, and pH (0–15 cm) as fixed effects. These effects were checked for autocorrelation, causing the removal of elevation, which was highly correlated with both MAT and MAP (0.97 and 0.77, respectively). Also correlated with each other were MAT and MAP (0.82), but excluding either from the model did not affect the significance of the results, so both were retained. We modeled total (0–100 cm), surface (0–30 cm), and deep (30–100 cm) SOC stocks separately, recognizing that the CASH values are based on measurements taken in the top 15 cm. We also ran the model between stocks and environmental predictors using total (0–1032 kg m^{-2}), surface (0–237 kg m^{-2}), and deep (238–1032 kg m^{-2}) ESM stocks instead of fixed depth stocks. For this model, we kept the same predictors as for fixed-depth stocks, except for presence of ledge, as ESM stocks already accounted for this difference. Additionally, we analyzed the relationship between soil health (CASH overall score) and SOC stocks at the three depth intervals described above using the same model structure.

To evaluate the effects of the BD method and its interaction with depth on SOC stock estimates, we conducted a separate linear mixed-effects model for each PTF. The linear mixed-effects model included method (PTF or empirical), depth interval, and their interaction as fixed effects and core nested in farm as random effects.

To assess the relationship between surface and deeper soil carbon stocks, we conducted Spearman correlation analyses using both fixed depth and ESM stocks and compared our findings with a recent study that predicted deep SOC stocks from surface stocks in forests (Garrett et al., 2024). We applied the same approach to the NCSS grassland and Vermont datasets. Carbon stocks were summed across surface (0–15 cm), mid (15–30 cm), and deep (30–100 cm) depth intervals for each soil core. Spearman correlations were then used to evaluate the strength of the association between surface and mid- or deep-carbon stocks.

3 | RESULTS

SOC stock to 1-m depth averaged across all sampled pastures was 12.9 kg C m^{-2} (±3.09; $n = 12$ farms; range: 8.8–19.2 kg C m^{-2}; Table 1; Figure 3). Using the ESM approach, SOC to a soil mass representative of 1 m, 1032 kg m^{-2}, was estimated to be 12.6 kg C m^{-2} (±3.21; n = 12 farms; range: 7.6–18.8 kg C m^{-2}; Table 1; Figure 3). On average, 62% (range: 50%–73%; for ESM, 62.8%, range 48%–73%) of the carbon in the top meter (or 1032 kg m^{-2} ESM) was contained in the upper 30 cm (or 237 kg m^{-2} ESM) of the soil profile. Inorganic carbon was detected on four of the 12 farms and in 20.5% of all cores (Figure 1; Table S1). On average, the samples with detectable inorganic carbon had 75% higher carbon content before accounting for the inorganic carbon (Figure S1). All samples with detectable inorganic carbon were collected from depths >50 cm with 70% of these samples found below 80 cm, likely reflective of parent material-derived carbonates (Table S1). Mean stocks to 1 m for grasslands in the United States calculated from NCSS data were 13.1 kg C m^{-2} (±7.01, $n = 1993$), though the range was much greater (6.8–67.2 kg C m^{-2}). Vermont forests contained 12.9 kg C m^{-2} (±6.17, $n = 74$, range: 5.9–54.7 kg C m^{-2}) to 1 m. Both means are within the range of the pastures measured in this study (Table 2).

SOC stocks decreased with depth. The linear mixed-effects model revealed a significant effect of depth on carbon stock per centimeter ($F_{4,\,256} = 287$, $p < 0.001$) indicating that the variance in mean SOC is largely explained by depth. The estimated mean carbon stock per centimeter from 0- to 5-cm depth was 0.36 kg C m^{-2} (95% confidence interval = 0.33–0.39). Compared to this surface layer, SOC stock per centimeter decreased by 0.04 kg C m^{-2} at 5–15 cm ($p = 0.001$), by 0.18 kg C m^{-2} at 15–30 cm ($p < 0.001$), by 0.28 kg C m^{-2} at 30–60 cm ($p < 0.001$), and by 0.29 kg C m^{-2} at 60–100 cm ($p < 0.001$). The marginal R^2 (0.73) indicated that the effect of depth alone explained 73% of the variation, while the conditional R^2 (0.86) indicated that the random effects of farm and core added 13% to the explanatory power of the model. The depth effect was similar in the linear mixed effect model using ESM data (Table S2).

SOC stock variability was also affected by depth. The variability of SOC stocks, as measured by the average CV within a depth interval at each farm, increased with depth ($F_{4,54} = 3.94$, $p = 0.007$; Figure 4). The model explained 22.6% of the variance in SOC stock variability across depth intervals ($R^2 = 0.226$). The variability among cores at each farm is greater (mean CV 36.3%) in deeper (15–100 cm) than surface (0–15 cm) soils (mean CV 21.3%). The mean CV of 19.7% at the surface (0–5 cm) was significantly less than mean CV at 15–30 (34%, $p = 0.021$), at 30–60 cm (38%, $p = 0.003$), and at 60–100 cm (36.9%, $p = 0.007$).

Ledge presence and clay content emerged as key factors influencing SOC stocks, while other environmental variables had limited predictive power. When cores were <1 m in depth due to ledge impeding the sampling, we noted significantly lower SOC stocks (total core: $\beta = -5.23$, $p = 0.003$, deep SOC: $\beta = -6.79$, $p < 0.001$) than those sampled to the full 100 cm. The regression coefficient (β) indicates that hitting ledge resulted in a 5.23 kg m^{-2} lower total SOC stock, with a stronger effect on deep SOC stocks (30–100 cm). The linear mixed-effects model assessing the influence of environmental and soil properties on the total SOC stock and deep (30–100 cm) stocks did not identify any other significant predictors (Table 3). In contrast to deep soils, ledge presence was rare in surface soils and thus did not affect surface SOC stocks. Surface SOC stocks to 30 cm were higher in soils with greater clay content ($\beta = 0.14$, $p = 0.027$)

TABLE 2 Comparison of soil organic carbon (SOC) stocks with other studies, ecosystems, and locations.

SOC stocks (kg m^{-2})	Maximum depth (cm)	Ecosystem	Location	Method	Source
12.9	100	Pastures	Vermont	Measured	This study
7.8	15–25	Pastures	Vermont	Calculated based on SOM measurements	(Wiltshire & Beckage, 2022)
9.6	30	Pastures	Vermont	Measured	(White et al., 2022)
8.7–12.4	50	Pastures	New Hampshire	Modeled	(Arndt et al., 2022)
14.7	50	Pastures	Vermont	Measured	(Contosta et al., 2021)
14.6	30	Pastures	North Carolina	Measured	(Bolstad & Vose, 2005)
7.7	30	Pastures and Hay Fields	Vermont	Measured	(Soil Survey Staff & Loecke, 2016)
11.2	100	Pastures and Hay Fields	Vermont	Measured	(Soil Survey Staff & Loecke, 2016)
13.1	100	Grassland	USA	Measured	(NCSS, 2025)
11.7	100	Grassland	Global	Estimated	(Jobbágy & Jackson, 2000)
6.4	15–25	Crops	Vermont	Calculated based on SOM measurements	(Wiltshire & Beckage, 2022)
11.2	100	Crops	Global	Estimated	(Jobbágy & Jackson, 2000)
8.6	30	Agriculture	Vermont	Measured	(White et al., 2022)
12.9	100	Forests	Vermont	Measured	(NCSS, 2025)
8.0	20	Forests	Vermont	Measured	(U.S. Department of Agriculture, Forest Service, 2025)
5.4	20	Forests	US CONUS	Measured	(Domke et al., 2017)
11.0	100	Forests	US CONUS	Modeled	(Domke et al., 2017)
14.5	100	Temperate evergreen	Global	Estimated	(Jobbágy & Jackson, 2000)
17.4	100	Temperate deciduous	Global	Estimated	(Jobbágy & Jackson, 2000)
6.8	30	All Ecosystems	Vermont	Modeled	(Zeraatpisheh et al., 2023; Poggio et al., 2021)
13	100	All ecosystems	Vermont	Measured	(NCSS, 2025)
3.1–77.6	100	All	Global	Estimated	(Batjes, 1996)

TABLE 3 Results of linear mixed-effects models examining the effects of predictor variables on total soil organic carbon (SOC) in kg C m^{-2} to 1-m depth ($n = 68$), surface SOC (0- to 30-cm depth), and deep SOC (30- to 100-cm depth). Significant effects ($p < 0.05$) are given in bold. For each model, ICC represents the intraclass correlation coefficient, or variation due to core nested within farm, while marginal R^2 indicates the variance explained by fixed effects alone, and conditional R^2 represents the variance explained by both fixed and random effects. Results for a similar analysis using equivalent soil mass (ESM) SOC stocks are in Table S3.

	SOC		surface SOC		deep SOC	
Predictor	Regression coefficient	*p*-value	Regression coefficient	*p*-value	Regression coefficient	*p*-value
Ledge	**−5.23**	**0.003**	−0.83,	0.69	**−6.79**	**≤0.001**
Clay	0.1	0.55	**0.14**	**0.027**	−0.07	0.61
MAT	−2.21	0.24	−1.17	0.09	−1.25	0.40
MAP	−0.03	0.87	0.01	0.83	−0.07	0.62
pH	0.09	0.97	1.24	0.14	−1.41	0.46
Marginal R^2	0.55		0.66		0.56	
Conditional R^2	0.85		0.87		0.92	
ICC	0.67		0.62		0.81	

Abbreviations: MAP, mean annual precipitation; MAT, mean annual temperature.

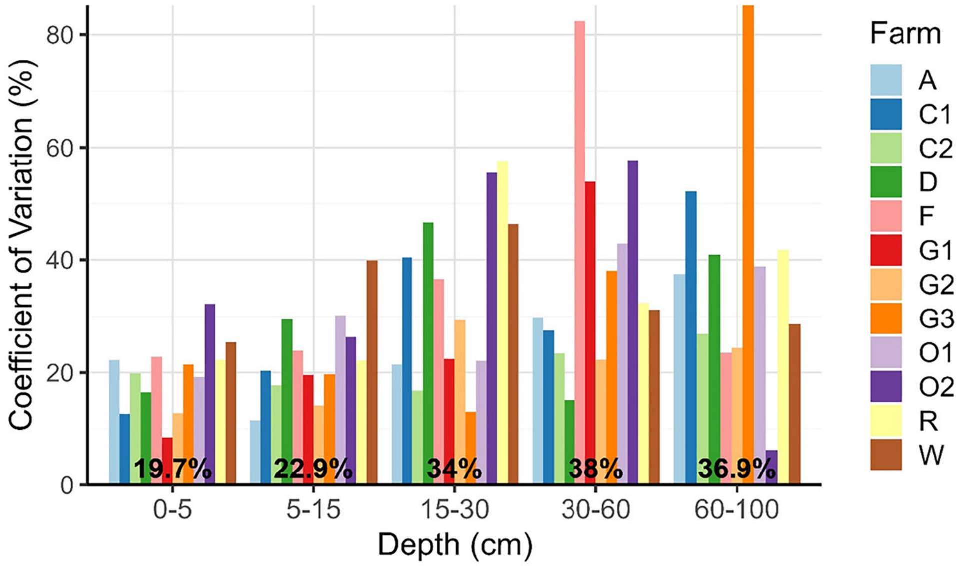

FIGURE 4 Variability among cores at each farm, shown as coefficients of variation (CV) for each depth, is greater in deeper soils (15–100 cm) than surface (0–15 cm) soils. The mean CV value for each depth interval is displayed above the *x*-axis. CV at the surface (0–5 cm) was significantly less than CV at 15–30 cm ($p = 0.021$), at 30–60 cm ($p = 0.003$), and at 60–100 cm ($p = 0.007$). Shallower depth (5–15 cm) showed nonsignificant increases in CV relative to the surface ($p = 0.59$). The mean CV across all farms was 30.2% (range: 5.2%–48.1%, Table 1).

predicting an increase of 0.14 kg C m^{-2} for each 1% increase in clay. As with total and deep SOC stocks, few of the individual environmental predictors significantly influenced surface SOC stocks, though cooler sites trended toward higher stocks ($\beta = -1.17$, $p = 0.09$). Collectively, however, environmental predictors explained 55%–66% of SOC stock variation (marginal R^2), with additional variation explained by the random effect of farm (85%–92% conditional R^2). Results from the similar analysis performed on ESM stocks had similar results (Table S3). In this case, given that ledge was not included in the analysis, the only significant predictor was clay for surface (0–237 kg m^{-2} stocks).

Soil health index predicted carbon stock in surface soil but not at depth. For surface (0–30 cm) soil, soil health had a slightly positive and marginally significant relationship with SOC stock (surface: $F_{1,10} = 11.69$, $\beta = 0.08$, $p = 0.007$; total to 100 cm: $F_{1,10} = 3.82$, $\beta = 0.10$, $p = 0.079$). For every unit increase in soil health score, the model predicts 0.10 kg C m^{-2} more SOC stock in the surface. In the deeper soil layers (30–100 cm), there was no significant relationship between soil health and SOC stock ($F_{1,10} = 0.30$, $\beta = 0.021$, $p = 0.59$).

PTFs resulted in higher estimates of SOC stocks than empirical BD measurements. Using the PTFa to calculate BD, the overall average carbon stock was 16.3 kg C m^{-2} (range 11.6–24.5) or 26.4% greater than stocks derived from empirically measured BD. (Table S4). The linear mixed-effect model showed a significant difference between PTFa and empirical measurements ($F_{1,603} = 36.01$, $p < 0.0001$). When exploring the interaction between depth and method, PTFa did not respond to depth differently than empirical data ($F_{4,603} = 1.87$, $p = 0.114$), indicating that the overestimation was consistent across the soil profile (Figure 5). PTFa overestimated SOC by 0.66 kg C m^{-2} on average per depth interval ($df = 11$, $p < 0.0001$). Using PTFb, the overall average carbon stock was 26.2 kg C m^{-2} (range 17.4–38.3) or 103.1% greater than empirical, and SOC stocks on all 12 farms were overestimated (Table S4). Again, there was a significant difference between PTFb and empirical measurements ($F_{1,603} = 249.78$, $p < 0.0001$). In contrast to PTFa, there was a significant interaction with depth, where the difference between it and the empirical method was greater in surface soils ($F_{4,\,603} = 4.26$, $p = 0.002$; Figure 5). PTFb overestimated SOC stocks by 2.79 kg C m^{-2} on average per depth interval. PTFa demonstrated a lower error and bias (RMSE = 4.71; bias = 27.77%) compared with PTFb (RMSE = 16.70; bias = 110.60%) indicating PTFa was superior to PTFb for estimating SOC stocks in this dataset.

The ability of surface SOC stock to predict deeper SOC stocks varied by dataset, with surface soils generally more strongly correlated with adjacent layers than with deeper layers. Surface soil (0–15 cm) within our pastures was moderately correlated with soil from the middle depth (15–30 cm) and less correlated with deeper soil (>30 cm) (Table 4; Figure 6). Correlations between surface (0–133 kg m^{-2}) and very deep (528–1032 kg m^{-2}) ESM layers were slightly stronger (r = 0.39, p = 0.04) than the same correlations using fixed depth stocks ($r = 0.22$, $p = 0.08$; Table S5). The Vermont NCSS data showed higher correlations across depths, though correlations were only moderate in soil deeper than 30 cm.

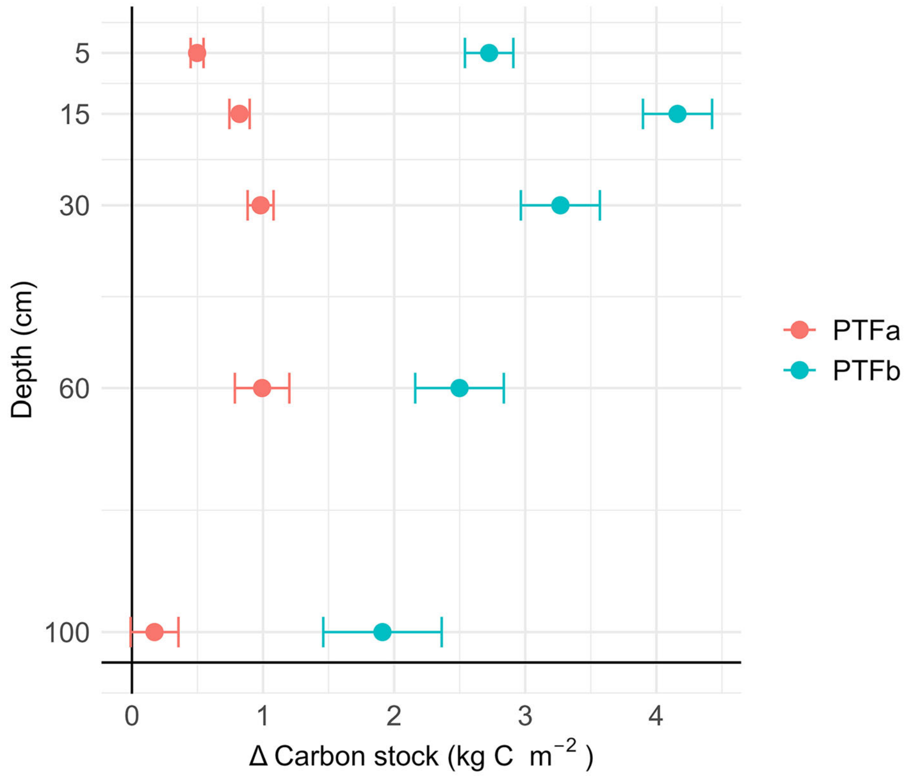

FIGURE 5 Relationship between carbon stocks calculated using pedotransfer functions and empirical bulk density across soil depths. The *x*-axis shows the mean difference in carbon stocks, calculated as the difference between stocks derived using empirical bulk density and those estimated using pedotransfer functions. Points represent the mean difference at each depth interval, and the horizontal error bars indicate ± 1 standard error of the mean.

TABLE 4 Spearman correlations for the relationship between soil organic carbon stocks (kg C m^{-2}) in the top (0–15 cm) layer of the soil with the mid (15–30 cm), deep (30–60 cm), and very deep (60–100 cm) layers.

	Mid (15–30 cm)	Deep (30–60 cm)	Very deep (60–100 cm)
Pastures (this study)	0.67 ($p < 0.0001$)	0.21 ($p = 0.097$)	0.22 ($p = 0.084$)
Vermont (NCSS data)	0.69 ($p < 0.0001$)	0.43 ($p < 0.0001$)	0.43 ($p < 0.0001$)
Grasslands (NCSS data)	0.83 ($p < 0.001$)	0.89 ($p < 0.001$)	0.95 ($p < 0.001$)
Forests (Garrett et al., 2024)	0.77 ($p < 0.01$)	0.27 ($p = 0.1$)	0.98 ($p < 0.01$)

Abbreviation: NCSS, National Cooperative Soil Survey Soil Characterization Database.

However, surface soil in US grasslands was highly correlated with all deeper depths.

4 | DISCUSSION

4.1 | Stocks and variability

Carbon stocks in the top meter of Vermont pastures (12.9 kg C m^{-2}) were remarkably consistent with stocks measured in similar ecosystems (Table 2) and closely matched stocks calculated from NCSS data across all land cover types in Vermont and across US grasslands (Table 2). Despite the lower average BD in our study in comparison to the NCSS data, SOC stocks and the proportion of SOC stocks in surface soil remained consistent across all three datasets, likely due to higher mean carbon concentrations found in our pastures (2.6%) compared to mean carbon concentrations in NCSS data for Vermont (1.9%) or US grasslands (1.3%). These differences in carbon and BD could be related to inputs like manure (Bolinder et al., 2020) and forage residuals, which are common on pastures. Comparing stock measurements is complicated by differing methods and depths, and this study only sampled pastures. Despite the variance, our pasture stocks also fall within the range of stocks in local forests and croplands (Table 2).

Comparing our results to published inventories suggests that land use may not strongly influence SOC stocks calcu-

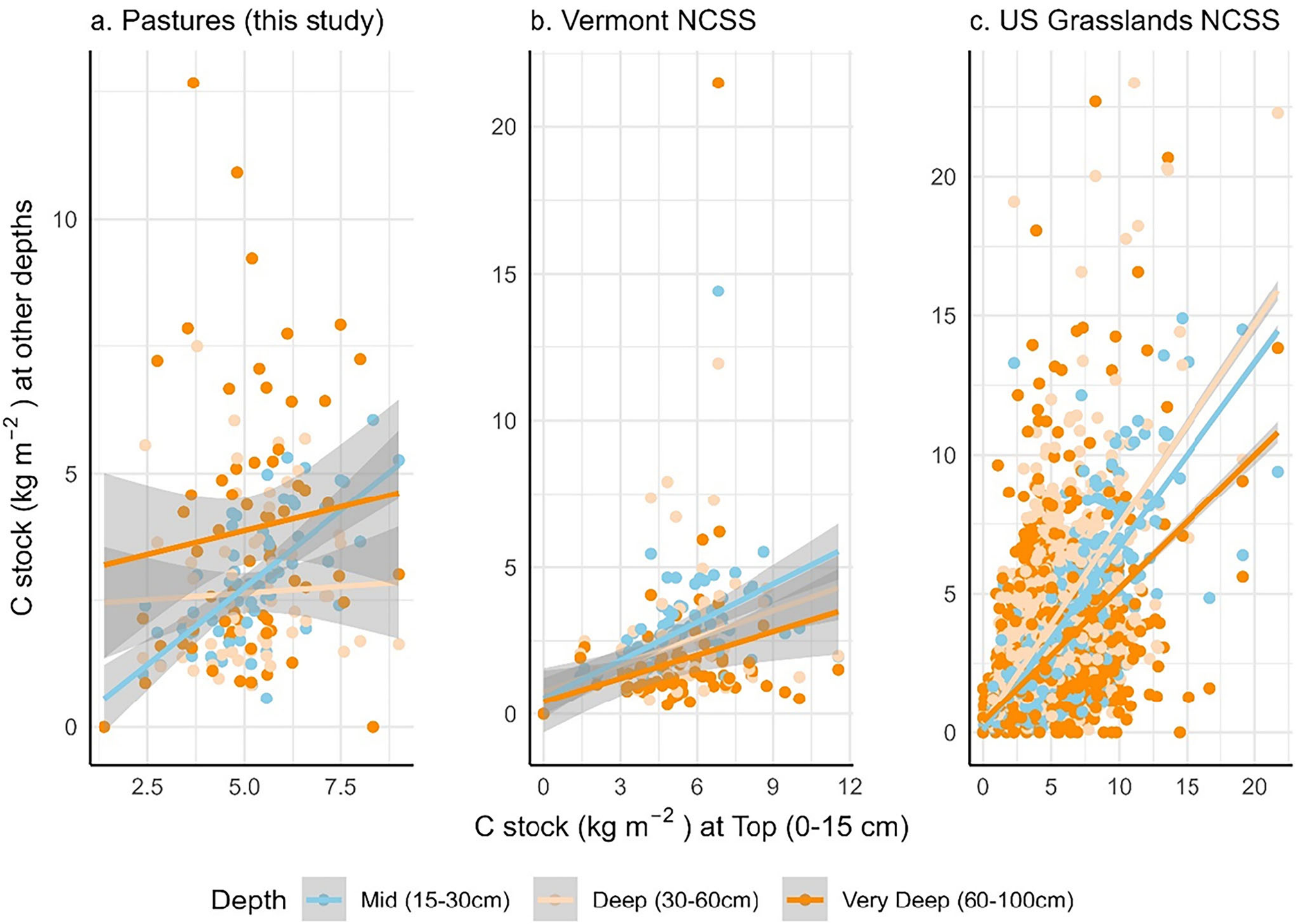

FIGURE 6 Relationships between soil organic carbon (SOC) stocks in the top 15 cm of soil with SOC stocks at mid (15–30 cm), deep (30–60 cm), and very deep (60–100 cm) depths for (a) pastures in this study, (b) National Cooperative Soil Survey Soil Characterization Database (NCSS) data from Vermont, and (c) NCSS data from grasslands. Shown are the best-fitting regression lines and 95% confidence intervals for each (gray shaded area). See Table 4 for corresponding Spearman correlations. Axis ranges differ among panels.

lated to a depth of 100 cm in our region, which contradicts our expectation that pastures would have lower stocks than forests. We cannot rule out this observation being caused by differences in methods or site selection; for example, perhaps pastures in our study were of high quality given that farmers who allow scientists to work on their land are a nonrandom sample. However, this observation aligns with previous studies reporting no significant differences in SOC stocks among land uses, even when pastures were included (Wäldchen et al., 2013). In the same region as our study, researchers found no consistent differences in SOC stocks to 100 cm among forests, warm-season grasses, and cool-season grasses (Corre et al., 1999). Our observations, along with others (Corre et al., 1999; Davidson & Ackerman, 1993; Wäldchen et al., 2013), indicate that long-term SOC stocks may exhibit greater resiliency and lower sensitivity to land use than previously thought.

One reason that SOC stocks may be less sensitive to land use changes over the long term is that roots are key contributors to SOC storage (Dodd et al., 2011; Jackson et al., 2017), but roots can simultaneously build up and destabilize soil carbon. Carbon inputs from roots and exudates (i.e., rhizodeposition) contribute to carbon storage (Rasse et al., 2005; Panchal et al., 2022). However, root exudates can also cause a positive priming effect, in which the exudates stimulate microbial activity and accelerate SOC decomposition (Villarino et al., 2021). For example, a recent mesocosm study found no difference in SOC storage among plant species despite large differences in root biomass (Fitch et al., 2024). As a result, even if pastures have less root biomass than forests (Jackson et al., 1996), on balance these different land covers may be maintaining similar SOC levels if priming in forests offsets the additional inputs from root biomass or exudates in pastures offset lower root biomass.

Deeper soil layers make a significant contribution to overall SOC storage. In the pastures we sampled, an average of 38% (range: 27%–50%) of SOC was located in depths between 30 and 100 cm of the soil. These data correspond with other estimates from grasslands showing that roughly 47% (Balesdent et al., 2018) to 58% (Jobbágy & Jackson, 2000) of the upper 1 m of SOC is found below 30 cm. In the NCSS data, 46% of

SOC in US grasslands and 33% of the SOC in Vermont forests were found between 30 and 100 cm (Table S6).

In our pastures, SOC stocks became more variable with depth. This variability makes it difficult to assess and quantify carbon stocks at depth and could also indicate that distinct processes influence SOC stocks in surface versus deep soils. First, similarities in managing all these sites as pastures may have homogenized surface soil conditions, leading to consistent SOC content. In deeper soils, however, variation in bedrock and pedogenic processes across and within these sites (Table S1) could influence edaphic conditions, such as soil mineralogy and pH, that affect carbon sequestration at depth (Conant & Paustian, 2002). We qualitatively noted the general rockiness of each site and found that the SOC stocks were more variable in rockier fields. The mean CV of the two rockiest farms was 45.5%, while the mean CV of the two least rocky was 20.5%. The quantity of coarse rock fragments may contribute to variability in carbon stocks due in part to sampling difficulties and subsequent uncertainty in soil BD (Goidts, 2009; Poeplau et al., 2018). The spatial distributions of SOC may be considered in assessments of management strategies to increase soil health and carbon sequestration potential. The higher variability in deeper layers also suggests that more precise and extensive sampling methods may be needed for deeper soils.

4.2 | Predictors of SOC stock

Incorporating deeper layers of the soil profile into baseline quantification efforts can improve the accuracy of SOC assessments and inform more effective strategies for management of grazed lands (Harrison et al., 2011). We tested potential predictors of carbon stock in line with our goal to test whether easier-to-measure surface variables could be used to predict deep SOC stocks. Climate variables including MAT and precipitation were not significant predictors of SOC stock, likely due to their limited range in our study region and the fact that there was high variability in carbon stocks among cores within a farm. We found the presence of ledge and clay content influenced SOC stocks, while pH did not. Because of their truncated sampling depth, cores that ended before 1 m due to bedrock had significantly lower total SOC stocks. Surface SOC increased with clay content, consistent with research showing that fine-textured soils are more effective at retaining organic carbon (Rasmussen et al., 2018). In contrast, no relationship was observed between clay content and deep SOC, likely because surface (0–15 cm) clay content may not reflect deeper soil texture. The lack of significant predictors overall was surprising given that regional and global analyses often find that climate, pH, and clay are significant predictors of C stocks (Rasmussen et al., 2018; Wu et al., 2025; Zhang et al., 2023). The lack of predictors of deep SOC stocks was partly because properties like pH and clay were only measured in the surface soil. Furthermore, at the small regional scale of Vermont wherein variability in climate and pH is relatively constrained, local-scale factors including management practices, landscape position, and land use history likely have greater impacts on SOC distribution (Ritchie et al., 2007; White et al., 2022). However, similarities in total SOC stock among land cover types indicate that land use alone is not a good predictor of SOC stock.

We investigated the relationships between stocks and soil health as another potential predictor of deep carbon stocks. Soil health reflects the integration of physical, chemical, and biological properties of soils and is highly sensitive to management practices (Doran & Zeiss, 2000; Garg et al., 2025; Karlen et al., 2019). However, the soil health concept and the framework for quantifying it have only focused on the top 15 cm (Moebius-Clune et al., 2016). Thus, the positive relationship between SOC stock and the soil health index in surface soils was expected, as soil carbon is a key indicator in soil health assessments due to its crucial role in soil function and structure (Lehmann et al., 2015; Moebius-Clune et al., 2016). The lack of significant effects of soil health index on deep carbon stocks suggests that deep SOC is decoupled from surface soil health indicators because it is less or more slowly responsive to management due to the time it takes SOC to be transported from the surface to deeper soil (Franzluebbers & Stuedemann, 2002). This pattern may arise from the complex interactions between soil properties and carbon dynamics at depth (Gross & Harrison, 2019). Furthermore, the parameters that constitute a healthy surface soil may differ from what constitutes a healthy deep soil. Unlike surface layers, where SOC is actively cycled through biological inputs and activity, deeper SOC is often more stabilized through mineral associations and physical protections (Hicks Pries et al., 2023; Rumpel et al., 2015). The nature of deep soils may merit the adoption of an alternative soil health framework.

Lastly, surface soil stocks did a poor job of predicting carbon stocks in deeper layers across our pastures. The stronger surface-to-mid-depth correlation observed in the larger NCSS grassland dataset likely reflects the broader spatial extent and wider range of SOC stocks captured across sites. In such datasets, extremely high or low carbon values tend to align across depths, but this relationship is relatively coarse. Differences in surface-to-depth correlations further highlight the influence of land use and vegetation on depth-dependent SOC distributions (Hobley & Wilson, 2016). Pastures, which are typically more intensively managed than natural grasslands, often experience surface homogenization due to grazing and soil amendments, while deeper layers remain relatively unaffected. As a result, the disparity between surface and deep SOC may be greater in pastures than in less-managed systems where roots run deep. This is supported by evidence that surface SOC is more responsive to environmental and management factors than deeper SOC (Smith, 2008). The presence of ledge, which reduced deep carbon stocks, is another likely reason behind the poor correlations. When using the ESM method to quantify stocks, which gets rid of the effect of ledge, surface and deep stocks showed a slightly greater correlation.

One way to reduce the sampling effort needed to quantify deep C stocks is to use a PTF to estimate BD instead of measuring it directly. Although PTFs are commonly used in soil carbon surveys, the PTFs we evaluated overestimated SOC stocks. The two differed in accuracy: PTFb greatly overestimated stocks, while PTFa produced estimates that were statistically different from empirical measurements by a much smaller margin. These results suggest that functions like PTFa may provide reasonable estimates for some sites, but that validation for soil type, region, and land use is critical (Abdelbaki, 2018; Palladino et al., 2022). In our case, PTFa, designed for Inceptisols and Spodosols, performed reasonably well for Vermont pastures, while the other was substantially inaccurate, highlighting the need to test predictive functions against empirical data before applying them more broadly.

4.3 | Best practices for quantification

High spatial variability and low predictability of deep soil carbon stocks limit our ability to estimate total SOC stocks without direct measurement. Thus, digging or coring deeper is critical for accurate quantification of deep SOC stocks at local scales. Our results underscore the importance of sampling to depth rather than relying on surface-to-depth correlation functions or assumptions based on land use. Given this reality, we now consider the best practices for empirical measurements of deep soil carbon. First, in our region, the presence of ledge had a significant influence on the amount of SOC at depth. Using existing geospatial data layers (Ratcliffe et al., 2011), researchers can include depth to bedrock in sampling decisions and as a factor in models for estimating total SOC stock. Removal of inorganic carbon is also necessary to avoid over quantification of deep SOC even when the acidity of surface soils indicates that carbonates are unlikely. Lastly, PTFs demonstrate reliability after empirical verification, which means some labor-intensive sampling of deep soil BD cannot be avoided. While surface measurements can offer general insights and may best reflect changes due to management or land use, the substantial variability in deeper soils suggests that reliable SOC stock estimates are best achieved with direct sampling of the deep soil.

5 | CONCLUSIONS

This study quantified SOC stocks to 100-cm depth in Vermont pastures and has broader implications for carbon assessment in agricultural systems. Our results show that SOC stocks in pastures are more variable at depth than in surface soil. When coupled with the similarity in mean SOC stocks across ecosystems and regions, these findings indicate that soil below the depth typically measured is critical for understanding total carbon storage at local scales. Measuring surface SOC may capture changes due to land management but fail to represent the inherent variability of deeper soil layers, and these deeper soil layers greatly influence whole-profile carbon accounting given that soil below 30 cm contributes 30%–50% of total carbon to 1 m. While this pattern was observed in pastures, the consistency in overall stocks across ecosystems suggests that these conclusions may apply more broadly to other regions and land use types. Unfortunately, as our study demonstrates, quantification will not be easy when spatial variability in SOC stocks increases and the predictability of SOC stocks declines with depth. The high spatial variability of deep SOC presents an important consideration for future studies. Each study on soil carbon stocks contributes to an expanding baseline, allowing researchers to track changes over time and as management practices change. In the long term, this baseline will help optimize sequestration strategies and provide more accurate estimates of climate mitigation benefits.

AUTHOR CONTRIBUTIONS

Erin Lane: Conceptualization; data curation; formal analysis; investigation; methodology; visualization; writing—original draft. **Ashley Lang**: Conceptualization; formal analysis; validation; writing—review and editing. **Sarah Goldsmith**: Investigation; writing—review and editing. **Caitlin Hicks Pries**: Conceptualization; formal analysis; investigation; methodology; project administration; supervision; validation; visualization; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at: https://doi.org/10.6084/m9.figshare.31333630.v1

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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