Cryptic carbon: The hidden carbon in forested wetland soils

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Abstract

Inland wetlands are critical carbon reservoirs storing 30% of global soil organic carbon (SOC) within 6% of the land surface. However, forested regions contain SOC-rich wetlands that are not included in SOC maps, which we refer to as 'cryptic carbon'. To demonstrate the magnitude of cryptic carbon, we map SOC as a function of a continuous, upland-to-wetland gradient across a large catchment. Total catchment SOC was comparable to global SOC maps but wetlands delineated by our approach contained $1.7 \pm 0.3$ TgC compared to $0.3 \pm 0.2$ TgC in currently mapped wetland SOC. Cryptic carbon, the wetland SOC outside of currently available maps, was $1.5 \pm 0.3$ TgC or 383% higher than the current estimates. When combined, the new total wetland SOC including cryptic carbon increased to $1.8$ TgC $\pm 0.5$ or by 483%, highlighting vast stores of SOC are not mapped and contained in unprotected and vulnerable wetlands.

Introduction

Conserving Earth’s carbon-rich ecosystems is critical in order to meet the goals of balancing carbon sources and sinks for the Paris Climate Agreement. Among ecosystems with high carbon stocks, inland freshwater wetlands and peatlands contain greater than 30% of the total soil organic carbon (SOC) stock of 1,500-2,400 PgC but only cover approximately 6% of the land surface. However, below the global scale, wetland SOC mapping is considerably more uncertain due to poor spatial representation. Estimates of wetland SOC stocks often rely on coarse resolution mapping and broad scale inventories that omit many wetlands outside of large homogenous wetland complexes such as peatland plateaus in the high latitude northern hemisphere ($> 60^\circ$). In the more heterogeneous, complex terrain of mid-latitude temperate forested regions ($30^\circ-60^\circ$), wetlands still disproportionately contribute towards terrestrial carbon storage compared to upland areas, but are difficult to map and can occur subtly within a forested landscape and remain hidden under the canopy. This temperate wetland area has been a frequent target of land use conversion to agriculture and urban land uses contributing to the recently estimated loss of 21% of the original global wetland area since 1700 AD. Estimating SOC lost from anthropogenic disturbance requires comprehensive SOC mapping that accounts for high SOC in forested wetlands and wet areas which are not contained in contemporary inventories. Omitting these high SOC stocks propagates a potential underestimation of the terrestrial carbon stock in forested regions which contain SOC stores that have accumulated over centuries making them invaluable but irrecoverable if lost within the timeframe to reach net-zero emissions.

Freshwater inland wetlands make up most of the wetland area in the United States and contain a total SOC stock 8-10-fold higher than the total SOC stock in tidal saltwater wetlands. Within the inland wetland population, forested wetlands cover the largest extent, but, represent the most difficult wetland mapping category due to the canopy coverage, frequently small extent, and isolation from surface waters. Despite the limited appearance, forested wetlands have interconnective roles within terrestrial carbon cycle in addition to SOC storage, including but not limited to: accumulating carbon in aboveground
biomass; transporting of labile dissolved organic matter to streams; supplying dissolved CO$_2$ to surface waters leading to significant outgassing; and potentially acting as the highest non-ebulliative CH$_4$ flux from groundwater through tree stems. This diverse array of carbon functions highlights forested wetlands role as a hotspot or ecosystem control point within a landscape. Indeed, seemingly isolated wetlands can connect to surface waters through groundwater links throughout a catchment and integrating previously unidentified ‘cryptic’ forested wetlands can better explain catchment scale surface water chemistry patterns. Cryptic wetlands can also act as the transition between terrestrial and aquatic environments where rapid biogeochemical cycling can occur in spaces only a few meters wide. Mapping SOC along the terrestrial-aquatic gradient containing forested wetlands can reveal hidden SOC spatial patterns that help balance carbon budgets in heterogeneous landscapes. However, mapping the distribution of SOC stocks within forested landscapes is challenging, especially with small forested wet areas that do not exhibit conspicuous wetland indicators such as signs of water saturation affecting the aboveground vegetation.

Maps of SOC stocks are commonly generated with digital soil mapping (DSM) using geospatial land cover maps and remote sensing metrics relating to the spatial variation of soil forming factors. Wetlands integrated into DSM are often inconsistently defined with insufficiently measured wetland extent that promotes underestimation and inaccurate spatial distributions of SOC stocks. More recent approaches with machine learning models of wetland and peatland soil properties in DSM has improved wetland and peatland maps, yet there is still substantial variation and underestimates in extent measurements with persistent problems omitting high SOC stocks in forested wetlands and wet areas. In areas where forest canopy obscures wet areas, data driven machine learning approaches utilizing topography focused metrics can identify previously hidden forested wetlands and wet areas by capturing patterns of surface and groundwater flow that facilitate water accumulation within a landscape. Utilizing continuous probabilities simulated from presence/absence data, probabilistic wetland mapping can capture the spatial representation of the terrestrial to aquatic gradient, with wetlands as one end of a water saturation continuum. SOC is expected to increase with the higher probability of a wetland where soil saturation that inhibits microbial respiration and facilitates organic matter accumulation and potential wetland extent can be estimated above a chosen probability threshold.

We have yet to note SOC maps informed by potential wetland presence which: 1) identifies new unmapped SOC in potential wetland area; 2) compares potential wetland SOC with maps of existing wetland SOC estimates; and 3) compares overall SOC distributions with available SOC mapping products. Therefore, we conduct a new DSM SOC mapping approach in a densely forested, geomorphologically complex watershed using a continuous probabilistic wetland identification metric to reveal significant amounts of unmapped SOC contained in potential forested wetlands and wet areas. We adapt the term ‘cryptic wetland’ from Creed et al., as ‘cryptic carbon’ to distinguish hidden SOC stocks within potential forested wetlands that have not been mapped or estimated previously, with the caveat that we are not mapping jurisdictional wetland boundaries. Our approach represents an adaptable and
flexible way for natural resource managers and conservationists to identify cryptic carbon stocks and it reveals an immense SOC stock that has not been associated with potential forested wetlands.

**Methods**

**Study area**

This study takes place in the Hoh River Watershed (HRW) within the Pacific Northwest of the Conterminous United States (Fig. 1.) which contains some of the highest aboveground carbon and SOC stocks in the world reaching 375 MgC ha$^{-1}$ and 709 MgC ha$^{-1}$, respectively $^{34}$. In the HRW, mean annual air temperature is 7.2$^\circ$C and mean annual precipitation is 274 cm and can exceed 300 cm with most of the precipitation in winter. Precipitation mainly falls as rain but snowfall is more common in the upper elevations $^{35}$. The mountains of the HRW were created 17–20 million years ago during the Miocene to Eocene periods with the uplifting of marine sedimentary rock over the denser ocean crust. The uplifted marine sedimentary rock also formed hills and terraces in the lower HRW. During the end of the Pleistocene and the period of deglaciation, large floods from glacial melt deposited material over the lower elevation so the HRW creating large floodplains. Rivers continued to incise this deposited glacial material over the Holocene and into the present depositing alluvium near the present main channel of the Hoh river that bisects the HRW $^{36}$. Current topography varies from mountains with steep slopes (> 40%) in the eastern portion of the HRW to rolling hills and flat areas in the lower floodplain that drains eastward to the Pacific Ocean. Soils of the HRW reflect this geologic history and topography with dominant soils containing loamy to sandy-clay coarse textures although there is a moderate presence of volcanic ash and which promotes andisol soil development $^{37}$. The HRW has a mix of both private and public forestlands dominated by Sitka Spruce and Western Hemlock in the lower elevations that is actively managed for timber harvest (Pelt, 2001). An area along the coast and in the upper watershed is part of the Olympic National Park and is protected old-growth forest with trees up to 4 m in diameter and 80 m in height (Harmon and Franklin, 1989). The mapped wetlands within the HRW are diverse, from precipitation-driven bogs to riparian wetlands (Fig. 1. insets). Many of the wetlands are under dense forest overstory but in some forested areas with high levels of inundation trees are stunted in size and have a lower overall height and biomass. The most prominent Hydrogeomorphic wetland classes are Riverine, Mineral Flats, Organic Flats, and Depressional $^{38}$. There is a notable difference between Riverine wetlands and the other wetland classes for SOC and we mark this distinction with grouping all wetland hydrogeomorphic classes into two classes for our soil pedon dataset: Riverine and Palustrine (non-riverine).

**Mapping wetlands with the Wetland Intrinsic Potential Tool (WIP)**

We mapped wetlands using the Wetland Intrinsic Potential (WIP) tool, a multi-scale terrain-based wetland identification and mapping tool developed by Halabisky et al., $^{39}$. The WIP tool models wetland presence in a spatially explicit, continuous pixel approach using input parameters related to hydrophytic vegetation, hydrology, and hydric soils. The topographic and terrain input data layers are derived from
discrete point aerial lidar which was processed to create a digital elevation model at a 4 m resolution of the terrain surface (Lidar source: 2012–2013 Puget Sound LiDAR Consortium (PSLC) Topographic LiDAR: Hoh River Watershed, Washington (Deliveries 1 and 2). Unlike aerial or satellite imagery, lidar can detect small topographic features under tree canopy and terrain metrics were integrated into a random forest model that was trained on wetland presence/absence point datasets derived from the National Wetland Inventory (NWI) and validated with additional field collected ground-truthed datasets. The WIP tool was specifically developed to identify wet areas missing in most wetland inventories because they do not have standing water or are hidden under tree or vegetation canopy making them difficult to detect in satellite or aerial imagery. We refer the readers to Halabisky et al., 39 for the full summary of how the WIP tool was implemented in the HRW. The output produces a wetland probability score based on the proportion of classification trees in the random forest model of how likely a pixel is a wetland (0%-100%) which is the estimated likelihood that the wetland class label is correct for a given input of terrain, hydrology, and vegetation parameters. For example, a pixel that has a wetland probability of 80% will contain a combination of landscape features that generate a wetland within 80% of the dataset. Wetlands, therefore, represent the high end of continuum corresponding to landscape soil moisture and inundation and the other end is an absence of these conditions. Because the wetland probability is continuous across the entire landscape, it enables SOC stock to be modeled continuously across the entire HRW. However, setting a threshold probability also allows estimates of wetland extent. In order to determine potential wetland extent, we chose the threshold value of 50%, above which classifies a pixel as a wetland and below which classifies pixels as non-wetland or upland. WIP model accuracy for the HRW in Washington State using wetland probability ≥ 50% to create a binary class of wetland (> 50%) vs. upland (< 50%) was 93.0%. Readers should consider that wetlands defined by the WIP tool do not have jurisdictional boundaries which require field delineation and verification to determine their exact extent based on hydrology, hydric soil, and hydrophytic vegetation at a much smaller scale.

Field sampling

We developed a stratified random sampling approach across the HRW wetland probability distribution. We utilized 30 probability bins, and sampled 1 pedon at a random location per bin then added 6 additional pedons at the highest and lowest probabilities as time allowed. Once sampling locations were selected, we used Garmin Handheld Global Positioning System (GPS) to navigate to each point. After designating the pedon sampling location, we then used a JAVAD GNSS Triumph-2 for more precise georeferencing. In total, we sampled 8 wetlands and 28 uplands according to the WIP probability ≥ 50% cutoff for the wetland class from the mapped model. Within the wetland class defined by the WIP ≥ 50%, we classified two distinctive wetland types: riverine and palustrine, which differed in their parent material and organic matter content. Riverine wetlands consisted of recently deposited alluvial material and exhibited very little soil development. We classified these observations in the field and later used a surficial geology map to delineate riverine areas with lower predicted SOC described below.

At each pedon site, a pit was excavated to at least 100 cm depth or to a restricting layer to characterize soil horizons, color, texture, structure, and redoximorphic features 40. Samples were collected by each soil
horizon for bulk density and total carbon analysis. Bulk density was carefully extracted from the pedon face for each horizon using a fixed volume metal cylinder for mineral soils with a volume of 98.175 cm$^3$ or a beveled polyvinylchloride (PVC) cylinder with a volume of 132.536 cm$^3$ for organic soils. Bulk soil samples were taken from each horizon for total carbon analysis. All samples were transported in coolers and stored in refrigerated spaces between 4-6$^\circ$C until laboratory preparation and analysis. Laboratory sample preparation included drying all soil samples for at least 48 hrs or to a constant weight in drying ovens at 75$^\circ$C. Soil samples were then sieved to extract the fraction less than 2 mm and remove coarse fragments. Bulk density was calculated as the mass of the less than 2 mm fraction divided by the volume of the fixed volume soil core sampler. SOC was measured with the less than 2 mm fraction in both the loss on ignition method and in a Perkin Elmer Co. 2400 model Total Carbon, Hydrogen, and Nitrogen (CHN) Analyzer. Soil samples were prepared for the CHN Analyzer by ball milling a small subsample for 2 minutes at 1/30 second frequency to homogenize the sample. Then a 20 mg subsample was balled into tin capsules and run on the CHN Analyzer. SOC stocks for each horizon were calculated from the total carbon percentage from the CHN analyzer ($C$) multiplied by the bulk density ($BD$) and the soil horizon thickness ($D$) (Eq. 1).

$$1)\text{SOC stock} = \sum C_i \times BD_i \times D_i \times (1 - CF_i)$$

Where, $C$ denotes the carbon percentage, $BD$ represents bulk density, $D$ represents the horizon thickness, and $CF$ represents the coarse fragment fraction of the soil sample $i$. For the purpose of this analysis we do not spatially predict SOC deeper than 1 m soil depth. Soil pedon landscape classes were defined as wetlands for pedons with WIP $\geq$ 50%, as uplands for WIP < 50%, and as riverine wetland or palustrine wetlands when the sample location was inside or outside the Hoh River floodplain defined by the surficial geology, respectively.

SOC stock modeling and covariates

To generate a prediction model for SOC, we used a linear mixed effects modeling approach using the ‘lme4’ R package with fixed and random effects to conduct our SOC carbon stock spatial prediction. Linear mixed effect models were used to specify the fixed effect as the WIP probability metric for our primary covariate for SOC. We also investigated multiple remote sensing metrics such as NDVI, EVI, MNDWI, and single band reflectance from Landsat imagery as additional fixed effects in the model. We used surficial geology of the HRW as our random effect due to the mapping of riverine quaternary sediments which represent river floodplains that are strongly predicted as wetland areas in the WIP tool but do not develop soil or accumulate organic matter due to recent river water scouring. Surficial geology data were downloaded as 1:100,000 scale polygons from the Washington State Department of Natural Resources geologic information portal. Four broad classes of lithological material and geologic age were extracted from the surficial geology data to provide grouping for SOC samples: Clastic, Glacial Drift, Till/Outwash, and Alluvium. Step-wise variable selection using Akaike information criterion (AIC) was used to determine fixed effect covariates in addition to the WIP tool probability metric and surficial geology random effect. However, there were no significant effects from adding remote sensing metrics to
the WIP and surficial geology. Further, the heterogeneity of the forested landscape due to forest harvest was prohibitive for using spectral remote sensing metrics or lidar metrics of forest structure to predict SOC which could weight clearings or reflective surfaces inappropriately in SOC modeling. Additional terrain metrics were also excluded to avoid intercorrelations with the WIP probability covariate which already incorporates terrain information. Overall, the best model according to AIC was also simplest using just the WIP probability with surficial geology classes (Eq. 2).

\[
2) \sqrt{({\text{SOC Stock}}}_{ij}} = X_\beta_{WIP} + Z_{\alpha_{SurficalGeology}} + \epsilon_{ij}
\]

\[
\epsilon_{ij} \sim N(0, \sigma^2) \\
\alpha_{SurficalGeology} \sim N(0, \sigma^2)
\]

Where $X$ is the fixed effects design matrix for the $\beta_{WIP}$ in pedon $i$, $Z$ is the random effects design matrix for the random effects $\alpha_{SurficalGeology}$ for an geology type $j$, and $\epsilon_{ij}$ is our model error. The model error $\epsilon_{ij}$ follows a normal distribution with $\sigma^2$ error. Pedons sampled from the random effect $\alpha_{SurficalGeology}$ are considered a random sample from a separate normal distributions for each surficial geology type $j$.

SOC Stock Prediction

The Eq. 2 model was used to predict SOC stock at a 1 m and 30 cm depth with a R² of 0.63 and 0.61 respectively. The Root Mean Square Error (RMSE) for the 1 m model was 96.8 MgC ha⁻¹ and 31.0 for the 30 cm model. A leave one out cross validation computed a cross-validation RMSE of 22.8 MgC ha⁻¹ for 1 m SOC stocks and 11.7 MgC ha⁻¹ for 30 cm SOC stocks. Bootstrapped model predictions for the 1 m model showed 95% confidence intervals (2.5–97.5%) around the mean based on 1000 simulations were 216 to 511 MgC ha⁻¹ for the WIP; 3.67 to 129 MgC ha⁻¹ for the intercept; 77.0 to 131 MgC ha⁻¹ for the variance; and 49.5 to 145 MgC ha⁻¹ for the surficial geology random effect intercept. Bootstrapped model predictions for the 30 cm model, were 51.8 to 147 MgC ha⁻¹ for the WIP; 36.7 to 76.1 MgC ha⁻¹ for the intercept, 24.4 to 41.4 MgC ha⁻¹ for the variance, and 24.3 to 55.8 MgC ha⁻¹ for the surficial geology random effect intercept. We note these bootstrapped confidence intervals were computed on the non-transformed model which potentially widens the confidence intervals but allows for better interpretation with results in SOC response variable units of MgC ha⁻¹.

Rasters data layers for the WIP probability and surficial geology were projected to the NAD83 UTM Zone 10 (EPSG:26910), and resampled to match the WIP original 4 m pixel resolution. SOC stocks at 30 cm and 1 m depths were predicted across the HRW using the two raster data layers and the model from Eq. 2 which resulted a spatially continuous map of the square root SOC that was then back transformed with squaring to result in SOC stocks in MgC ha⁻¹. We masked surface water presence by using the median modified normalized difference water index (MNDWI) across a five year period from 2016 to 2021. We
examined the riverine classification and classified all MNDWI values above 0.30 as river surface water to be masked out. The masking process also removed a small lake located in the mountains on the eastern portion of the watershed and small gravel pits in the center of the watershed. The resulting SOC prediction map was used to calculate the total HRW SOC stock, wetland SOC stock, forested wetland SOC stock, riverine wetland SOC stock, palustrine wetland SOC stock, and non-wetland/upland SOC stock. Wetland SOC stock was estimated by classifying pixels as wetlands with WIP probability \( \geq 50\% \) and we refer back to Halabisky et al.,\textsuperscript{39} for the discussion of error with this threshold. We note that this WIP-based classification reflects potential wetland extent but is not meant to confer jurisdictional wetland extent which requires ground truth delineations. Surficial geology delineation of the Hoh River main channel and floodplain was used to classify riverine wetland and palustrine wetland SOC stocks. Forested wetland SOC stocks were estimated from a forest/non-forest mask of wetland SOC stocks derived from tree cover \( \geq 50\% \) in the Global Tree Cover product in Sexton et al.,\textsuperscript{42}. Non-wetlands were delineated as the total area outside of the WIP probability \( \geq 50\% \) and we classify this area and SOC stock as uplands.

We quantified uncertainty in several methods. First, we examined the \( R^2 \) value of the fit vs. the predicted values in the final model output to judge the overall fit of the model on the actual SOC values in the current dataset. Next we calculated confidence intervals using the confint.merMod function in the lme4 R package\textsuperscript{41}. Next, we generated a prediction interval for the model using the `predictInterval` function in the `merTools`\textsuperscript{43} R package. This function computes a simulated distribution for all parameters in the model. For the random effect simulation, the distribution is simulated by sampling from a multivariate normal distribution defined by the best linear unbiased prediction estimate and the variance-covariance matrix for each level of the grouping terms. The result is a matrix of simulated values for the linear mixed effects model and each random effect grouping term has a matrix for each observation. The 5th and 95th percentiles of the final simulated distribution were used to define the uncertainty in the prediction and root mean square error was calculated from the difference in the fit vs. the predicted values. Finally, we calculated the mapped SOC prediction uncertainty with a bootstrapping approach. Bootstrapped datasets were constructed by sampling the pedon SOC values from the current dataset with replacement, then integrating that dataset into the prediction model in Eq. 1 which was used to further predict SOC across the HRW. In total we used 300 bootstrapped SOC prediction maps where each pixel contained 300 predictions to simulate a distribution from which we extracted the standard deviation to represent the prediction interval uncertainty. We then compared the WIP wetland SOC stocks with 1m SOC stocks from the National Wetland Condition Assessment (NWCA)\textsuperscript{12}. Uhran et al., provides the latest mapped wetland SOC stocks at 1 m depths for the continental U.S. modeled from harmonized pedon data from NWCA and mapped using the NLCD wetland extents at a 30 m resolution. NWCA SOC stocks were also subtracted from the WIP wetland SOC stocks.

Wetland size distribution
Wetland size and extent was derived defining wetlands from the WIP tool probability greater than 50%. All wetland pixels greater than 50% were classified as wetland and converted to polygons using the ‘terra’\textsuperscript{44} and ‘sf’\textsuperscript{45} R packages. The wetland polygons were filtered to remove all wetlands below 64 m\textsuperscript{2} which is the area equivalent to 2x2 pixels in order to conservatively estimate wetland size classes. Examination of the wetlands below 64 m\textsuperscript{2} did not reveal significant cumulative proportions of SOC or extent. Wetlands above 64 m\textsuperscript{2} were used to extract SOC values in MgC ha\textsuperscript{-1} from the prediction raster. Size classes were defined as quantiles: 1%, 25%, 50%, 75%, 96.4% and 100% and cumulative sums for SOC and areal extent were calculated. The 96.4% quantile marks the 1-acre or 0.40 ha extent that is the minimum mapping unit of the NWI and is used as a threshold for small wetlands. The NWI defines this as the minimum mapping unit but wetlands are still mapped at smaller extents less consistently\textsuperscript{13}.

**Results**

Field collected pedon SOC stocks

We investigated the distribution of SOC stock across the field collected pedon sample depth profile where 95 cm was the overall mean pedon depth with 94 cm for uplands and 106 cm for wetlands. Within pedon dataset, wetlands contained 38% of the entire SOC stock in the top 30 cm, 91% in the top 60 cm, 96% in the top 1 m, and 100% in the top 120 cm. The mean depth sampled for wetlands was 99 cm with a maximum of 120 cm (Table 1.). Uplands contained 48% in the top 30 cm, 94% in the top 60 cm, 97% in the top 1 m, and 99% in the top 120 cm. Overall, 96% and 97% of the entire soil carbon stock was contained in the top 1 m of the soil profile for wetlands and uplands, respectively, which we used as a standardized depth for spatial predictions across the HRW. Mean 1 m depth SOC stocks within our field pedon dataset was $226 \text{ MgC ha}^{-1} \pm 27 \text{ MgC ha}^{-1}$ standard error of the mean ($\frac{\sigma^2}{\sqrt{n}}$). Wetlands in our field pedon dataset contained a higher mean 1 m SOC stock of $346 \pm 89 \text{ MgC ha}^{-1}$ which was also much higher compared to $192 \pm 22 \text{ MgC ha}^{-1}$ in uplands (Table 1.). Within wetlands, we classified riverine and palustrine wetlands due to differences in soil parent material leading to significant differences in SOC. Palustrine wetlands contained an mean 1 m SOC stock of $447 \pm 29 \text{ MgC ha}^{-1}$ compared to an mean of $68 \pm 18 \text{ MgC ha}^{-1}$ in riverine wetlands. Palustrine wetland SOC stock was slightly more evenly distributed in the soil profile with 36% of the SOC stock in the top 30 cm, 91% in the top 60 cm, and 95% in the top 1 m. We also made field observations that pedon locations with WIP probabilities between 25–50% that were included as wetlands appeared to maintain a mesic soil moisture environment between wetland and upland ends of the WIP probability range. Pedons within the mesic zone contained an mean of $251 \pm 39 \text{ MgC ha}^{-1}$ SOC stock which is elevated above uplands in our dataset and within the standard error range of the overall WIP wetland class. Pedons with WIP probabilities below 25% contained an mean of $154 \pm 19 \text{ MgC ha}^{-1}$.  

\[ \hat{\sigma} \]
Table 1
SOC stocks, sample depths, and sample numbers collected in the HRW. ± indicates standard error. * indicates landscape class subsets from WIP wetlands.

<table>
<thead>
<tr>
<th>Landscape Class</th>
<th>30 cm SOC stock (MgC ha⁻¹)</th>
<th>60 cm SOC stock (MgC ha⁻¹)</th>
<th>1 m SOC stock (MgC ha⁻¹)</th>
<th>120 cm SOC stock (MgC ha⁻¹)</th>
<th>Sample Depth (cm)</th>
<th>Sample Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>WIP Wetland</td>
<td>138 ± 23</td>
<td>329 ± 82</td>
<td>346 ± 89</td>
<td>362 ± 97</td>
<td>99 ± 7</td>
<td>8</td>
</tr>
<tr>
<td>WIP Wetland (Riverine)</td>
<td>50 ± 13</td>
<td>68 ± 18</td>
<td>68 ± 18</td>
<td>69 ± 18</td>
<td>89 ± 9</td>
<td>2</td>
</tr>
<tr>
<td>WIP Wetland (Palustrine)</td>
<td>171 ± 8</td>
<td>424 ± 27</td>
<td>447 ± 29</td>
<td>468 ± 31</td>
<td>106 ± 6</td>
<td>6</td>
</tr>
<tr>
<td>WIP Upland</td>
<td>96 ± 8</td>
<td>186 ± 20</td>
<td>192 ± 23</td>
<td>197 ± 22</td>
<td>94 ± 6</td>
<td>28</td>
</tr>
<tr>
<td>All Landscapes</td>
<td>105 ± 25</td>
<td>230 ± 25</td>
<td>226 ± 27</td>
<td>219 ± 29</td>
<td>95 ± 4</td>
<td>36</td>
</tr>
</tbody>
</table>

Model predictions and mapping of SOC stocks

We used the model shown in Eq. 2 and graphed in Fig. 2 to predict SOC stocks across the HRW (Fig. 3) and calculated a mean 1 m SOC stock of 131 Mg C ha⁻¹ ± 28 Mg C ha⁻¹ standard deviation from the bootstrapped mapped predictions and a mean 30 cm SOC stock of 74.2 ± 16 Mg C ha⁻¹ (See Methods for model fit evaluation, Table 2. for tabulated 1 m and 30 cm SOC stocks, Supplementary Fig. 1 for mapped 1 m SOC stock standard deviation, and Supplementary Fig. 2. For 30 cm prediction vs. actual scatterplot). The overall total 1 m and 30 cm SOC stocks of the HRW were 8.9 ± 1.9 TgC and 5.1 ± 1.1 TgC, respectively. We focus on the 1 m SOC stocks for mapped predictions with wetlands. Comparisons where wetlands defined by the WIP probability ≥ 50% covered 6,115 ha of the HRW and contained a mean 1 m SOC stock of 278 ± 53 Mg C ha⁻¹ which was more than twice as high as the overall HRW concentration and the mean upland SOC concentration of 116 ± 16 Mg C ha⁻¹. Wetlands in our study also contained disproportionally more SOC for a total of 1.7 ± 0.3 TgC SOC stock or 19.1% of the overall HRW SOC stock in 9.0% of the total landscape surface area for an SOC:Extent ratio of 2.1. Comparatively, uplands contained 7.2 ± 1 TgC or 81% of the HRW SOC stock in 91% of the HRW surface area for a SOC:Extent ratio of 0.9. Within overall wetlands, we identified 4,935 ha of forested wetlands with canopy coverage ≥ 50% that contained higher mean SOC stocks of 293 ± 54 Mg C ha⁻¹ for a total of 1.4 ± 0.3 TgC SOC stock. These forested wetlands composed 81% of the overall wetland extent and 85% of the overall WIP wetland SOC stock for an SOC:Extent ratio of 2.2. Lower wetland SOC stocks were found in 1,726 ha of riverine wetlands that had a mean concentration of 100 ± 37 Mg C ha⁻¹ and a total SOC stock of 0.2 ± 0.1 TgC and 0.8 SOC:Extent ratio. Conversely, palustrine wetlands contained a significantly higher 348 ± 60 Mg C ha⁻¹ SOC stock which was the highest SOC stock in our delineated landscape classes and totaled to 1.5
± 0.3 TgC or 17% of the total landscape SOC within 6% of the surface area of the HRW for a 2.8 SOC:Extent ratio.

Wetland SOC stocks measured from the NWCA derived dataset in Uhran et al., contained a mean stock of 184 MgC ha$^{-1}$ ± 108 MgC ha$^{-1}$ standard deviation (Fig. 3 inset and Fig. 4). Using the 1,640 ha wetland extent measured within the HRW, we calculated a total of 0.3 ± 0.2 TgC across the HRW for a SOC:Extent ratio of 1.4 (Table 2.). Within the NWCA wetlands, forested wetlands defined by our canopy coverage ≥ 50% composed 90% of the wetland SOC and 88% of the wetland extent. Compared to the WIP-derived wetland SOC estimates, the mean concentration NWCA wetland SOC stock was approximately two-thirds or 66% of the mean WIP wetland SOC stock. Due to the large differences in wetland extent, the total wetland SOC of the WIP-derived estimates (1.7 TgC) was 462% higher than the total wetland SOC stock in NWCA (0.3 TgC) showing that only 18% of the total potential wetland SOC stock is currently mapped. By removing overlapping wetland areas covered by the NWCA datasets within our WIP dataset we estimated 5,308 ha of unmapped potential wetlands which we designate as cryptic carbon. This cryptic carbon contained a mean SOC stock of 275 ± 53 MgC ha$^{-1}$ and a total SOC stock of 1.5 ± 0.3 TgC for an SOC:Extent ratio of 2.1 (Table 2.). The total SOC stock of cryptic carbon is 383% higher than the currently mapped total wetland SOC and approximately 16% of the total HRW SOC stock. Within cryptic carbon, 82% is considered forested with canopy cover ≥ 50% and contains 85% of the total SOC. Adding the overall new wetland SOC of 1.5 ± 0.3 TgC to the 0.3 ± 0.2 TgC in the NWCA increases total wetland SOC stock in the HRW by 483% to 1.8 ± 0.5 TgC and more than quadruples the estimated SOC stored in wetlands. Most of the cryptic carbon stock is due to the 272% increase in potential wetland extent from the WIP ≥ 50%, However, new wetland extent contained wetlands with a higher mean SOC stock (275 ± 53 MgC ha$^{-1}$) compared to the mean SOC stock in NWCA wetlands (184 ± 108 MgC ha$^{-1}$) showing a new inclusion of wetlands with high SOC stocks.
Table 2
Metrics from mapping 1 m and 30 cm depth SOC stocks across the HRW. The ± indicates the standard deviation of the bootstrapped model predictions for the WIP derived estimates and published standard deviations from the NWCA datasets in Uhran et al. Landscape class metrics were determined by masking the map of 1 m SOC stocks with surficial geology, canopy cover ≥ 50%, or WIP ≥ 50%.

<table>
<thead>
<tr>
<th>Source</th>
<th>Landscape Class</th>
<th>Surface Area (ha)</th>
<th>Mean SOC Stock (MgC ha⁻¹)</th>
<th>Total SOC Stock (TgC)</th>
<th>Mean SOC Stock (MgC ha⁻¹)</th>
<th>Total SOC Stock (TgC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WIP</td>
<td>Wetland</td>
<td>6,115</td>
<td>121 ± 24</td>
<td>0.7 ± 0.1</td>
<td>278 ± 53</td>
<td>1.7 ± 0.3</td>
</tr>
<tr>
<td></td>
<td>Riverine Wetland</td>
<td>1,726</td>
<td>59 ± 29</td>
<td>0.1 ± 0.1</td>
<td>100 ± 37</td>
<td>0.2 ± 0.1</td>
</tr>
<tr>
<td></td>
<td>Palustrine Wetland</td>
<td>4,390</td>
<td>146 ± 23</td>
<td>0.6 ± 0.1</td>
<td>348 ± 60</td>
<td>1.5 ± 0.3</td>
</tr>
<tr>
<td></td>
<td>Forested Wetland</td>
<td>4,935</td>
<td>127 ± 24</td>
<td>0.6 ± 0.1</td>
<td>293 ± 54</td>
<td>1.4 ± 0.3</td>
</tr>
<tr>
<td></td>
<td>Upland</td>
<td>62,030</td>
<td>69.6 ± 15</td>
<td>4.3 ± 0.9</td>
<td>116 ± 16</td>
<td>7.2 ± 1</td>
</tr>
<tr>
<td></td>
<td>Total HRW</td>
<td>68,145</td>
<td>74.2 ± 16</td>
<td>5.1 ± 1.1</td>
<td>131 ± 28</td>
<td>8.9 ± 1.9</td>
</tr>
<tr>
<td>NWCA</td>
<td>Wetland</td>
<td>1,640</td>
<td>89 ± 51</td>
<td>0.1 ± 0.1</td>
<td>184 ± 108</td>
<td>0.3 ± 0.2</td>
</tr>
<tr>
<td></td>
<td>Forested Wetland</td>
<td>1,442</td>
<td>91 ± 52</td>
<td>0.1 ± 0.1</td>
<td>188 ± 110</td>
<td>0.3 ± 0.2</td>
</tr>
<tr>
<td>WIP - NWCA</td>
<td>Wetland</td>
<td>5,308</td>
<td>121 ± 24</td>
<td>0.6 ± 0.1</td>
<td>275 ± 53</td>
<td>1.5 ± 0.3</td>
</tr>
<tr>
<td></td>
<td>Forested Wetland</td>
<td>4,236</td>
<td>126 ± 24</td>
<td>0.5 ± 0.1</td>
<td>291 ± 54</td>
<td>1.2 ± 0.2</td>
</tr>
<tr>
<td>Combined (WIP + NWCA)</td>
<td>Wetland</td>
<td>6,949</td>
<td>113 ± 31</td>
<td>0.8 ± 0.2</td>
<td>254 ± 66</td>
<td>1.8 ± 0.5</td>
</tr>
<tr>
<td></td>
<td>Forested Wetland</td>
<td>5,678</td>
<td>117 ± 31</td>
<td>0.7 ± 0.2</td>
<td>265 ± 68</td>
<td>1.5 ± 0.4</td>
</tr>
</tbody>
</table>

In our analysis of the wetland extent distribution from the WIP model (Fig. 4), our minimum wetland extent ranged from 64 m² or 0.0064 ha to the largest wetland with 400 ha. In total, we found 31,981 individual wetlands of which approximately 96% were smaller than the minimum mapping unit of 1 acre (0.40 ha) used by the NWI (Supplementary Table 2.). After extracting SOC stocks from our earlier WIP-based model prediction, the SOC distribution across WIP wetlands sizes showed that a majority of wetland surface area (86%) and SOC stock (87%) was contained in wetlands greater than 1 acre (0.40 ha). Indeed, the largest 5 wetlands in terms of extent are above all above 100 ha with the largest 400 ha wetland containing 0.15 TgC or 18% of the total wetland SOC stock (1.7 TgC). The relationship
between SOC stock and individual wetland extent was shown to be linear in a log-log plot indicating that there is a non-linear increase in total SOC stock with increasing wetland extent (Supplementary Fig. 2). Mean stock SOC density across the size distribution showed was consistent around 254 Mg C ha$^{-1}$ with slight increase with surface area with the smaller wetlands containing 254 Mg ha$^{-1}$ compared to the largest wetlands containing 264 Mg ha$^{-1}$ (Supplementary Table 2.).

**Discussion**

Our results show continuous representation of potential wetlands and wet areas integrated into DSM SOC mapping approach greatly improves the spatial representation of SOC. The results explicitly show high SOC stocks in potential wetland areas along with gradients between wetland and upland areas corresponding to the terrestrial to aquatic gradient. Overall, the spatially continuous WIP probability metric was a significant covariate for SOC when combined with surficial geology corresponding to soil parent material and enabled wall-to-wall mapping across the large heterogenous and geomorphologically complex HRW catchment. Probabilistic modeling of wetland presence has become increasingly relevant in wetland mapping research instead of more discrete land cover classification, and the WIP probability model generated with fine resolution topography metrics, identified cryptic wetland features beneath a forest canopy. We found that cryptic carbon defined as the WIP-defined wetland SOC outside of currently mapped areas potentially contains the majority of the modeled wetland SOC stock with approximately 83% of the wetland SOC mapped outside of the NWCA wetland SOC dataset. Consequently, cryptic carbon increased the total wetland SOC stock in the HRW from 0.3 Tg C to 1.8 Tg C or by 483%. This wetland SOC was predominantly contained in the first 1 m of soil depth and within large wetland extents although there are potentially numerous small wetlands within the HRW. We note, however, that wetlands identified within our study do not represent jurisdictional wetlands and wetland boundaries. But the framework of our study begins to address the the critical gap in omitting small potential wetlands and wet areas in SOC mapping and provides an initial step towards monitoring and metrics related to their formation.

Comparisons to other SOC mapping studies

While our study focused on potential wetland SOC, upland SOC is the largest fraction of the total HRW SOC stock. Two global models that provide readily accessible gridded 30 cm SOC maps are SoilGrids 2.0 and the Global Soil Organic Carbon (GSOC) Map. Our estimates are lower than those of SoilGrids 2.0 but higher than GSOC (Supplementary Table 2.) indicating the lower end of the WIP probability may represent soil moisture regimes and their control on SOC in non-wetland areas. Compared to GSOC and our results, SoilGrids 2.0 potentially overestimates SOC stocks in the HRW but is also within the range of other studies using data from the National Forest Inventory. Soils are typically carbon dense in the Pacific Northwest region due to the humid temperate climate of the region and tends to be higher than SOC measurements in other systems for both wetlands and uplands. The region our study takes place in, is the southern portion of the North Pacific Coastal Temperate Rainforest, a region that expands north
to central Alaska and where McNicol et al., 49 measured a median SOC stock of 168.4 MgC ha\(^{-1}\) and mapped mean SOC stock of \(228 \pm 111\) MgC ha\(^{-1}\), much higher than our mapped SOC of \(131 \pm 28\) MgC ha\(^{-1}\) in the HRW due to the presence of numerous northern peatland SOC stocks >500 MgC ha\(^{-1}\) in the region. Peat formation is more frequent farther north in cooler and wetter climates and can accumulate organic material in deposits as deep as 3–5 m 27. Our estimates in the HRW are potentially missing these high SOC stocks due to lack of peat samples in the sampling scheme and limiting the model prediction to 1 m depth. Similarities to the remote-sensing driven peatland probability model developed by Delancey et al., 30 show our approach could apply towards landscape areas with containing peatlands but additional classification may be needed since peatlands store significantly more SOC than mineral soil wetlands per unit area 50. The forested wetlands in our study can be compared to findings from Davidson et al., 14 who measured mean forested wetland SOC concentrations across the Eastern-to-Midwest U.S. and Canada ranging from 165 ± 12 MgC ha\(^{-1}\) to 264 ± 46 MgC ha\(^{-1}\) noting the highest amounts in broad-leaved and shrub/thicket wetland types and lowest in needle-leaved forests. However it is not uncommon for SOC to be higher in needle-leaved forests which can accumulate significant amounts of carbon in colder and wetter climates 51. Across different climatic zones in CONUS, Uhran et al measured 114.8-398.5 MgC ha\(^{-1}\) wetland SOC stocks with higher SOC stocks in the Eastern Mountain region due to presence of peatlands and lower SOC stocks in the arid West and Coastal Plains. Lower wetland SOC stocks are prevalent in more arid regions shown by Tangen and Bansal 52 who measured 81.97 MgC ha\(^{-1}\) wetland SOC in the semi-arid prairie pothole region. Applying the framework of SOC modeling based on wetland probability across larger regional and continental scales would require adjusting the wetland probability with additional covariates corresponding to climatic controls on SOC in order to accurately represent changes in SOC accumulation in different wetland types. Additional improvements to mapping SOC would also include modeling the probability of different wetland classes, especially peat-forming wetlands, by using classification data available from open sources such as the NWI and NLCD 53.

Implication for scaling up cryptic carbon to forested wetlands in CONUS

The wetlands we identified with the WIP and that were not included in the NWCA map contained 1.2 TgC or 73% of the 1.7 TgC total HRW wetland SOC. We believe that a similar result would be found across the forested wetland inventory of CONUS by implementing cryptic carbon estimation. Forested wetlands are the most extensive wetland type in CONUS according to the inventory of palustrine forested wetlands from the NWI 13. However, many forested wetlands remain mis-classified as upland forest due to difficulty in confirming soil moisture conditions due to dense canopies that obscure surface features from remote imagery. We suggest that there is significant potential to improve on previous work from Nahlik and Fennessey, 11 and Uhran et al., 12, the latter of which was used for the wetland SOC baseline comparison in this study. Nahlik and Fennessey used the NWCA and NWI inventory to calculate mean concentrations of \(283 \pm 35.4\) MgC ha\(^{-1}\) and an extent of \(20.1 \times 10^6\) ha in forested wetlands of CONUS for a total stock of 5.92 PgC. Uhran et al., updated wetland SOC estimates from Nahlik and Fennessey by revising the NWCA SOC dataset, harmonizing it with the hydric soil data in the gridded Soil Survey Geographic Database
(gSSURGO) and mapping across wetlands in the NLCD. Uhran et al., reported 191 ± 103 MgC ha⁻¹ mean SOC stock density over 33.9 x 10⁶ ha of woody wetland extent for a total stock of 6.49 PgC in woody wetlands. We emphasize any extrapolation is highly uncertain but a more than 3-fold increase in wetland extent (1,640 ha in NWCA to 6,949 ha in NWCA + WIP) could substantially drive a similar increase in cryptic carbon within forested areas of CONUS which we estimate to be up to 31% ± 11% of the current 64.2 PgC total CONUS SOC stock calculated by extrapolating the mean and uncertainty from Uhran et al., and Nahlik et al., by the 324% increase in wetland extent observed in this study. The underestimation of SOC stocks due to wetland omission has been proposed in previous research and our analysis supports improving SOC estimates with new approaches using probabilistic models that better reflect the spatial distribution of soil moisture conditions.

Cryptic carbon vulnerability to anthropogenic disturbance

Due to the forested overstory, cryptic carbon is likely to experience deforestation as a disturbance but it is detection and frequency is unknown due to its omission from current wetland maps and inventories. The SOC stored as cryptic carbon depends on consistently wet soil conditions and forest harvest practices negatively affect SOC stocks by utilizing intensive site preparation through draining wet areas for tree extraction. Cryptic carbon in headwaters may be especially sensitive to hydrologic disturbance from forestry activities due to more intimate connections to groundwater. Removal of forest canopy in forested wetlands and exposing soil to warmer temperatures can lead to higher rates of SOC decomposition. But long periods of recovery post-harvesting can allow SOC and soil nutrients to return to pre-harvest levels ameliorating impacts on forest wetland function. The effects of deforestation on forested wetlands will also vary by ecosystem type and region. Significant SOC stock destabilization and export of fluvial organic carbon was found in tropical forested wetlands and peatlands that experience deforestation and drainage. More work is needed to improve wetland mapping under forest canopy in tropical regions which are one of the largest sources of uncertainty in the global carbon cycle. While deforestation itself may not lead to complete wetland drainage, land use conversion to agriculture is another persistent threat to wetlands that more effectively drains wetlands and produces substantial carbon release as greenhouse gases.

Globally since 1700, the main driver of wetland loss has been drainage and conversion to agriculture with regional hotspots in the United States, Europe, Central and Southeast Asia, and Japan. Land use conversion is a top contributor to carbon emissions after fossil fuels and is driven mostly by deforestation. Carbon emissions and losses of SOC from disturbed soils are more uncertain than forest biomass carbon loss in the global carbon budget but as much as 133 PgC of SOC has been lost from soils over the course of 12,000 years of human agriculture. There is yet to be a consensus estimate of total global SOC losses due to wetland conversion, but there is consistent evidence of increased carbon emissions and SOC loss when wetlands, and in particular peatlands, are drained and converted to agriculture. Utilizing the newest global wetland maps which model inundation
frequency could help improve spatial estimates of SOC with large global soil pedon databases \(^4,6\). At the continental or country scale, research with moderate resolution remote sensing from Landsat has been used to map wetland extent with SOC stock declines showing significant reductions in the last half century \(^69\). Non-peatland wetlands also experience SOC stock destabilization and emit previously stored carbon as CO\(_2\) due to conversion to cropland \(^11,52\). It is uncertain how the inclusion of cryptic carbon stocks will affect the total estimates of wetland SOC stock affected by disturbance and the magnitude of potential SOC release as CO\(_2\). But more accurate mapping of forested wetland extent and SOC stock will improve conservation of a valuable carbon sink that is underestimated with currently mapped wetland extents.

**Conclusions**

Our study provides an adaptable DSM approach that is informed by a continuous wetland identification metric which maps and reveals high SOC stocks driven by wetland potential on the landscape. This mapping revealed the vast stores of unmapped forested wetland SOC stocks or cryptic carbon compared to currently available wetland SOC maps. We show cryptic carbon contained a higher mean SOC stock than both currently mapped wetlands and uplands. When added to the currently available estimates of wetland SOC stock in the HRW, cryptic carbon increased the total SOC stock from 0.3 TgC to 1.8 TgC or by 483\%. The majority of this cryptic carbon was contained in wetlands greater than the NWI minimum mapping unit of 1-acre or 0.4 ha. There are still considerable uncertainties in extrapolating SOC increase results to the greater population of forested wetlands in the U.S., but the potential magnitude of cryptic carbon supports the need for more wetland identification in forested regions in ways that can inform SOC spatial patterns. We provide one DSM approach which integrates potential wetlands into a SOC prediction model but future research should explore variations of this type of modeling. Metrics that represent the landscape as a gradient of wetlands to uplands can better represent the terrestrial to aquatic gradient that includes potential wetlands and, therefore, areas of SOC accumulation. Land and natural resource managers will be able to use this framework to improve future estimates of SOC spatial patterns as well as wetland SOC vulnerability to land use change.

**Declarations**

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Author Contributions

L.M.M conceived the study and assisted with model analysis. M.H. designed the study, performed modeling analysis with the WIP tool, and contributed data analysis on SOC mapping with contributions from C.B. D.B. and D.V.D assisted with study development, sample collection, and data analysis. A.J.S. led the sample collection, laboratory analysis, and SOC mapping. All authors provided contributions to manuscript writing and interpretation of results.

Competing Interests

The authors declare no competing interests.

References


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**Figures**
Figure 1

The HRW is located in the Pacific Northwest of the United States on the coast of Washington State. The eastern portion of the HRW is mountainous and drains westward to the ocean. Insets show the eastern and wester portions of the lower watershed with wetlands from the National Wetland Inventory (NWI)
Figure 2

Model predicted SOC stock compared to field sampled pedon SOC stock. Modeled SOC stocks were back transformed from square root values in the original linear mixed effects model with the fixed effect of WIP probability and random effect of surficial geology. Prediction intervals are based on bootstrapped 95% confidence intervals.
Figure 3

a) Shows the surficial geology categories of the HRW, b) shows the WIP wetland probability spatial distribution, c) shows the predicted 1 m SOC stock across the HRW with inset showing fine scale SOC patterns overlain by both NWCA wetlands with SOC values and NWI wetlands. We added a hill shade layer to highlight terrain and removed the river surface water shown in light blue for the final prediction map.
Figure 4

a) shows the WIP wetland probability distribution overlain by NWI wetlands for a section of the HRW, b) shows the WIP ≥ 50% classified wetlands and the individual wetland extent, c) shows the 1m WIP modeled SOC stock distribution overlain by SOC estimates from NWCA in Uhran et al., 2021, d) shows the 30 cm WIP modeled SOC stock distribution, e) shows the 30 cm SoilGrids 2.0 modeled SOC stock
distribution, and f) shows the 30 cm SOC stocks from the Global Soil Organic Carbon Map. All maps are set to the same extent and overlain by the same hillshade.

**Supplementary Files**

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementarymaterialCrypticCarbon.docx](#)
- [DataandAnalysis.zip](#)