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Key Points:

- Mountain stream floodplains retain substantially higher soil organic carbon compared to adjacent uplands and floodplains of larger rivers
- Soil organic carbon content along mountain floodplains of the study area is dependent on relative elevation and distance from the channel
- Soil organic carbon does not vary across floodplain geomorphic features and can be estimated from ~11 randomly located samples

Supporting Information:

- Supporting Information S1

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Substantial soil organic carbon retention along floodplains of mountain streams

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Abstract Small, snowmelt-dominated mountain streams have the potential to store substantial organic carbon in floodplain sediment because of high inputs of particulate organic matter, relatively lower temperatures compared with lowland regions, and potential for increased moisture conditions. This work (i) quantifies mean soil organic carbon (OC) content along 24 study reaches in the Colorado Rocky Mountains using 660 soil samples, (ii) identifies potential controls of OC content based on soil properties and spatial position with respect to the channel, and (iii) and examines soil properties and OC across various floodplain geomorphic features in the study area. Stepwise multiple linear regression (adjusted $r^2 = 0.48$, $p < 0.001$) indicates that percentage of silt and clay, sample depth, percent sand, distance from the channel, and relative elevation from the channel are significant predictors of OC content in the study area. Principle component analysis indicates limited separation between geomorphic floodplain features based on predictors of OC content. A lack of significant differences among floodplain features suggests that the systematic random sampling employed in this study can capture the variability of OC across floodplains in the study area. Mean floodplain OC (6.3 ± 0.3%) is more variable but on average greater than values in uplands (1.5 ± 0.08% to 2.2 ± 0.14%) of the Colorado Front Range and higher than published values from floodplains in other regions, particularly those of larger rivers.

Plain Language Summary Rivers serve as conduits for water, sediment, carbon, and nutrients through the landscape, but they also function as active components of the terrestrial carbon cycle. They are important for foodwebs, which support ecosystems and the services upon which societies have evolved to depend. These services include fisheries and clean freshwater by mitigating pollutants and other freshwater contaminants. Many of these services occur within the land alongside rivers called floodplains. Floodplains retain organic matter and carbon, which can constitute a significant storage of carbon to offset increases in atmospheric CO_2, serve as the foundation of food chains in ecosystems, and filter contaminants from river water. Results of this study show that mountain streams in Colorado have relatively high amounts of carbon along floodplains. Analysis presented here uses surveys of floodplain surfaces and 660 soil samples to determine that organic carbon content of the soil is dependent upon the spatial position within the floodplain and other soil properties.

1. Introduction

Soils are the largest terrestrial reservoir and the third largest reservoir for global organic carbon (OC), exceeded only by the ocean and deep geologic storage [*Jobbágy and Jackson*, 2000; *Ruddiman*, 2001]. Thus, soils are a significant component of the terrestrial carbon cycle, but feedback among Earth's surface, atmosphere, and biosphere make quantification of terrestrial carbon reservoirs difficult and subject to the greatest uncertainty among the largest OC reservoirs (i.e., surface ocean, deep ocean, atmosphere, and deep geologic storage) [*Friedlingstein et al.*, 2006; *Gregory et al.*, 2009; *Ballantyne et al.*, 2012; *Arora et al.*, 2013]. The mechanistic source of an increasing uptake of atmospheric carbon occurring at the land surface has yet to be identified and has been termed the missing terrestrial carbon sink [*Ballantyne et al.*, 2012].

Terrestrial carbon budgets identify freshwater systems as a mediator to storage within the geosphere [*Cole et al.*, 2007; *Battin et al.*, 2009; *Aufdenkampe et al.*, 2011; *Hoffmann et al.*, 2013], and recent work has identified the potential for at least some riparian ecosystems and floodplain soils, previously unaccounted for in carbon stocks, to be a component of the missing terrestrial carbon sink [*Hoffmann et al.*, 2009; *Wohl et al.*, 2012; *Sutfin et al.*, 2016]. Concave depressions in the landscape appear to accumulate higher soil organic carbon (OC) content within small catchments [*Holleran et al.*, 2015], so river valleys likely facilitate OC retention within basins. Because valley bottoms funnel sediment, nutrients, and organic matter through the landscape, they have the capacity to facilitate accumulation of high carbon concentrations along low gradient floodplains relative to adjacent uplands. The vertical distribution of carbon content in mountainous floodplains, however, is likely to differ significantly from the typical negative correlation of soil OC content with depth [*Jobbágy and Jackson*, 2000] because the dynamic fluvial environment may create discontinuities of highly concentrated lenses and locally variable OC content.

Understanding of future changes in OC stocks is complicated by uncertainty in anticipated changes in and feedback between moisture and temperature as a result of global climate change [*Trumbore and Czimczik*, 2008; *Falloon et al.*, 2011]. Uncertainty associated with changes in moisture is particularly large for floodplain soils and sediment. Increase in the magnitude and frequency of shifts in longitudinal, vertical, and lateral hydrologic connectivity are anticipated [*U.S. Environmental Protection Agency (EPA) National Center for Environmental Assessment*, 2015], including higher frequency of extreme events and floods [*Bates et al.*, 2008]. Snowmelt-dominated mountain streams are highly susceptible to these changes in hydroclimatic regime because of decreased annual average snowpack and earlier timing of snowmelt, which could leave floodplain sediment drier for longer periods throughout the year [*U.S. EPA National Center for Environmental Assessment*, 2015]. Hydrologic and geomorphic alterations from flow augmentations, channelization, and land use could result in similar changes that influence floodplain carbon dynamics [*Sutfin et al.*, 2016].

Climate change could also influence floodplain soil OC content through impacts on wildfire and other drivers of increased tree mortality (e.g., beetle infestation), particularly in mountainous regions. Although some researchers argue that wildfire can have no effect on total soil OC [*Johnson and Curtis*, 2001], increased frequency and intensity of wildfire [*Westerling et al.*, 2006; *Abatzoglou and Williams*, 2016] may reduce OC inputs to the floodplain and alter the quantity and quality of OC in soils. Although wildfire may immediately decreases the quantity of organic matter content in soil [*Certini*, 2005], it can protect OC from microbial decomposition [*Schmidt and Noack*, 2000] and result in eventual increases in soil OC content after 10 years [*Johnson and Curtis*, 2001; *Certini*, 2005].

Forest disturbances and mortality confound uncertainty in soil OC relating to precipitation, snowpack, and soil moisture, by introducing complex feedback involving the relative accessibility of OC by microbes, loss of shading, increased surface temperatures, photodegradation of OC, and potential rapid regrowth of forests [*Johnson and Curtis*, 2001; *Certini*, 2005]. Identifying the natural variability, spatial patterns, and potential drivers in organic carbon content across floodplain soils that have had relatively little human disturbance is a necessary step to determine the role of rivers in terrestrial carbon cycling and organic carbon retention.

Hoffmann et al. [2014] analyzed spatial variability of OC within an alpine catchment including floodplains, and earlier work by *Hoffmann et al.* [2009] found an increase in organic carbon content from the channel bed, up the sloped river bank, on overbank deposits, and in abandoned channel fill, respectively, along the Rhine River, Germany (basin area $> 20,000$ km^2). Examining spatial patterns of sediment and OC accumulation associated with hydrologic and geomorphic floodplain features across transects on the Atchafalaya River (5670 km^2) in the southeastern U.S., *Hupp et al.* [2008] found the highest OC accumulation rates at topographic lows that were frequently inundated for long periods of time with multiple sources of sediment-laden water. Additional work is required to explain observed variation in OC among floodplain features and the number of samples needed to accurately estimate mean OC content of floodplains, particularly where limited work has been conducted, such as small mountain streams ($<$200 km^2).

Cool, wet conditions are likely to result in the highest OC content along river networks because available moisture supports vegetation growth and high organic matter inputs, whereas the potential for saturated conditions and cooler temperatures is likely to limit decomposition and microbial metabolism of OC [*Jobbágy and Jackson*, 2000; *Falloon et al.*, 2011; *Sutfin et al.*, 2016]. These conditions are met at high latitudes and high altitudes, particularly where wetlands are present along river corridors. Because headwater streams account for the majority of river kilometers globally, relatively unconfined portions of small mountain streams could be a significant component of terrestrial OC storage along river networks. In a small mountain watershed in the Colorado Front Range, *Wohl et al.* [2012] found that floodplains covered ~1% of the surface area but stored ~25% of the OC estimated in upland carbon stocks. The dynamic depositional and erosional environments of small mountain streams, however, are likely to increase variability of OC content across floodplains because channel bedforms and planform geometry largely regulate the transport and distribution of organic matter [*Battin et al.*, 2008; *Tank et al.*, 2010].

This study examines spatial patterns in soil OC across floodplains of small, steep mountain streams in the Colorado Front Range and relationships between soil organic carbon (SOC), soil grain size distributions, and specific geomorphic floodplain features such as stream banks, overbank channels, and wet meadows. Floodplain soils can be highly variable in OC content within a single study area, particularly within the dynamic environment of mountain streams [*Sutfin et al.*, 2016], and exhaustive systematic sampling necessary to capture variability can be costly as well as time- and labor-intensive. We employ a bootstrap approach to identify a threshold where variability and bias of estimated reach-average OC content ceases to decline rapidly with increasing sample size to identify a minimum number of soil samples needed to accurately estimate mean OC content. Using the determined sample size as a sampling guide, the objectives of this paper are to (1) identify potential predictors of soil OC content based on spatial position with respect to the channel and soil properties, (2) investigate differences in predictors of OC across various floodplain geomorphic features to identify potential hotspots for OC content in the study area, and (3) compare organic carbon content along floodplains of the study area to published values in nearby uplands and larger floodplains in lowland regions to examine the relative importance of mountain streams as terrestrial carbon reservoirs.

2. Study Area

The study area in north-central Colorado, USA, lies primarily within Rocky Mountain National Park (RMNP). Established in 1915, RMNP has limited development and has preserved natural conditions along many mountainous streams. The underlying geology of RMNP is a core of granite and schistic gneiss [*Braddock and Cole*, 1990], containing little to no $CaCO_3$, with few outliers for inorganic carbon content of riparian soils (0.01–12.7% IC, mean = 0.43%, median = 0.33%, and standard deviation = 0.6%), as evidenced in sediment and soil analyses presented here. Study reaches are located along streams on the eastern side of the continental divide, where Pleistocene alpine glaciation extended down-valley to as low as 2300 m in elevation [*Anderson et al.*, 2006].

Nineteen study reaches are located in the southeastern portion of RMNP along North Saint Vrain (NSV) and Glacier Creeks (Figure 1), and five additional study reaches extend eastward outside of the park and downstream along NSV, and into other drainages to the north. All study reaches are located in the subalpine and montane vegetation zones and encompass a range of drainage areas (10–180 km^2) and channel gradients (1–15%). Dynamic hydrologic and geomorphic conditions along floodplains of the mountainous study area interrupt the stability required to develop well-defined soil horizons. Shifts in seasonal and interannual erosional and depositional patterns preserve organic-rich deposits and lenses, including buried wood, beneath the surface of floodplains.

Vegetation in the study area differs with elevation. Forests in the subalpine zone (2850–3500 m elevation) are dominated by Engelmann spruce (*Picea englemannii*), subalpine fir (*Abies lasiocarpa*), lodgepole pine (*Pinus contorta*), aspen (*Populus tremuloides*), and limber pine (*Pinus flexilis*). Forests in the montane zone (2850–1750 m elevation) are dominated by ponderosa pine (*Pinus ponderosa var. scopulorum*) and Douglas-fir (*Pseudotsuga menziesii*) [*Veblen and Donnegan*, 2005]. Vegetation in riparian areas differs from adjacent uplands and includes willow (*Salix* spp.), blue spruce (*Picea pungens*), aspen (*Populus tremuloides*), river birch (*Betula fontinalis*), and grasses and sedges (*Carex* spp.) [*Veblen and Donnegan*, 2005]. Distinct fluvial process domains are defined by elevation and lateral valley confinement in the study area and are linked with different vegetation communities, such that aspen, willow, and birch occur more commonly in relatively wider, unconfined valleys, particularly where beaver have influenced channel form and hydrology [*Polvi et al.*, 2011].

3. Methods

3.1. Field-Based Data Collection

Field work and sample collection was conducted between June and August of 2011, 2012, and 2013 along 24 study reaches, each defined by 11 transects oriented perpendicular to the down-valley direction and spaced approximately one bankfull-channel width apart (Figure 2). Study sites included primarily straight, single-thread channels, but three study reaches had complex channel planforms with multiple subparallel,

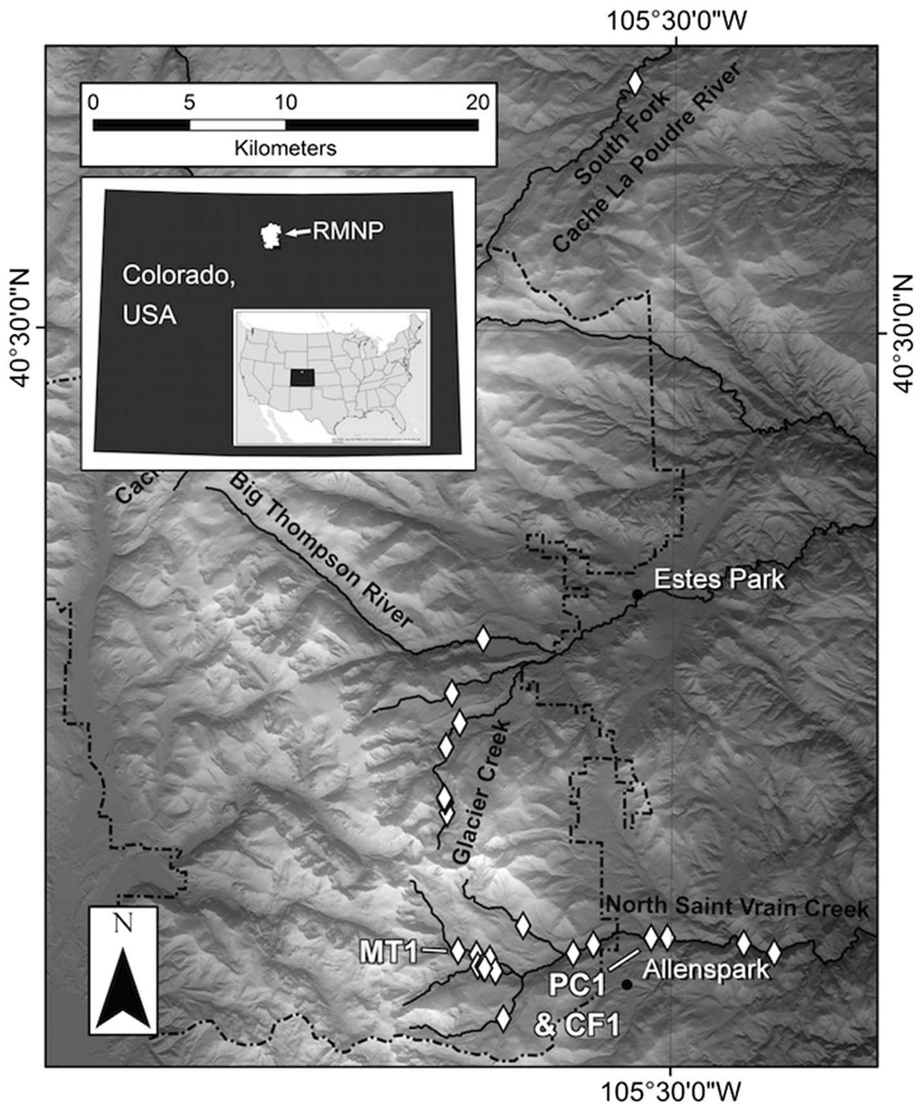

Figure 1. Twenty-four study reaches (indicated by white diamonds) concentrated near the southeastern portion of Rocky Mountain National Park (RMNP) in northern Colorado, USA, and located within the North Saint Vrain Creek, Glacier Creek, and South Fork Poudre River basins. The three primary study reaches (CF1, PC1, and MT1) located on North Saint Vrain Creek were sampled more intensively to determine the number of samples needed to estimate mean SOC content (Section S1.2 in the supporting information).

or anabranching, channels [*Nanson and Knighton*, 1996] that spread across the valley bottom and contained flow throughout the year around semistable, vegetated islands. These complex channel segments are herein referred to as multithread channels and are facilitated by the presence of large, abundant logjams that persist for years to decades [*Wohl and Goode*, 2008; *Collins et al.*, 2012]. Disturbances such as tree throw from high velocity winds and bank erosion create dynamic environments with channel avulsions and periodic shifts in island configuration, channel planform, and cross sectional profiles in these multithread channel segments. Where beaver (*Castor canadensis*) are present in the study area, they engineer dams to obstruct flow, which may result in changes in channel planform and sedimentation patterns analogous to those associated with logjams [*Ives*, 1942; *Persico and Meyer*, 2009; *Polvi and Wohl*, 2013].

Stratification was conducted across various degrees of valley confinement to include those study reaches with and without the influence of logjams and beavers to capture the variability in floodplain hydrologic conditions, connectivity of water and sediment between the channel and the floodplain [*Wainwright et al.*, 2011; *Bracken et al.*, 2013], and potential differences in resulting soil carbon content. In this study, floodplains are considered to be regularly inundated at least every decade, as indicated by riparian vegetation species in

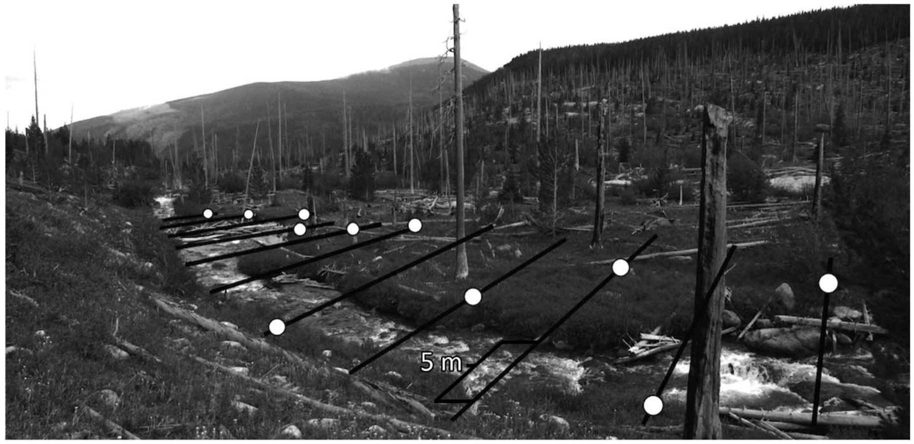

Figure 2. Systematic random sampling used along 24 study reaches to identify sampling locations along 11 transects spaced ~1 bankfull width apart and oriented orthogonal to the down-valley direction. The white circles indicate examples of randomly selected sample locations on each transect.

the study area [*Veblen and Donnegan*, 2005; *Merritt et al.*, 2010]. We define valley confinement (c_v) as the width of the valley bottom (w_v) or floodplain divided by the width of the channel (w_c).

Topography of the floodplain was surveyed along the 11 transects at each study reach using a Laser Technology TruPulse 360B laser rangefinder and stadia rod. The rangefinder is accurate to $\pm$0.1 m and was used to calculate relative elevation, horizontal distance from the active channel for each transect point, and soil sampling location. At each sampling location, litter (identifiable organic matter such as leaves, cones, and needles) and humus (unidentifiable and partially decomposed organic matter) were removed from the surface of the soil profile before sampling. Litter and humus (organic horizon) are not included in this analysis because they are relatively transient and vary greatly in thickness within this dynamic fluvial environment. At all sampling locations, soils were sampled at 15 cm depth increments using an ~6.4 cm (2.5 inch) diameter stainless steel hand auger. Augering penetrated to the depth of bedrock or gravel or to a maximum depth of 180 cm in finer sediment.

Three study reaches were sampled intensively (ranging from 34 to 51 samples depending on reach configuration), and random bootstrap analysis was conducted to determine the number of samples and sample locations where variance leveled off and bias of mean soil organic carbon estimates no longer decreased with increasing sample size. The bootstrap analysis indicated that approximately 11 systematic random sampling locations were sufficient to minimize bias and variance (Section S2 and Figure S1 in the supporting information). All the samples collected from the three intensive study reaches were used in the analysis, and the bootstrap results were used to guide the number of samples for 21 additional reaches in this study area.

Systematic random sampling was used, such that a random location was selected for a soil sample along each transect. This was done by measuring the width of the valley bottom in the field using the laser range finder and by estimating the width between two points on either side of the valley using a GPS when the valley was significantly wide (i.e., $>$50 m). Each transect was then divided into segments of a meter, and a random location was selected by increments of a meter from the valley edge using a random number generator in the field. Where random locations fell within the channel, another location was selected randomly. Where sediment or soil was not present along an entire transect (primarily where valleys were confined by bedrock), a second randomly located sample was collected on the bank of a different transect, where a sample had not already been taken. Where possible, each study reach had 11 sampling locations, but in some reaches confinement restricted the number of samples.

3.2. Analytical Methods

Random samples were collected from a total of 294 locations along the 24 study reaches, resulting in a total of 660 soil samples, which were frozen until analyzed for OC content by the Colorado State University Soil and Water Testing Laboratory. Samples were weighed before and after drying to determine gravimetric soil moisture content. Samples were sieved to $<$2 mm, and homogenized before subsamples were ground using a mortar and pestle. Samples were gently mixed in the vial with 6M HCl to neutralize the inorganic C. The pressure built up in the serum bottle due to the evolution of CO_2 was measured with a pressure transducer and compared to standards made from known quantities of $CaCO_3$ [*Sherrod et al.*, 2002]. Inorganic C was calculated as the equivalent of $CaCO_3$. Soil was introduced into the LECO furnace and burned at 900°C. The evolution of CO_2 was measured and expressed as total carbon (TC) [*Nelson and Sommers*, 1982]. Total organic carbon content by weight was calculated as TC minus CO_3-C.

Grain-size analysis was conducted on a subset of samples for all depths at randomly selected sampling locations for each study reach. Four soil sampling locations were selected from each study reach, and all depth increments for each location were processed. A total of 186 samples were sieved for grain size analysis by weight to determine percent gravel (>2 mm), coarse sand (0.5–2 mm), medium-to-fine sand (0.062–0.5 mm), and the silt-clay fraction (<0.062 mm).

3.3. Statistical Analyses

General statistics and correlations between study reaches, OC content, and grain size were conducted using R statistical software [*R Core Team*, 2014]. All univariate correlation coefficients (*r*) listed here are Spearman correlations. Pairwise comparisons to test differences in OC and grain size between geomorphic features were conducted using Welch's *t* test with the *Holm* [1979] correction in the *pairwise.t.test* function of the *stats* package in R.

3.3.1. Variable Selection

The number of variables for multiple linear regression was reduced by elimination depending on the correlation coefficients and collinearity with other variables for 660 soil samples from all 24 study reaches. Potential variables for the first regression analysis included horizontal distance from the active channel, valley confinement, total maximum soil depth or thickness at a sampling location, elevation of the floodplain surface relative to the active channel along the sampling transect, sample depth (the center of each 15 cm long soil sample), and relative elevation of the sample from the active channel as predictors for OC content. A second regression analysis conducted on a subset of samples included the above listed variables as well as grain size composition (i.e., percent silt and clay, percent sand, and percent gravel). Although soil moisture typically has a positive correlation with SOC until saturation begins to limited microbial respiration [*Chapin et al.*, 2011], it exhibits high temporal variability, so it was not included in the regression analysis. Grain size variables, which correlate with soil moisture, were included instead because they represent characteristics of the soil.

Variable selection began with the variable that was most strongly correlated with SOC. All variables cross correlated with the retained variable such that $r \geq 0.5$ ($r^2 = 0.25$) were eliminated. The variable with the next strongest correlation with OC was then selected, and this process was repeated until all variables had either been eliminated or retained. Spearman correlation coefficients between all independent variables examined in stepwise multiple linear regression ($r < 0.5$) were less than the threshold value of $r = 0.5$–0.7 recommended by *Dormann et al.* [2013].

3.3.2. Identifying Predictors of Soil Organic Carbon Content

Stepwise multiple linear regression was conducted using the *step* function of the *stats* package in R statistical software [*R Core Team*, 2014] to examine potential relationships between OC and predictor variables. The regression analysis was conducted on two separate data sets, all 660 soil samples, and the subset of 186 samples for which grain size analysis was conducted (Tables S2 and S3 in the supporting information). The best model was selected from the lowest value of the Akaike information criteria (AIC). Leave-one-out v-fold cross validation was conducted using the *cv.glm* function of the *boot* package in R [*Canty and Ripley*, 2017].

The Breusch-Pagan test was conducted using the *ncvTest* of the *car* package in R [*Breusch and Pagan*, 1979; *Fox and Weisberg*, 2011]. Results suggested homoscedasticity for regression analyses based on the failure to reject the null hypothesis of constant variance ($p = 0.46$ and 0.43 for the 660 and 186 samples, respectively) after a boxcox power transformation [*Box and Cox*, 1964] of the dependent variable determined using the *boxcox* tool of the *MASS* package [*Venables and Ripley*, 2002] with $\lambda = 0.06060606$ for both regression analyses. The boxcox transformation produced normally distributed errors for a linear regression model of the 186 samples, as indicated by a Shapiro-Wilk test of the residuals ($p = 0.87$) using the *Shapiro.test* function of the *stats* package in R [*R Core Team*, 2014]. In contrast, the transformation did not yield normally distributed errors for a linear regression model that considered all 660 samples ($p = 0.02$, Shapiro-Wilk test). A qqplot and histogram of the model residuals, however, illustrate approximate normality (Figure S2). We note that the assumption for normality of

Table 1. Basic Statistics of Eight Variables for 660 Soil Samples From 24 Study Reaches

	Sample Elevation Relative to the Channel (m)	Sample Depth (m)	Soil Moisture (%)	Distance From the Channel (m)	Maximum Soil Thickness (m)	Surface Elevation Relative to the Channel (m)	Confinement (m/m)	Total Organic Carbon (%)
Minimum	−0.8	0.02	3.0	0.0	0.0	−0.2	1.1	0.1
Maximum	1.9	1.63	86.2	160.0	1.7	2.3	45.2	58.0
Range	2.7	1.61	83.2	160.0	1.7	2.5	44.1	57.9
Median	−0.020	0.26	33.8	4.5	0.5	0.5	5.2	3.7
Mean	0.030	0.32	37.0	17.1	0.56	0.55	6.8	6.3
Variance	0.221	0.05	372.4	1032.1	0.10	0.17	34.5	59.4
Standard deviation	0.470	0.23	19.3	32.1	0.31	0.41	5.9	7.7
Standard error of mean	0.02	0.01	0.75	1.25	0.01	0.02	0.23	0.30

model errors is relaxed and becomes less important with relatively large data sets (e.g., 660 samples) where deviations from normality and failure of formal tests have been shown to result in only minor deviations from the mean, regression coefficients [*Lumley et al.*, 2002; *Williams et al.*, 2013], and confidence intervals [*Osborne*, 2013]. These deviations are of minor importance, particularly when the results of the regression model are not being used to make predictions and inferences based on formal hypothesis tests [*Plackett*, 1950; *Lumley et al.*, 2002; *Osborne*, 2013; *Williams et al.*, 2013]. Instead, multiple linear regression is used here to identify whether a combination of spatial and state variables could be significant predictors of soil organic carbon content in floodplain soils of the Colorado Front Range.

3.3.3. Examining Predictors of OC Across Floodplain Features

Principle component analysis was conducted on the subset of 186 samples to visually examine groups of floodplain geomorphic features in multivariate space with the goal of determining differences in SOC among floodplain features (Table S1). All principle component analysis (PCA) input variables were standardized by dividing each observation by the standard deviation and centered using the *prcomp* command of the *stats* package in R [*R Core Team*, 2014]. Geomorphic floodplain features included the channel banks, the far edge of the valley/floodplain extent, overbank channels (including side channels and inactive abandoned channels), wet meadows (including beaver meadows, ponds, and shallow standing water <5 cm), elevated tree berms or hummocks, islands, and the generic class of floodplain, which was designated where one of the other more distinct classes was not present. Nonparametric permutational multivariate analysis of variance (permanova) was conducted on the eight principle components to test for significant differences between floodplain features in the subset of 186 samples using the *adonis* function of the *vegan* package in R with 999 permutations [*Anderson*, 2001; *Oksanen et al.*, 2017].

4. Results

4.1. Independent Variable Characteristics, Correlations, and Reduction

The 660 samples were characterized by a range of elevations from the channel (−0.8 to 1.9 m), mean soil depths of 2 to 163 cm, confinement ratios ranging from 1.1 to 45.2 m/m, and a mean OC content of 6.3 ± 0.3%

Table 2. Spearman Correlation Coefficients (r) for Eight Variables From 660 Soil Samples[a]

	Sample Elevation Relative to the Channel	Maximum Soil Thickness	Distance From the Channel	Surface Elevation Relative to the Channel	Soil Moisture	Sample Depth	Confinement	Total Organic Carbon
Sample Elevation Relative to the Channel	1	**−0.37**	−0.07	**0.7**	**−0.08**	**−0.23**	**−0.1**	**0.17**
Maximum soil thickness		1	**0.31**	**0.19**	−0.01	**0.59**	**0.22**	**−0.22**
Distance from the channel			1	**0.2**	**0.09**	**0.17**	**0.56**	**−0.07**
Surface Elevation Relative to the Channel				1	**−0.13**	**0.1**	**0.12**	0.01
Soil moisture					1	−0.02	**0.34**	**0.66**
Sample depth						1	**0.11**	**−0.4**
Confinement							1	**0.08**
Total organic carbon								1

[a]Numbers in bold indicate correlations significant at the 95% confidence level ($p \leq 0.05$).

Table 3. Basic Statistics of 11 Variables for the Subset of 186 Soil Samples With Grain Size Data From 24 Study Reaches

	Surface Elevation Relative to the Channel (m)	Maximum Soil Thickness (m)	Confinement (m/m)	Soil Moisture (%)	Percent Silt and Clay	Percent Sand	Percent Gravel (>2 mm)	Sample Depth (m)	Distance From the Channel (m)	Sample Elevation Relative to the Channel (m)	Total Organic Carbon (%)
Minimum	0.00	0.00	1.25	3.01	0.00	14.96	0.00	0.05	0.30	−0.65	0.16
Maximum	1.60	1.65	45.19	77.89	48.19	99.52	76.12	1.20	160.00	1.51	41.91
Range	1.60	1.65	43.93	74.88	48.19	84.56	76.12	1.15	159.70	2.16	41.75
Median	0.50	0.55	4.73	33.66	12.01	78.17	1.66	0.26	3.90	0.21	3.50
Mean	0.56	0.60	7.25	36.12	15.24	75.81	8.11	0.33	21.85	0.23	5.48
Variance	0.16	0.11	44.00	282.66	122.80	182.62	183.41	0.05	1582.18	0.18	42.02
Standard deviation	0.40	0.34	6.63	16.81	11.08	13.51	13.54	0.23	39.78	0.43	6.48
Standard error of mean	0.03	0.02	0.49	1.23	0.81	0.99	0.99	0.02	2.92	0.03	0.48

(Table 1). The maximum soil thickness, distance from the channel, and floodplain surface elevation were eliminated as potential predictors because of cross correlations with stronger variables (Table 2). Soil organic carbon content for all 660 soil samples was strongly correlated with moisture content ($r = 0.66$, $p < 0.0001$) and soil sample depth ($r = -0.4$, $p < 0.0001$). Because soil moisture is highly variable depending on the time of sampling and because samples were not all collected within a reasonable time frame for comparison, moisture content was removed as a meaningful predictor. Instead, grain-size variables, which are strongly correlated with soil moisture, were used in the regression with subset of 186 samples and more accurately represent spatial variability of soil characteristics and the ability of the soil to retain water.

The subset of 186 samples indicated that all samples contained sand and the mean percent sand content across all study reaches was 75.8 ± 13.5%. Some samples, however, contained 0% gravel and 0% silt and clay (Table 3). Results from the subset of 186 samples indicated correlation of OC content with percent silt and clay ($r = 0.47$, $p < 0.0001$) and moisture content ($r = 0.61$, $p < 0.0001$; Table 4). Moisture and silt and clay content were also strongly positively cross correlated ($r = 0.65$, $p < 0.0001$). Silt-and-clay content (sc) and percent sand (*ps*) were retained as grain size variables in the regression, but percent gravel was eliminated because of cross correlation. Other variables included in the regression analysis of 186 samples were sample depth (d_s), horizontal distance from the channel (x_d), and elevation of the sample relative to the channel (z_s).

4.2. Predictors of OC Content

The stepwise multiple linear regression using all 660 soil observations indicated that spatial position across the floodplain and valley confinement influenced OC content. Sample depth (d_s; $p < 0.0001$), elevation of the sample relative to the channel (z_s; $p = 0.0038$), and valley confinement ($p = 0.91$) were significant variables

Table 4. Spearman Correlation Coefficients (*r*) for 11 Variables From a Subset of 186 Soil Samples[a]

	Surface Elevation Relative to the Channel	Maximum Soil Thickness	Confinement	Soil Moisture	Percent Silt and Clay	Percent Sand	Percent Gravel	Sample Depth	Distance From the Channel	Sample Elevation Relative to the Channel	Total Organic Carbon
Surface Elevation Relative to the Channel	1	**0.28**	**0.27**	**−0.2**	−0.02	−0.01	0.02	**0.18**	**0.54**	**0.85**	−0.06
Maximum soil thickness		1	0.12	0.05	0.08	−0.03	0	**0.65**	**0.4**	−0.08	**−0.23**
Confinement			1	0.13	**0.16**	−0.04	−0.08	0.09	**0.58**	**0.21**	−0.06
Soil moisture				1	**0.65**	**−0.27**	**−0.28**	−0.07	−0.05	**−0.16**	**0.61**
Percent silt and clay					1	**−0.36**	**−0.43**	−0.12	0.12	0.04	**0.47**
Percent sand						1	**−0.63**	0.01	−0.01	−0.01	**−0.41**
Percent gravel							1	0.11	−0.09	−0.04	−0.13
Sample depth								1	**0.29**	**−0.36**	**−0.31**
Distance from the channel									1	**0.35**	**−0.13**
Sample Elevation Relative to the Channel										1	0.11
Total organic carbon											1

[a]Numbers in bold indicate correlations significant at the 95% confidence level ($p \leq 0.05$).

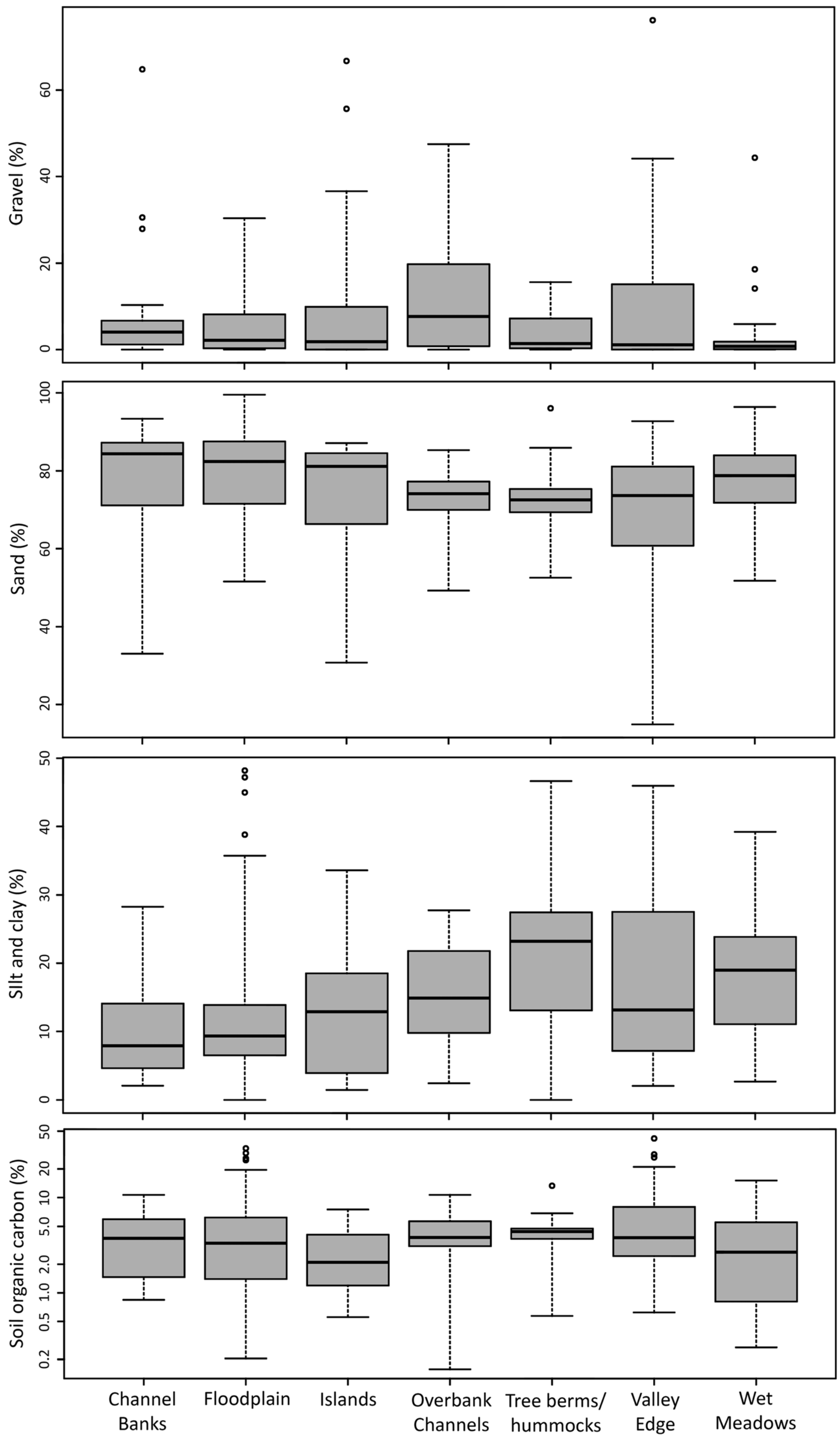

Figure 3. Boxplots of grain size distributions and soil organic carbon by geomorphic feature.

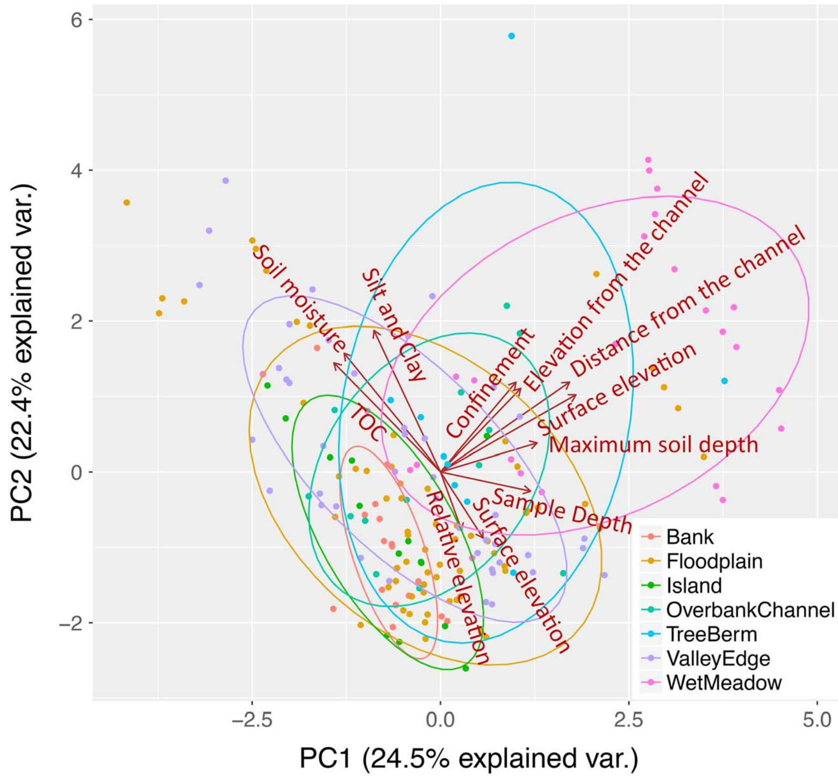

Figure 4. Principle component analysis with biplot for 186 samples and predictor variables, where TOC is total organic carbon. The ellipsoids denote the 68% probability (1 standard deviation) of each geomorphic group in principle component space.

at the 99%, 99%, and 95% confidence level, respectively. The model had an adjusted multiple r^2 of 0.15 ($p < 0.0001$), a cross-validation mean square error (MSE) of 0.0046, a residual standard error (ε) of 0.0677, and a reduction in the AIC value from −3442.97 for the null regression model to −3550.49 (Tables S2 and S3). The optimum regression model described by equation (1)

$$\text{SOC} = 1.1135 - 0.1166\,(d_s) + 0.01656\,(z_s) - 0.0008\,(c_v) \tag{1}$$

indicated that OC had a positive correlation with sample elevation relative to the channel (z_s) and a negative correlation with sample depth (d_s) and valley confinement (c_v). This means that soils nearer the surface and highest in elevation across a relatively confined portion of the floodplain favor higher OC content.

Stepwise multiple linear regression using the subset of 186 samples with grain size data resulted in a stronger model than the 660-sample regression analysis ($r^2 = 0.48$, $p < 0.0001$, $\varepsilon = 0.05051$, MSE = 0.0027, reduced AIC from −986.75 to −1104.72), shown in equation (2) (Tables S3 and S4).

$$\text{SOC} = 1.1255 + 0.0029(sc) - 0.10978(d_s) - 0.0008(ps) - 0.0004(x_d) + 0.0191\,(z_s) \tag{2}$$

Percent silt-clay content and elevation of the sample relative to the channel had a significant positive correlation with OC at the 99% confidence level ($p \leq 0.0001$ and $p = 0.083$), whereas sample depth ($p < 0.0001$), percent sand ($p = 0.009$), and distance from the channel ($p = 0.002$) had a significant negative correlation with SOC. These results agreed with the multiple regression output from 660 soil samples such that soils, closer to the surface, higher in elevation, and closer to the channel are likely to have higher OC content. The regression analysis including grain size for 186 samples, however, indicated that soils with more silt and clay and less sand were more likely to have higher SOC.

4.3. Organic Carbon Across Different Floodplain Geomorphic Features

Pairwise Welch's t tests indicate a significant difference in OC between the generalized floodplain and both the channel banks ($p = 0.081$) and the valley edge ($p = 0.068$) at the 90% confidence level for the complete data set of 660 samples but no significant differences in OC between geomorphic features for the subset of

Table 5. Published Soil Organic Carbon Content of Floodplains in Various Regions and Uplands of the Colorado Front Range

Location	Mean OC (%)	Standard Error (%)	Study
Colorado, USA (uplands)[a]	1.5 to 2.3[b]	±0.08 to 0.14	[*Licata and Sanford*, 2012]
Colorado, USA	10 to 14[c]	–	[*Wohl et al.*, 2012]
Colorado, USA[d]	6.3	±0.3	This study
Mid-Atlantic USA (piedmont floodplains)			[*Walter and Merritts*, 2008]
Mineral topsoil	1 to 2	–	
Buried organic horizon	2 to 9	–	
Alberta, Canada[e]	1.3 to 1.5	±0.14 to 5.8	[*Hoffmann et al.*, 2014]
Chamela, Mexico	1.6 to 3.1	–	[*Jaramillo et al.*, 2003]
Rhine River, Germany	0.2 to 2	–	[*Hoffmann et al.*, 2009]

[a]Values from uplands in the study area.
[b]Values represent the range of mean OC conducted across stratified elevation zones in different forest types of uplands in the same region as this study.
[c]Values represent mean OC from unconfined and confined study reaches.
[d]Values from this study.
[e]Only selected values from floodplains cited.

186 samples (Figures 3, S5, and S6). Percent sand differed significantly at the 99% confidence level between floodplains and the valley edge (p = 0.01) and was the only grain-size fraction that differed significantly among geomorphic features for the subset of 186 soil samples (Tables S7–S9).

Principle component analysis (PCA) conducted on the subset of 186 samples with grain size information including all 11 independent variables and OC content indicated abundant overlap between geomorphic floodplain features in principle component space (Figure 4). The first and second principle components explain 24.5% and 22.4% of the variability, respectively. The PCA biplot of PC1 and PC2 indicated that wet meadows were most unlike other features and suggested that these differences were driven primarily by confinement, elevation and distance from the channel, surface elevation, soil depth, and sample depth. Channel banks were the most dissimilar from wet meadows because the 68% probability ellipsoids, which represent a single standard deviation, do not overlap, as do ellipsoids for all other groups. Islands also had only a slight overlap with wet meadows and share much of the same space on the PCA plot with channel banks. This is reasonable since islands are composed of banks and share characteristics including a short distance from the channel and low relative elevation. Although permanova analysis indicated that all groups do not share the same means in principle component space ($p < 0.001$), the PCA plot indicated much overlap between groups. This suggests that systematic random sampling conducted in this study is enough to capture the variability along floodplains of the Colorado Front Range, but the first two principle components only explain a total of 46.9% of the variability. Further examination is needed to explore differences across floodplain features in greater detail.

5. Discussion

Results indicate that soil organic carbon content of floodplains in the Colorado Front Range (6.3 ± 0.3%) are higher than published values for uplands in the study area (Table 5). *Licata and Sanford* [2012] examined upland soil carbon content along a gradient from the foothills to the subalpine zone in the Colorado Front Range, including ponderosa forests to spruce and subalpine fir forests (which encompasses our study area), and found soil OC contents of 1.5 ± 0.08 to 2.2 ± 0.14%. Although floodplain soil OC content presented here is much higher and more variable than those on adjacent hillslopes of the Colorado Front Range, our values are lower than those from *Wohl et al.* [2012], who found organic carbon contents of 10–14%. Higher values reported by *Wohl et al.* [2012] in the same study area may reflect a smaller sample size (in terms of both the number of sites and samples per site). Anomalously high OC values at a small number of sites from *Wohl et al.* [2012] do not represent the variability of the OC content presented here. Our systematic random sampling scheme and greater number of study sites likely provide a more accurate estimate of soil OC content along floodplains of the Front Range.

Mean organic carbon content at our study sites is generally higher than that reported for other floodplain rivers (Table 5). Beyond our study area, the only other published results of floodplain SOC content that are within the same range of values are buried organic horizons in the Mid-Atlantic region of the U.S. (2–9%) [*Walter and Merritts*, 2008]. The Mid-Atlantic sites were influenced by historic milldam sedimentation so that the topsoil had much lower OC content (1–2%; Table 5) compared with the underlying, preindustrial, organic-rich soils (2–9%; Table 5), suggesting that human alteration to rivers and floodplains may alter carbon storage along river corridors [*Wohl et al.*, 2017]. Perhaps SOC values in the buried soils from *Walter and Merritts* [2008] and those presented here are higher than those from other studies because they both represent soils from relatively undisturbed floodplains.

Our study sites were also prone to wildfire, but this is unlikely to influence observed OC values. Although wildfire can render a portion of OC inaccessible to microbes, relatively undeveloped upland regions of the Colorado Rocky Mountains do not contain higher soil OC content than more developed mountainous and lowland regions. Decreased frequency and severity of wildfire along riparian corridors [*Dwire and Kauffman*, 2003] are also likely to reduce any potential differences between relatively undisturbed Rocky Mountain floodplains and more developed floodplains in other regions with less frequency of wildfire.

Regardless of potential differences as a result of wildfire, it is important to develop approaches for estimating carbon storage in floodplains of relatively undisturbed areas in various regions. Understanding potential controls on the variability of soil OC across floodplains will inform methods to estimating storage and may increase understanding of OC processing along streams and how that may be impacted by disturbance.

Results presented here indicate that soil OC content along floodplains of mountain streams in the Colorado Front Range correlates with soil grain size distributions and spatial position across the floodplain. Soil OC content correlates significantly and positively with sample elevation relative to the channel but not to the floodplain surface elevation at the sampling location. *Hupp et al.* [2008] found a correlation with surface elevation and deposition rate of sediment and soil organic matter (SOM), but their study was along the much larger and lower gradient Atchafalaya River. The expansive, low-gradient floodplain of the Atchafalaya River likely creates a predominantly depositional environment in which low-energy floodwaters mobilize fine sediment that accumulates more rapidly in depressions. Although *Hupp et al.* [2008] found lower surfaces experienced more rapid deposition rates of sediment and longer periods of floodplain inundation, higher floodplain surfaces accumulated more OC. Conversely, *Holleran et al.* [2015] found that soil OC content was higher in topographic depressions of an upland catchment, but the study was not conducted along floodplains. Alternating periods of saturation and/or frequent wetting-and-drying periods common to floodplains could facilitate more rapid decomposition of soil OC in surface depressions.

Although differences in soil OC content between most geomorphic features in the study area are statistically insignificant (Figures S5 and S6), what little differences there are appear to be driven by spatial position along the floodplain, as indicated by the direction of arrows in the PCA biplot relative to the differences in groups for the 186 samples (Figure 4). Soil OC content generally decreases with distance from the channel (Tables 2 and 4), which is reflected in significant differences in OC content between the floodplain and channel banks for analysis of the full data set of 660 samples ($p = 0.08$, Figure S5) but not for analysis of the subset of 186 samples. The only other significant difference in OC for the 660 samples is that between the floodplain and valley edge, which counteracts the negative correlation between OC and distance from the channel and could be a result of inputs from adjacent hillslopes or the fact that valley edges tend to be higher in elevation and experience inundation much less frequently. Significant difference in sand content between the floodplain and the valley edge reflects differences in OC content between those features and sand content as a predictor for OC. Differences in mean soil OC content and grain size between most geomorphic features are insignificant for the 186-sample data set (Figure 3 and Tables S6–S9), but relatively small sample size within each geomorphic feature may limit the ability to detect differences in OC between valley edges and banks. Insignificant differences in OC content and the lack of clear distinction in PCA space (Figures 3 and S3) between geomorphic features in the 660- and 186-sample analyses suggest that stratification by all features may not be necessary to capture the variability across the floodplain. Higher OC content along banks and valley edges in the 660-sample analysis, however, may warrant stratification of sampling either by feature or with distance from the channel in the study area.

Bootstrap random sampling analysis suggests that an investigator can capture the variability of the mean soil OC content in snowmelt-dominated mountain streams of the Colorado Front Range without an increase in bias by sampling all depths at approximately 11 systematic random sampling locations. These results, however, are likely not applicable to other regions and climates, although a similar technique can be applied to determine the appropriate number of samples needed in other study areas.

6. Conclusion

Quantifying soil organic carbon content of floodplains will increase understanding of ecosystem processing of carbon, aquatic-riparian linkages, carbon stocks, and interactions between terrestrial and global carbon budgets. Comparison with other studies indicates that floodplain sediments in mountain streams of the Colorado Front Range have higher organic carbon content than those in adjacent uplands and other regions, particularly in larger rivers, which suggests that floodplain mountain streams could be a significant component of terrestrial carbon storage. Soil organic carbon content in the study area correlates significantly with grain size distributions and variables relating to the spatial position within the floodplain including sample depth, sample elevation relative to the channel, and distance from the channel. Mean soil OC is not equal across different geomorphic floodplain features, but PCA analysis suggests that it does not necessarily vary by geomorphic features such as berms, islands, hummocks, wet meadows, and overbank channels. This indicates that the approach used here of systematic random sampling along 11 transects effectively captures the variability of soil OC along floodplains of snowmelt-dominated streams in the Colorado Front Range. Similar approaches can be taken for determining the number of samples needed to capture variability in soil OC across floodplains in other regions.

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