EVALUATING ENVIRONMENTAL INFLUENCES ON GRASSLAND SOIL ORGANIC CARBON TEMPORAL AND SPATIAL DISTRIBUTION

By

DESTINY D. KERR

Bachelor of Science in Environmental Science

Oklahoma State University

Stillwater, Oklahoma

2017

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
July, 2019

EVALUATING ENVIRONMENTAL INFLUENCES

ON GRASSLAND SOIL ORGANIC CARBON

TEMPORAL AND SPATIAL DISTRIBUTION

Thesis Approved:

Tyson Ochsner

Thesis Adviser

Chris Zou

Jason Warren

ACKNOWLEDGEMENTS

This thesis would not be possible without the support of my family, academic advisor, and fellow graduate students. Thank you to my husband for bringing me dinner during my late nights in the office. Thank you to my parents and grandparents for continuously encouraging me. Thank you to my sister and cousin for always being ready to celebrate with me. Thank you to my aunt for always making time to come visit and buy me dinner. Thank you to my fellow graduate students for taking time to listen to my questions, for looking at my newest figures, and for sending me relevant research articles when you see them. Thank you to my committee and other faculty for the time and thoughtfulness you gave me. Lastly, I need to thank my academic advisor; your support and guidance were invaluable. I appreciate that you gave me the room to figure things out for myself, but you were still always there to help me when I asked. Many amazing people have touch my life these last two years and I will be forever grateful.

I would also like to thank the sources of data I used in my two studies: the Oklahoma Mesonet, Dr. Elliot's research team, and the Soil Physics research team, in particular Bethany Scott. The Oklahoma Mesonet continuously collects quality data used by many researchers; I was able to use this invaluable dataset in both of my studies. Dr. Elliot and his research team, and Bethany Scott and other fellow OSU Soil Physics research students collected and processed hundreds of soil samples years before I began my research. Though I never got to meet many of the people who had a hand in collecting these samples, it was because of their hard work and diligence I was able to inherit these datasets and use them in my own research.

Name: DESTINY D. KERR

Date of Degree: JULY, 2019

Title of Study: EVALUATING ENVIRONMENTAL INFLUENCES ON GRASSLAND

SOIL ORGANIC CARBON TEMPORAL AND SPATIAL DISTRIBUTION

Major Field: PLANT AND SOIL SCIENCES

Abstract: The soil is the largest terrestrial carbon sink, and soil organic carbon (SOC) accounts for twice as much carbon as is stored in the atmosphere. A large portion of recent atmospheric carbon increases is due to the loss of carbon from soil. There are significant uncertainties as to the degree in which environmental factors influence SOC dynamics. A better understanding of how SOC is influenced by environmental factors is needed to inform global carbon budgets, climate projections, and analyses of SOC-climate change feedbacks. In this report, we analyzed SOC data from grassland sites across Oklahoma, USA to evaluate the relationships between soil carbon and environmental factors. We found SOC is more strongly influenced by soil-climate, particularly soil moisture, compared to climate data. Including soil-climate data in soil carbon predictions resulted in more accurate SOC predictions and indicate that soil moisture was the climate-related variable with the greatest influence on SOC. We also found that changes in SOC over time are significantly influenced by the initial SOC and soil depth. Vertical distribution of SOC in these soil profiles became more stratified during the study period, with the SOC in the top 5 cm increasing in relation to SOC at deeper depths.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure Page

CHAPTER I

Introduction

Climate change is a global issue that is bringing to light the importance of carbon to researchers, citizens, and policy makers. Atmospheric carbon dioxide has increased by 40% since the Industrial Revolution (Jay et al., 2018). Increases in atmospheric carbon caused by anthropogenic activities, such as the burning of fossil fuels and land-use change, contributes to rising global temperatures (Oreskes, 2005). Rising global temperatures has the potential to cause a loss of carbon from the soil by accelerating soil respiration. This loss of soil carbon can negatively affect ecological services the soil provides, including soil productivity, erosion prevention, and carbon sequestration.

The soil is the largest terrestrial carbon reservoir and is able to store twice as much carbon as the atmosphere (Schlesinger and Andrews, 1992). Soil being a large carbon reservoir suggests the potential for soil carbon sequestration as a strategy to mitigate climate change, but there is also a potential for a positive feedback effect in which rising temperatures cause global soils to become a net source of carbon. There are significant uncertainties regarding the presence and strength of this potential positive feedback effect between rising temperature and soil carbon loss (Davidson et al., 2000; Fang et al., 2005; Giardina and Ryan, 2005; Knorr et al., 2005). These uncertainties arise, partially, from the complex relationships between climate conditions, soil properties, biological processes, and soil carbon storage. In particular, there is a need to better understand the effects that climate conditions have on soil carbon.

This thesis consists of two studies focusing on grassland soil organic carbon (SOC). The objectives of the first study are to evaluate the relationships between SOC, climate, and soil-climate, and to determine if including soil-climate variables could improve statistical SOC prediction models. The objectives of the second study are to determine how SOC has changed over a 15-year span in Oklahoma grasslands, and to evaluate the influence climatic conditions have on these changes. These two studies will add to the growing body of knowledge on climatic influences on SOC spatial and temporal variations.

CHAPTER II

Soil organic carbon under grassland is more strongly related to soil moisture than to soil or air temperature

Abstract

The soil stores far more carbon than the atmosphere and better understanding of how soil carbon is influenced by environmental factors is needed to inform climate change predictions and mitigation efforts. Current statistically-derived soil organic carbon (SOC) models are problematic as they differ substantially regarding the degree to which precipitation and air temperature influence SOC. These discrepancies contribute to uncertainties regarding the potential feedback effects of climate change on SOC levels. Meanwhile, well-known relationships between SOC and soil moisture and soil temperature have not been utilized in statistical SOC models. We hypothesized that using soil-climate variables, such as soil moisture and soil temperature, would improve soil carbon estimates. We investigated the influence of soil-climate on SOC using >10 years of daily climate and soil-climate data from 67 grassland sites across Oklahoma, USA, along with soil physical properties, and corresponding SOC data at 5, 25, and 60-cm depths. Least absolute shrinkage and selection operator (LASSO) regression analysis was used to select a subset of candidate variables, which were most important for SOC predictions. Soil moisture was the most influential predictor variable for all three soil depths studied. The effect of precipitation

and air temperature were insignificant, apart from a weak negative effect of precipitation at 25 cm. We infer that future soil moisture conditions, not precipitation or air temperature, will be the key determinant of climate change – SOC feedback effects at these grassland sites and similar sites worldwide.

Introduction

Substantial changes in the global climate have been attributed to the 40% increase in atmospheric CO_2 which has occurred since the Industrial Revolution (Jay et al., 2018) and up to a third of atmospheric CO_2 accumulation is due to carbon loss from the soil due to land use change (Ciais et al., 2000). Soils store more carbon than the atmosphere, with estimated global soil carbon storage nearly double that of the atmosphere. The size of soil carbon storage is uncertain, however the median SOC storage across 27 studies is about 1,450 Pg C (Scharlemann et al., 2014) compared to about 880.3 Pg of carbon in the atmosphere as of April 2019, based on an atmospheric CO_2 concentration of 413.3 ppm (NOAA ESRL) assuming 1 ppm CO_2 = 2.13 Pg C (Clarke, 1982). Soil carbon exists in two forms, soil inorganic carbon (SIC) and soil organic carbon (SOC) with more than two thirds of soil carbon existing as the latter (Batjes, 1996). Loss of SOC due to human alterations of land use and land cover increases atmospheric CO_2, which contributes to rising global temperatures. Increases in global temperatures may accelerate decreases of SOC resulting in a potential positive feedback, though the existence and strength of this feedback is debated (Davidson et al., 2000; Fang et al., 2005; Giardina and Ryan, 2005; Knorr et al., 2005).

SOC levels and changes in SOC at global and regional scales are often estimated using statistical models because large-scale measurement campaigns are costly and rates of change are often relatively slow. Many of the published statistical models for SOC use climate variables such as precipitation and air temperature, along with other covariates, to predict SOC (e.g. Jobbagy and Jackson, 2000; Homann et al., 2007; Evans et al., 2011; Doetterl et al., 2015). In such models, these climatic variables serve as indirect proxies for soil-climate variables, i.e. soil moisture and soil temperature, which exert more direct influences on SOC loss and gain. Well-known relationships between soil carbon processes and soil moisture and soil temperature are not directly utilized.

The absence of soil moisture and soil temperature as predictor variables in statistical SOC models was understandable in the past when large-scale observing systems for these soil-climate variables were non-existent. However, present in situ monitoring networks, such as the USDA National Resources Conservation Service Soil Climate Analysis Network and the National Oceanic and Atmospheric Administration Climate Reference Network, provide soil moisture and soil temperature observations for hundreds of sites across the US, and similar networks exist in other countries around the world (Ochsner et al., 2013). In addition, various satellites provide global observations of surface soil moisture and land surface temperature, variables with potential value for enhancing SOC estimates. While such promising datasets have remained largely unused for SOC modeling, statistical SOC models continue to give conflicting results regarding the influence of climate on SOC levels (Ogle et al., 2010; Gray and Bishop, 2016; Luo and et al., 2016).

Some research suggests precipitation has a strong positive correlation with SOC (Burke et al., 1989; Alvarez and Lavado, 1998; Evans et al., 2011), while other studies show precipitation has little to no influence on SOC (Percival et al., 2000; Doetterl et al., 2015). Similarly, a few studies have concluded that air temperature has a strong negative influence on SOC (Burke et al., 1989; Alvarez and Lavado, 1998; Evans et al., 2011), while others report air temperature has minimal effect on SOC (Nichols, 1984; Percival et al., 2000; Doetterl et al., 2015). Improved understanding of the influence climatic factors have on SOC levels is necessary to clarify the strength of SOC - climate change feedback and to improve SOC modeling and climate change projections. Here we explore the possibility of improving statistical SOC models through the utilization of soil moisture and soil temperature observations from a large-scale monitoring network.

The objectives of this study are i) compare the relationships between SOC, climate, and soil-climate variables and ii) quantify the accuracy of statistical SOC models with and without soil-climate variables. The central hypothesis of this study is that SOC is more strongly related to soil-climate variables than to climate variables, and that including soil-climate information in statistical SOC models will improve the accuracy of SOC predictions. This study tests the hypothesis using a unique long-term soil-climate and SOC dataset.

Methodology

Research Domain and Study Sites

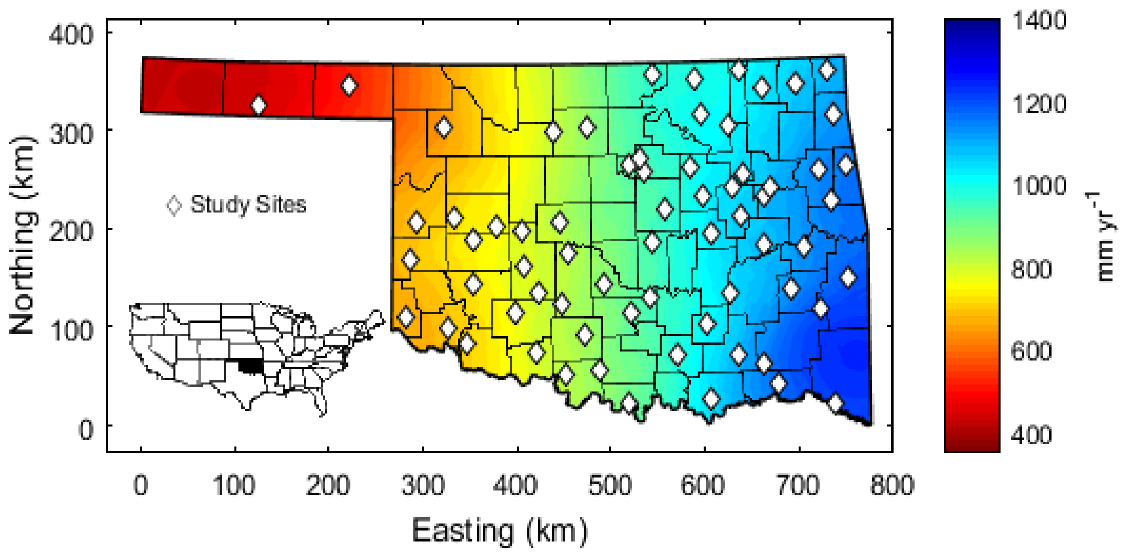


Fig 2.1. Map of Oklahoma with the location of the 67 study sites marked in white diamonds. Mean annual precipitation (mm year^{-1}) over the time span of this study (1994-2010) is shown by the gradient overlay. Mean annual precipitation during the study period shows the climate gradient across the study sites, ranging from about 400 mm year^{-1} to about 1400 mm year^{-1}.

Study sites for this research are long-term environmental monitoring stations of the Oklahoma Mesonet, which monitors atmospheric and soil conditions at approximately 120 sites across the state of Oklahoma, USA. This study includes data from 67 sites, which met data quality standards described below and which span a strong climate gradient (Figure 1). The climate ranges from humid subtropical in the southeast portion of the state with a mean annual precipitation of 1,415 mm to semi-arid in the northwestern Panhandle with a mean annual precipitation of 428 mm. The mean annual temperature increases southward, ranging from 12°C in the Panhandle to 17°C at the state's southern border (Johnson, 2008). Oklahoma's native vegetation transitions from predominantly oak forest in the east, to tallgrass prairie and Cross Timbers in central Oklahoma, mixed grass prairie in the west, and shortgrass prairie in the Panhandle (Hoagland, 2008). Oklahoma Mesonet sites are located in relatively flat, non-irrigated grassland with little to no influence from water bodies or structures. Common soil orders in the state, according to the USDA classification system, include Mollisols, Alfisols, Inceptisols, and Ultisols (Soil Survey Staff, 1999).

Soil Sampling and Processing

Soil cores were collected from 104 study sites between late April to late May of 2009, and early May to early August of 2010 using a hydraulic soil probe. Replicate 7.47-cm cores were collected at each site, with each core subsampled at fixed depth increments including 3-10 cm, 20-30 cm, and 55-65 cm from the surface where available, totaling 583 soil samples. Sampling methods are further detailed by Scott et al. (2013). Soil sample processing included determining bulk density, particle size distribution, soil-water retention at -33 kPa and -1500 kPa, pH, and inorganic and total carbon content. Bulk density, soil-water retention, and particle size distribution methodology were described by Scott et al. (2013). Soil pH was measured using pH meters and electrodes (In-Lab Expert Pro ISM, Mettler Toledo, Columbus, OH; Orion 815660, Thermo Scientific, Waltham, MA) at a 1:2 soil-water ratio. The pH meters were calibrated using a three-point calibration curve at 4, 7, and 10 pH. Calibration was monitored using a check soil with a known pH. Soil total carbon (STC) was determined using the dry combustion method (Leco Total Carbon and Total Nitrogen Analyzer, Leco Corp., Saint Joseph, MI). Soil inorganic carbon (SIC) content was measured using the modified pressure-calcimeter method (Sherrod et al., 2002) for samples with a pH > 7.2. The soil physical properties chosen as candidate predictor variables for this study were bulk density, percent sand, silt, and clay, and soil-water retention at -33 and -1500 kPa.

To avoid small negative SIC values, a limit of detection was applied to the SIC results based on the standard deviation of the response residuals and the slope of the calibration curve (ICH Expert Working Group, 1994). The SOC value for each soil sample was then determined by the difference between STC and SIC. For soil samples with a pH less than 7.2, SOC was equal to STC. In the case of two of the 583 samples, the estimated SOC was a negative value (SIC was greater than STC) and was set equal to zero. The SOC values at each depth were averaged between the two duplicate cores.

Mesonet Climate Data

Climate data from the Oklahoma Mesonet consisted of daily climate and soil-climate observations for each site. Candidate soil-climate predictor variables included: soil temperature, volumetric water content, effective saturation, and soil matric potential at 5, 25, and 60-cm depths. Effective saturation is the difference between the current volumetric water content and the residual water content divided by the total range in volumetric water content from saturation to the residual water content. The saturated and residual water content for each site and depth were obtained from the Meso-Soil database version 1.3 (Scott et al., 2013). Candidate climate predictor variables included: daily maximum and minimum air temperature, precipitation, wind speed at 2 meters above ground, maximum and minimum relative humidity, and solar radiation. The dataset for each station was trimmed to only include data from the beginning of Mesonet data collection for that site to the soil sampling date for that site. The trimmed data were used to calculate the long-term mean for each climate variable. Sites with less than ten years of daily data, or less than 3650 daily data entries, were removed, leaving 67 sites available.

Soil matric potential (kPa) observations were calculated from the average normalized temperature rise reported by heat dissipation sensors (CSI 229, Campbell Scientific, Inc. Logan, Utah) utilized by the Oklahoma Mesonet (Illston et al., 2008). Soil matric potential is used in the calculation of volumetric water content (cm3 cm-3) using the van Genuchten equation with site and depth specific parameters taken from the Meso-Soil database version 1.3 (Scott et al., 2013).

From 1994 to 2013, soil temperature at Mesonet sites was measured using thermistors in sealed housings, but the sensors suffered frequent failures. Illston et al. (2013) showed that the CSI 229 sensors used to measure soil matric potential at the Oklahoma Mesonet sites provided accurate soil temperature measurements after modifications were made to the data acquisition system. These modifications were subsequently applied to the Oklahoma Mesonet, therefore the soil temperature data from 2014 onward are from the 229 sensors. Prior to 2014, the soil temperature sensors were placed at 5, 10, and 30-cm depths, while the 229 sensors are installed at 5, 10, 25, and 60-cm depths. Soil temperature estimates at 25 and 60 cm for the dates prior to soil sampling were needed for our study to ensure all of the data are from uniform depths. To resolve the unmatched depth measurements, we used soil temperature data from 2014 to 2017 to fit multiple linear regressions to predict 25 cm and 60 cm long-term mean soil temperatures using the 5 cm and 10 cm long-term mean soil temperatures. Based on this dataset from 2014 to 2017, mean soil temperatures at 25 cm and 60 cm were not significantly different ($p > 0.05$). The regression models calibrated on the 2014-2017 dataset were applied using the pre-sampling soil temperatures at 5 and 10 cm to estimate mean soil temperatures at 25, 30, and 60 cm. The models were validated by comparison against the observed mean temperature at 30 cm for the pre-sampling period. There were no significant differences in the measured soil temperature at 30 cm and the modeled soil temperature at 30 cm ($p > 0.05$), indicating that our estimated long-term mean soil temperatures at the 25 and 60-cm depths are reliable.

Statistical Analysis

A Pearson correlation matrix was produced for the SOC data, climate data, soil-climate data, and soil physical properties to identify and remove highly collinear candidate variables. Candidate variables were excluded if highly intercorrelated ($r > 0.70$) to one another, with the candidate variable having the strongest correlation to SOC retained. The exception was soil temperature and air temperature, which were highly correlated ($r = 0.90$ for 5 cm soil temperature, $r = 0.92$ for 25 cm soil temperature, and $r = 0.92$ for 60 cm soil temperature). Both were retained because they were essential to our objectives. The dataset was split by depth, with data from the 3-10 cm soil cores matched with soil-climate data at 5 cm, 20-30 cm soil core data matched with soil-climate data at 25 cm and, 55-65 cm soil core data matched with soil-climate data at 60 cm. Climate data were included in the dataset for each depth. Sites that were missing any candidate variable at a given depth were removed from the data set for that depth.

Least absolute shrinkage and selection operator (LASSO) regression was used to select an optimal subset of the candidate variables for accurate SOC predictions. LASSO produces relatively simple and interpretable models by utilizing a regularization coefficient (λ), which penalizes predictor coefficients and pushes the coefficients of nonessential predictor variables to zero. Each model was fit using each of 100 possible λ values chosen from an automatically generated geometric sequence. For each λ value, a k-fold cross-validation was used to quantify model accuracy, with $k = n - 1$, where n is the number of sites with valid data at the given depth. For each model, the λ value that produced a minimum mean square error during cross-validation was selected. The coefficients of the selected models were then standardized by multiplying each coefficient by the ratio of the standard deviation of the predictor variable and the standard deviation of the response variable. This standardization allows the coefficients of the predictor variables to be directly compared to one another. Akaike information criterion (AIC) (Zou et al., 2007) was used to compare model performance between models that included and excluded soil-climate variables among the candidate variables at each depth. Smaller AIC values indicate a higher quality model. All data analyses were performed using MATLAB R2017a (MathWorks, Inc., Massachusetts).

Results

After screening candidate variables to avoid strong collinearity, eight variables were retained as candidate variables for the LASSO regression from the full set of climate, soil-climate, and soil physical property variables. Those variables were mean annual precipitation (mm), mean air temperature (°C), mean soil volumetric water content (cm^3 cm^{-3}), which will subsequently be referred to as soil moisture, mean soil temperature (°C), sand content (%), clay content (%), and bulk density (g cm^{-3}). A statistical summary of the eight predictor variables and SOC (g kg^{-1}) measurements is shown in Table 2.1. Mean annual precipitation and mean air temperature differ slightly with soil depth due to the different number of sites with available data for each depth. Some sites were missing data at one or two depths. Mean SOC decreased with depth ($p <$ 0.0001); mean bulk density ($p < 0.0001$) and mean clay content ($p < 0.0001$) increased with depth; and there were no significant trends with depth for the remaining variables. Table 2.2 shows the Pearson correlation matrix between the eight candidate predictor variables and SOC at 5, 25, and 60-cm depths. Sand content, bulk density, and mean soil temperature all have negative correlations with SOC at all depths. Mean air temperature is negatively correlated with SOC at 5 cm. Clay content and mean soil moisture have positive correlations with SOC at all depths.

Table 2.1. Statistical summary of soil organic carbon, soil physical properties, climate, and soil-climate variables by depth. The number of sites (*n*), mean, standard deviation (SD), and range are shown.

Depth	*n*	Mean	SD	Range

5 cm	60			
Soil Organic Carbon (g kg^{-1})		13.6	6.30	1.0 - 31.1
Sand Content (%)		39.4	21.8	1.5 - 82.6
Clay Content (%)		18.7	8.2	2.9 - 44.1
Bulk Density (g cm^{-3})		1.40	0.17	1.01 - 1.83
Mean Annual Precipitation (mm)		922	178	421 - 1275
Mean Air Temperature (°C)		16.0	0.904	13.6 - 17.7
Mean Soil Moisture (cm^3 cm^{-3})		0.24	0.066	0.08 - 0.40
Mean Soil Temperature (°C)		16.3	0.980	14.1 - 18.4
25 cm	62			
Soil Organic Carbon (g kg^{-1})		7.19	3.19	0.3- 16.9
Sand Content (%)		34.8	20.4	5.0 - 78.0
Clay Content (%)		26.1	11.5	5.4 - 62.9
Bulk Density (g cm^{-3})		1.47	0.150	1.12 - 1.88
Mean Annual Precipitation (mm)		918	174	421 - 1240
Mean Air Temperature (°C)		16.0	0.916	13.6 - 17.7
Mean Soil Moisture (cm^3 cm^{-3})		0.25	0.060	0.10 - 0.36
Mean Soil Temperature (°C)		16.4	0.907	14.5 - 18.2
60 cm	44			
Soil Organic Carbon (g kg^{-1})		4.10	2.06	0.6 - 9.6
Sand Content (%)		32.5	19.9	3.3 - 77.4
Clay Content (%)		33.0	14.8	10.0 - 73.3
Bulk Density (g cm^{-3})		1.57	0.141	1.30 - 1.95
Mean Annual Precipitation (mm)		893	168	421 - 1142
Mean Air Temperature (°C)		15.8	0.967	13.6 - 17.7
Mean Soil Moisture (cm^3 cm^{-3})		0.25	0.07	0.11 - 0.44
Mean Soil Temperature (°C)		16.2	0.98	14.5 - 18.3

Table 2.2. Pearson correlation coefficients (*r*) between dependent variables and independent variables. Dependent variables include SOC at 5, 25, and 60-cm depths. Independent variables include sand content, clay content, bulk density, mean annual precipitation, mean air temperature, mean soil moisture, and mean soil temperature. Correlations not significant at α = 0.05 level are denoted as ns.

Dependent Variables	Independent Variables						
	Sand Content	Clay Content	Bulk Density	Mean Annual Precipitation	Mean Air Temperature	Mean Soil Moisture	Mean Soil Temperature
SOC at 5 cm	-0.57	0.39	-0.32	ns	-0.35	0.58	-0.46
SOC at 25 cm	-0.34	0.26	-0.30	ns	ns	0.36	-0.31
SOC at 60 cm	-0.49	0.48	-0.42	ns	ns	0.62	-0.33

The LASSO results for each of the six models can be found in Table 2.3. Candidate predictor variables whose coefficients were pushed to zero are not shown. For the models with soil-climate variables included, the predictor variables retained for the 5-cm depth were sand content, clay content, bulk density, mean soil moisture, and mean soil temperature. Predictor variables retained for the 25-cm depth were bulk density, mean annual precipitation, mean soil moisture, and mean soil temperature. At the 60-cm depth, the predictor variables retained were sand content, bulk density, and mean soil moisture. Bulk density and mean soil moisture were the only two predictor variables retained for all three depths. Mean soil moisture had the largest absolute standardized coefficient for each depth, followed by bulk density. The models excluding soil-climate variables retained sand content, clay content, bulk density, and mean air temperature at 5 cm and 25 cm. Sand content, clay content, bulk density, and mean annual precipitation were retained at 60 cm. The AIC was smaller and the coefficient of determination (R^2) was larger for the models including soil-climate variables than the models excluding those variables. The LASSO coefficients for the models including soil-climate variables were applied to the dataset to estimate SOC. A comparison of the modeled and measured SOC is shown in Figure 2, along with a 1:1 reference line. The R^2 values (shown in Table 2.3) for the modeled SOC are R^2=0.52, 0.38, and 0.50 for 5, 25, and 60-cm depths, respectively.

Table 2.3. SOC predictor variables retained at 5, 25, and 60-cm depths by LASSO regression. Models including soil-climate on the top, and models excluding soil-climate on the bottom. LASSO regression coefficients are standardized for direct comparison of predictor variables within each model. The coefficient of determination (R^2), mean error (ME), root mean square error (RMSE), and Akaike information criterion (AIC) are given to quantify the model fit.

		Including Soil-Climate Variables		
Dependent	Model Fit	Independent Variable	Coefficient	Standardized
SOC at 5 cm	R^2= 0.52	Intercept	30.9	
	ME = -2.72	Sand Content (%)	-0.0514	-0.178
	RMSE = 4.35	Clay Content (%)	0.0800	0.104
	AIC = 17.10	Bulk Density (g cm^{-3})	-7.08	-0.209
		Mean Soil Moisture (cm^3 cm^{-3})	31.1	0.325
		Mean Soil Temperature (°C)	-0.881	-0.137
SOC at 25 cm	R^2= 0.38	Intercept	25.2	

	ME = 0.603	Bulk Density (g cm^{-3})	-7.68	-0.362
	RMSE = 2.49	Mean Annual Precipitation (mm)	-0.002	-0.120
	AIC = 22.37	Mean Soil Moisture (cm^3 cm^{-3})	24.0	0.451
		Mean Soil Temperature (°C)	-0.647	-0.184
SOC at 60 cm	R^2= 0.50	Intercept	7.37	
	ME = -1.06	Sand Content (%)	-0.0027	-0.0263
	RMSE = 1.44	Bulk Density (g cm^{-3})	-4.37	-0.300
	AIC = 12.20	Mean Soil Moisture (cm^3 cm^{-3})	14.4	0.516
		Excluding Soil-Climate Variables		
Dependent	Model Fit	Independent Variable	Coefficient	Standardized
SOC at 5 cm	R^2= 0.42	Intercept	38.9	
	ME = -4.09	Sand Content (%)	-0.1275	-0.405
	RMSE = 4.76	Clay Content (%)	0.0287	0.0374
	AIC = 21.33	Bulk Density (g cm^{-3})	-6.5166	-0.1918
		Mean Air Temperature (°C)	-0.7325	-0.1052
SOC at 25 cm	R^2= 0.23	Intercept	21.3	
	ME = -0.586	Sand Content (%)	-0.0354	-0.2261
	RMSE = 2.77	Clay Content (%)	0.0246	0.0890
	AIC = 27.83	Bulk Density (g cm^{-3})	-5.1349	-0.2422
		Mean Air Temperature (°C)	-0.3755	-0.1079
SOC at 60 cm	R^2= 0.42	Intercept	9.09	
	ME = -1.15	Sand Content (%)	-0.0238	-0.2297
	RMSE = 1.55	Clay Content (%)	0.0256	0.1843
	AIC = 16.39	Bulk Density (g cm^{-3})	-4.6260	-0.3171
		Mean Annual Precipitation (mm)	0.0024	0.1999

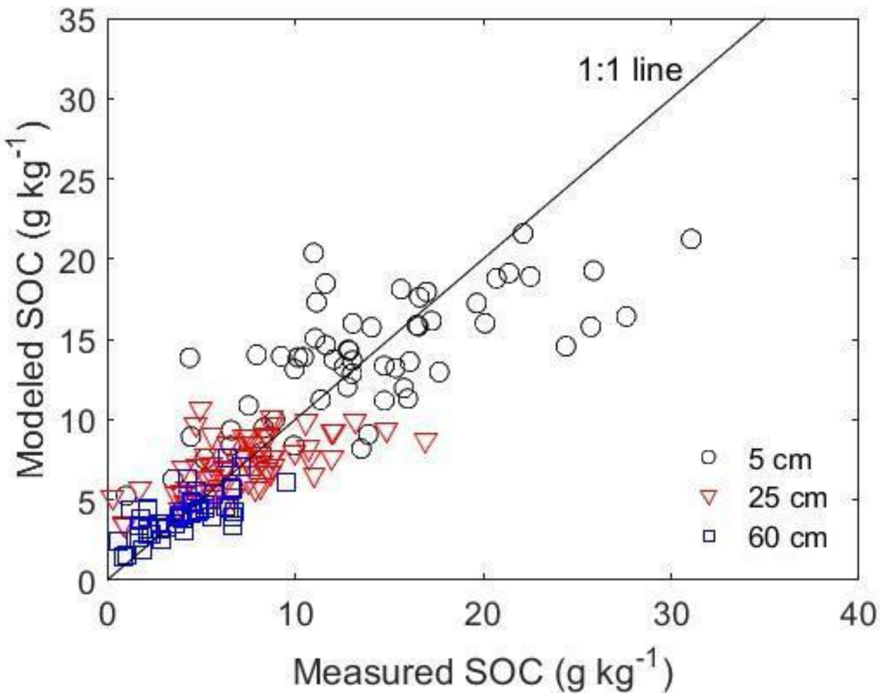


Fig. 2.2. Modeled versus measured soil organic carbon (SOC) for the 5, 25, and 60-cm depths at the Oklahoma Mesonet sites. Modeled SOC calculated from LASSO outputs including soil-climate variables. Model descriptions for each depth are provided in Table 3.

Discussion

The Pearson correlation coefficients and the standardized LASSO regression coefficients both show the primary importance of long-term mean soil moisture in SOC prediction, especially compared to mean annual precipitation. At all depths, soil-climate variables were more strongly correlated to SOC than climate variables. When soil-climate variables were included in the candidate variables set, mean air temperature was not a significant predictor of SOC at any depth, and mean annual precipitation was not a significant predictor of SOC at 5 cm or 60 cm. Based on the R^2 values, the proportion of the variance explained by the models was increased between 8% and 15% when soil-climate information was included. Comparing the modeled versus the measured SOC (Figure 2.2), the predictions follow the 1:1 line, although with some tendency to under predict at the highest observed levels of SOC.

Previous studies utilizing a variety of environmental factors in statistical SOC models have yielded inconsistent results in defining the influence of predictor variables on SOC levels. Table 2.4 summarizes four models from three studies similar to ours. These studies incorporated variations of precipitation, air temperature, evapotranspiration, silt content, and clay content into SOC prediction models. Burke et al. (1989) concluded mean annual air temperature was the most significant predictor of SOC, followed by annual precipitation, silt, and clay. Evans et al. (2011) found annual precipitation had to strongest impact on SOC. Evans et al. (2011) and Homann et al. (2007) both concluded climate and soil texture influences on SOC vary with location, but that climate and soil texture were the dominate predictors. We hypothesize that the varying strengths of previously reported correlations between precipitation and SOC are due to the fact that soil-climate, and particularly soil moisture, exerts a stronger and more direct influence on SOC. Notably, mean annual precipitation and mean soil moisture were not strongly correlated ($r < 0.40$, data not shown). Furthermore, the influence of soil temperature and air temperature on SOC were more clearly secondary to the stronger and more consistent influence of soil moisture.

Table 2.4. Summary of results from similar studies on predicting SOC including depths, number of data points (n) and R^2 values. Some studies included multiple depths or predictor variables sets. *Data from Humann et al., 2007 only includes two model results from the Southern Great Plains grassland portion of the study.

Publication	Statistical Analysis	SOC Units	Predictor Variables		Depth	*n*	R^2
Burke et al, 1989	All possible subset regression	kg m^{-2}	Mean annual temperatures	-	0-20 cm	500	0.51
			Mean annual temperatures^2	+			
			Mean annual precipitation	+			
			Mean annual precipitation^2	-			
			Mean annual precipitation*silt	+			
			Mean annual precipitation*clay	+			
Evans et al., 2011	Multiple linear regression	kg m^{-2}	Mean annual precipitation	+	0-20 cm	25	0.75
			Mean annual temperatures	-			
			Mean annual precipitation^2	-			
			Mean annual temperatures^2	+			

			Silt	+			
			Clay	+			
Homann et al., 2007*	Step-wise regression	Log-transformed kg m^{-2}	Log (Mean annual precipitation)	+	0-20 cm	523	0.45
			Mean annual temperature	-	0-100 cm		0.51
			Log(Clay)	+			
			Log (Actual evapotranspiration)	+	0-20 cm		0.46
			Temperature/Precipitation index	-			
			Log(Clay)	+			

In this study, the standardized coefficients indicate bulk density and mean soil moisture are the two most significant predictor variables when soil-climate variables are included. This result differs from that of Burke et al. (1989) who concluded mean annual air temperature was the most significant predictor variable. On the other hand, the Burke et al. results were consistent with our models that excluded soil-climate variables. This indicates models that exclude soil-climate variables or use climate variables to estimate soil-climate are missing key predictors of SOC. Even though soil temperature was retained in the 5 cm and 25 cm models, it had an absolute standardized coefficient smaller than that of mean soil moisture. This indicates soil moisture has a more significant impact on SOC storage compared to soil or air temperature. Therefore, changing moisture regimes would be expected to have a greater impact on SOC than changing temperature regimes in this and similar regions.

This study is limited by the range of temperature regime. Soil moisture is more strongly related to SOC in the temperate grassland sites discussed here, however, the relationships between soil moisture, soil temperature, soil physical properties, climate and SOC may vary. This study encompasses soils with an average soil temperatures ranging from 14.1°C to 18.4°C. SOC in soils with adequate moisture but extreme temperature regimes could be more strongly related to the variations in soil temperature.

This study used a one-of-a-kind dataset that included SOC measurements co-located with long-term climate and soil-climate observations across a large climate gradient. This is the first study, to our knowledge, to compare the importance of soil-climate variables versus climate variables in statistical SOC models. The results show that soil-climate variables, particularly mean soil moisture, have a stronger relationship with SOC than climate variables such as precipitation and air temperature. When soil-climate variables are available, climate variables have little to no importance for predicting SOC. Notably, this study also reveals that soil moisture, not soil temperature, has a dominant influence on SOC levels in the study region. Including soil-climate variables in statistical SOC models improve SOC predictions and should, therefore, improve predictions of SOC stocks and shed new light on the controls of feedbacks between climate change and SOC levels. The potential impacts on SOC levels of changing soil moisture regimes due to global climate change may be stronger than the impacts of rising soil temperatures in this study region and similar regions worldwide. The subsequent research on climate change - SOC feedbacks should place an emphasis on better understanding the mechanisms involved in the relationships between SOC and soil moisture, and predicting future soil moisture regimes.

CHAPTER III

Soil organic carbon increasing near the surface but decreasing at depth in temperate grasslands

Abstract

The soil is the largest terrestrial carbon sink, and soil organic carbon (SOC) accounts for twice as much carbon as is stored in the atmosphere. A significant portion of global SOC is stored in grassland soils. Better understanding of how grassland SOC amount and distribution are changing is needed to inform global carbon budgets, climate projections, and analyses of SOC-climate change feedbacks. Here we describe changes in SOC using data from 78 grassland sites in Oklahoma, USA collected in 1996-1999 and 2009-2010 at 5, 25, 60, and 75-cm. We evaluated how SOC concentrations, storage, and depth distributions changed between the two sampling periods and how environmental factors may have influenced these SOC changes. There was no significant change in mean SOC storage from the first sampling period to the second, and we did not find any evidence that climate or soil-climate significantly influenced changes in SOC storage within the span of this study. There was, however, an inverse relationship (Pearson correlation coefficient, r = -0.442) between initial SOC storage and the subsequent change in SOC storage, as soils with higher initial SOC lost more or gained less carbon compared to soils with lower initial SOC. Most importantly, there was a significant increase in SOC stratification (p = 0.022) across these grassland sites, with soils at 5 cm gaining SOC, while soils at depth lost SOC.

This unexpected finding raises new questions about the causes of this previously unreported increase in grassland SOC stratification and its possible effects on ecosystem services and carbon cycling.

Introduction

There has been a 40% increase in atmospheric CO_2 since the Industrial Revolution (Jay et al., 2018). Approximately one third of the atmospheric CO_2 increase since 1850 comes from loss of soil carbon due to land use change (Ciais et al., 2000). The soil is able to store more carbon than the atmosphere, with about two thirds of soil carbon being in the form of soil organic carbon (SOC) (Batjes, 1996). Current estimates indicate SOC stores two times as much carbon as is currently in the atmosphere (Scharlemann et al., 2014).

A substantial portion of global SOC is stored in grasslands, and current estimates of global grasslands SOC storage place it between 10 and 30% of the world's soil carbon (Scurlock and Hall, 1998; Jobbagy and Jackson, 2000). With grassland soils being such a large carbon reservoir, changes to grassland SOC could impact global carbon cycles. Increases in atmospheric CO_2 may increase global temperatures, which could accelerate SOC loss. Understanding how grassland SOC changes over time and the potential influences environmental factors, such as climate or soil texture, have on SOC can promote beneficial mitigation and adaptation strategies.

There have been numerous studies evaluating the change in grassland SOC across the world, with varying results on the degree, direction, and drivers of SOC change. A significant loss of SOC in the surface 15 cm was found by Bellamy et al. (2005), who evaluated SOC concentrations across more than 4,000 sites in England and Wales between 1978 and 2000. In contrast, significant gains in SOC in the surface 30 cm were reported by Chen et al. (2017) in the Tibetan Plateau grasslands between 2002 and 2011, with significant variation in SOC change based on ecoregions. Ramírez et al. (2019) reported both gains and losses of SOC in the surface mineral horizon (up to 29 cm deep) across 51 sites in central Chile, with the variation in SOC changes explained by aridity regime and soil order. Li et al. (2019) reported a significant loss in SOC in the surface 20 cm across northeast China's Horqin Grassland between the 1980s and 2010s, citing land cover change as a significant factor in SOC loss.

Studies evaluating the change in grassland SOC have identified a variety of environmental variables that potentially influence the change in SOC. Soil physical properties, such as soil texture, has been reported as both a significant (Ramírez et al., 2019) and insignificant (Bellamy et al., 2005; Crowther et al., 2016) environmental influence on changes to SOC. A strong inverse relationship between the change in SOC and the initial carbon content, or the carbon content at the time of the first sampling, have been reported in many studies (Bellamy et al., 2005; Crowther et al., 2016; Chen et al., 2017; Luo et al., 2017).

The influence of climatic factors on the change in SOC is unclear given the variety of results in the current literature. Lou et al. (2017) found climate, and in particular average precipitation, had a strong negative relationship to changes in SOC. Similarly, Chen et al. (2017) reported a significant negative correlation between changes in SOC and annual precipitation or seasonal precipitation, but no correlation between changes in SOC and annual temperature. On the other hand, no significant relationship between changes in SOC and precipitation was found by Bellamy et al. (2005). A comprehensive analysis by Crowther et al. (2016) on 49 SOC field experiments concluded neither mean annual precipitation nor mean annual air temperature were necessary for modeling changes in SOC, however warming trends, or the change in air temperature over time, was identified as a strong negative predictor. The loss of SOC reported in Li et al. (2019) had a statistically significant relationship to climate trends, although the correlation coefficient was small, suggesting an indirect relationship.

These inconsistent findings on the influence of climate in SOC trends could be due to the indirect relationship between SOC and climate variables. An evaluation of the potentially more direct influence of soil-climate, the climatic conditions below the soil surface as represented by soil moisture and soil temperature, on the changes in SOC over time is currently missing from the literature.

Sampling methods for many grassland SOC field studies focus on the surface soil, with a maximum 30 cm sampling depth. A review by Baker et al. (2007) highlights the importance of SOC measurements at depth beyond the surface 30 cm, as significant changes in SOC can occur in subsurface soils. To quantify the SOC distribution versus depth and evaluate the effects of management practices on SOC, the stratification ratio, or the ratio of SOC at the surface to the average SOC at deeper depths, is often used. SOC stratification ratio has been proposed as an indicator of soil health, with larger values indicating a healthier (more productive) soil (Franzluebbers, 2002). A strong positive correlation between stratification ratio and sequestration rates has been observed by de Moraes Sa and Lal (2009), thus a soil profile that is becoming more stratified may indicate early stages of carbon sequestration.

The objectives of this study are i.) to evaluate how organic carbon concentration, storage, and depth distribution in Oklahoma grassland soils have changed between 1996 and 2010, and ii.) to determine how these changes are related to environmental factors.

Methodology

Study area

The area of interest for this study consists of 78 grassland sites across the state of Oklahoma, USA. These are long-term environmental monitoring sites belonging to the Oklahoma Mesonet (McPherson et al., 2007) and are located on relatively flat landscapes, are non-irrigated, not used for crop production, and uninfluenced by bodies of water or structures. Oklahoma's native grasslands transition from tallgrass prairies in the East to shortgrass prairies in the West, with mixed grass prairies in between (Hoagland, 2008). Vegetation at these sites primarily consists of native and nonnative grass and forb species, with the most common nonnative species being Bermuda grass (*Cynodon dactylon*), tall fescue (*Festuca arundinacea*), and old world bluestem (*Bothriochloa Bladhii* and *Bothriochloa ischaemum*), and the most common native species being big bluestem (*Andropogon gerardi*) and little bluestem (*Schizachyrium scoparium*). The study period ranges from 1996 to 2010, with the first soil samples being collected between 1996 and 1999, and the second soil sampling conducted between 2009 and 2010.

Soil sampling

Soil cores were collected at each study site during the two sampling periods. Soil cores at the first sampling were subsampled at discrete depths centering at 5, 25, 60, and 75-cm. During the second sampling period, duplicate soil cores were taken at each site and subsampled at 3-10 cm, 20-30 cm, 55-65 cm, and 70-80 cm. Sampling methods for the second sampling are further detailed by Scott et al. (2013). It was not possible to sample to 80-cm depth at some sites due to restrictive layers or bedrock, therefore some of the locations have incomplete profiles. There were 261 total site-depth combinations sampled at the first sampling and 561 at the second sampling.

Climate/Soil-climate

Oklahoma's climate includes a precipitation and temperature gradient, ranging from the humid subtropical southeastern region to the semi-arid northwestern Panhandle. The mean annual precipitation decreases from 1,415 mm in the southeast to 428 mm in the northwest. The mean air temperature decreases from 17°C at the southern region to 12°C at the northern region (Johnson, 2008). Daily average climate and soil-climate observations for this study were obtained from the Oklahoma Mesonet. The observations consist of daily precipitation, average air temperature, soil volumetric water content (soil moisture) and soil temperature. Soil climate variables were measured at 5, 25, and 60-cm depths. Daily values were averaged over the study period to calculate the long-term average for each climate/soil-climate variable at each site. Changes in climate and soil-climate variables for each site were determined by linear regression of the average annual value of each variable versus time, except for precipitation where the annual total was used.

Soil property determination

Soil pH was measured at a 1:2 soil-water ratio using pH meters and electrodes (In-Lab Expert Pro ISM, Mettler Toledo, Columbus, OH; Orion 815660, Thermo Scientific, Waltham, MA) on oven-dried and 2-mm sieved soil from all of the soil samples. Soil texture and bulk density were determined on cores from the second sampling for each site at all available depths. Changes in bulk density and soil texture were assumed negligible over the study period. Bulk density was determined based on the volume and oven-dry weight of intact soil cores. Particle size distribution was determined using the hydrometer method (Gavlak et al., 2005) on oven-dried and 2-mm sieved samples. For a more detailed methodology see Scott et al. (2013).

SOC concentration and density

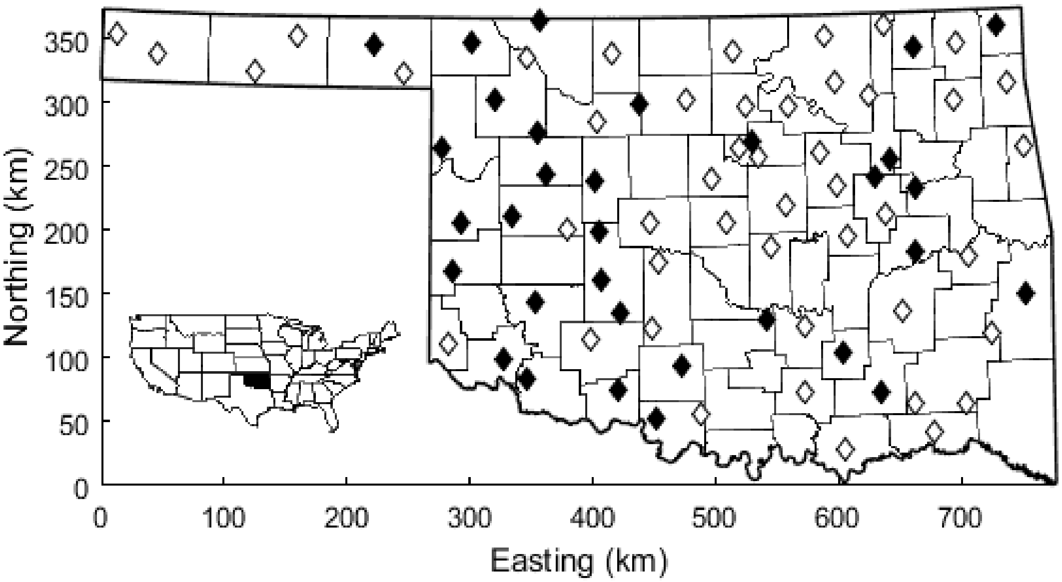
Total soil carbon was determined by dry combustion method (Leco Total Carbon and Total Nitrogen Analyzer, Leco Corp., Saint Joseph, MI) on all soil samples. Soil inorganic carbon was determined by the modified pressure-calcimeter method (Sherrod et al., 2002) for soils with a pH greater than 7.2. Soil organic carbon concentration (g kg^{-1}) (SOCc) was calculated as the difference between soil total carbon and soil inorganic carbon. SOCc for soil samples with a pH less than 7.2 was equal to soil total carbon. In the case of five samples across the two sampling periods, SOCc values that came out negative (soil total carbon was less than the soil inorganic carbon) were set to zero. The rate of change in SOCc (ΔSOCc) was determined based on the number of years between the two samplings.

The influence of soil depth, initial SOCc, and soil order on the ΔSOCc was evaluated by three-way ANOVA with first order interactions. Depth and initial SOCc were treated as continuous variables. Soil order for each site was determined by the USDA-NRCS Oklahoma soil survey (Soil Survey Staff, 1999). Soil organic carbon density (kg m^{-3}) (SOCd) was calculated as the product between SOCc and bulk density.

SOC storage

Soil organic carbon storage (kg m^{-2}) (SOCs) in the top 1 meter was calculated by fitting a piecewise cubic hermite interpolating polynomial (PCHIP) function to the SOCd at each of the discrete soil sampling depths. A PCHIP function was used in this study rather than a spline function, as used by Bishop et al. (1999) and Malone et al. (2009), to reduce overshooting and unrealistic oscillations while still achieving a smooth continuous result. Baseline corrections were applied to the PCHIP functions to simulate the expected decrease in SOCd with depth and prevent unrealistic negative SOCd values. An anchor data point of SOCd equaling 0 kg m^{-3} at 2 meters from the surface was added to each site. PCHIP functions were not fit for sites at which SOCd increased more than 5% from one depth to the next lower depth. The total SOCs at each site was approximated by numerically integrating the area under the PCHIP curve. Discrete SOCd estimates were created by the PCHIP function at 0.01-m intervals from the soil surface to 1 m. The SOCs for each site was calculated by trapezoidal integration of the SOCd estimates using the *trapz* function in Matlab (all data analyses were performed using MATLAB R2017a, MathWorks, Inc., Massachusetts). The change in SOCs between the two samples times was calculated as the difference between the SOCs at the first and second samplings.The SOCs rate of change (ΔSOCs) was calculated based on the number of years between samplings for individual sites. Only sites in which SOCd data were available at all four sampling depths for both sampling times were considered for the ΔSOCs calculations, resulting in the ΔSOCs being calculated for 32 sites (Figure 1, black diamonds).

Fig. 3.1. Map of study area within Oklahoma with 78 study sites marked with diamonds. Sites marked with black diamonds includes SOCd data at all four depths and the total storage to one meter for that site was calculated.



A paired t-test was applied to the SOCs values from the first and second samplings to determine if there was a statistically significant change ($\alpha = 0.05$). A Pearson correlation was used to determine the nature and significance of the relationship between ΔSOCs and potential predictor variables. Those potential predictor variables include the initial SOCs, climate, soil-climate, and soil physical property observations. Climate predictor variables include long-term average precipitation, long-term average air temperature, precipitation trends, and air temperature trends. Soil-climate predictor variables at 5, 25, and 60-cm depths included long-term average soil moisture, long-term average soil temperature, soil moisture trends, and soil temperature trends. Soil physical property predictor variables include the percent sand, silt and clay.

Stratification ratio

The stratification ratio was determined as the ratio between the mean SOCd based on the PCHIP function from the soil surface to 10 cm and the mean SOCd based on the PCHIP function from 10 cm to 1 meter. The rate of change in the stratification ratio was determined as the difference between the stratification ratio at each sampling divided by the number of years between samplings.

A paired t-test was applied to the stratification ratio values from the first and second sampling times to determine if there was a statistically significant change ($\alpha = 0.05$). A Pearson correlation was used to determine the nature and significance of the relationship between the change in stratification ratio and potential predictor variables. Those potential predictor variables include the initial stratification ratio, climate, soil-climate, and soil physical property observations.

Results and Discussion

Across all sites and depths, the SOCc ranged from 0.423 to 34.96 g kg^{-1} with a mean of 8.00 g kg^{-1} at the first sampling. At the second sampling, SOCc ranged from 0.19 to 33.43 g kg^{-1} with a mean of 7.84 g kg^{-1}. SOCc, on average, experienced a positive rate of change at the 5 cm depth, and negative rate of change at the deeper depths (Table 3.1). There was an inverse correlation between initial SOCc and ΔSOCc (Table 3.1). Soils with low initial SOCc gained SOC at a faster rate than soils with high initial SOCc. Soils with similar initial SOCc values experienced stronger increases in SOC at 5 cm compared to deeper depths. As depth increased, soils experienced a more negative change in SOCc.

Table 3.1. ΔSOCc at 5, 25, 60, and 75-cm partitioned based on initial SOCc. The number of sites (*n*), mean SOCc at first sampling, rate of change and percent change between samplings are shown.

Sampling Depth	Initial SOCc	*n*	Mean initial SOCc	Rate of change	Change in SOCc
cm	g kg^{-1}		g kg^{-1}	g kg^{-1} $year^{-1}$	%
5 cm	All	78	12.4	+0.078	+75.0
	0 - 5	8	2.9	+0.287	+646
	5 - 10	25	7.6	+0.129	+23.3
	10 - 15	18	12.1	+0.019	+4.65
	15 - 20	14	16.3	+0.002	+1.51
	20 +	13	23.4	+0.019	-0.19
25 cm	All	78	7.9	-0.063	-2.66
	0 - 5	20	3.8	+0.039	+17.4
	5 - 10	39	7.4	-0.061	-7.22
	10 +	19	13.3	-0.165	-13.9

60 cm	All	55	5.0	-0.065	-12.4
	0 - 5	28	3.3	-0.012	-6.24
	5 +	27	6.8	-0.120	-18.8
75 cm	All	42	4.0	-0.047	-4.72
	0 - 5	29	2.8	-0.006	-2.82
	5 +	13	6.6	-0.139	-28.1

The ANOVA showed a main effect of initial SOCc on ΔSOCc ($p = 0.021$) and a significant effect of depth on ΔSOCc ($p = 0.033$) (Table 3.2). There was also a significant soil order main effect on ΔSOCc ($p = 0.046$). There was a significant interaction effect between initial SOCc and soil depth on ΔSOCc ($p < 0.001$). There was also a significant interaction between initial SOCc and soil order on ΔSOCc ($p = 0.016$). Soils with an initial SOCc of 0-5 g kg^{-1} had significantly more positive ΔSOCc values than soils with a higher initial SOCc based on Fisher's LSD ($\alpha = 0.05$) (Figure 3.2A). Soils at 5 cm had a significantly more positive ΔSOCc compared to soil samples from deeper depths (Figure 3.2B). Ultisol soils lost significantly more SOCc than the other soil orders, though there were only two Ultisol soils included in this study (Figure 3.2C). The inverse relationship between initial SOCc and ΔSOCc is consistent with key findings from current literature (Bellamy et al., 2005; Crowther et al., 2016; Chen et al., 2017; Luo et al., 2017). The significant relationship between soil depth and changes in grassland SOCc has not been previously reported as prior studies have evaluated changes in SOC of a single depth layer at the soil surface (Virto et al., 2012; Crowther et al., 2016; Chen et al., 2017; Li et al., 2019).

Table 3.2. Analysis of Variance table evaluating the effect and interaction of soil depth, initial SOCc, and soil order on ΔSOCc.

Source	Sum of square error	Degrees of freedom	Mean square error	F	Prob > F
Soil Depth	0.201	1	0.200	4.59	0.0331
Initial SOCc	0.236	1	0.236	5.4	0.021
Soil Order	0.503	5	0.100	2.3	0.0455
Depth * Initial SOCc	0.851	1	0.851	19.51	0
Initial SOCc * Soil Order	0.620	5	0.124	2.84	0.0163
Error	10.210	234	0.044		
Total	14.119	252			

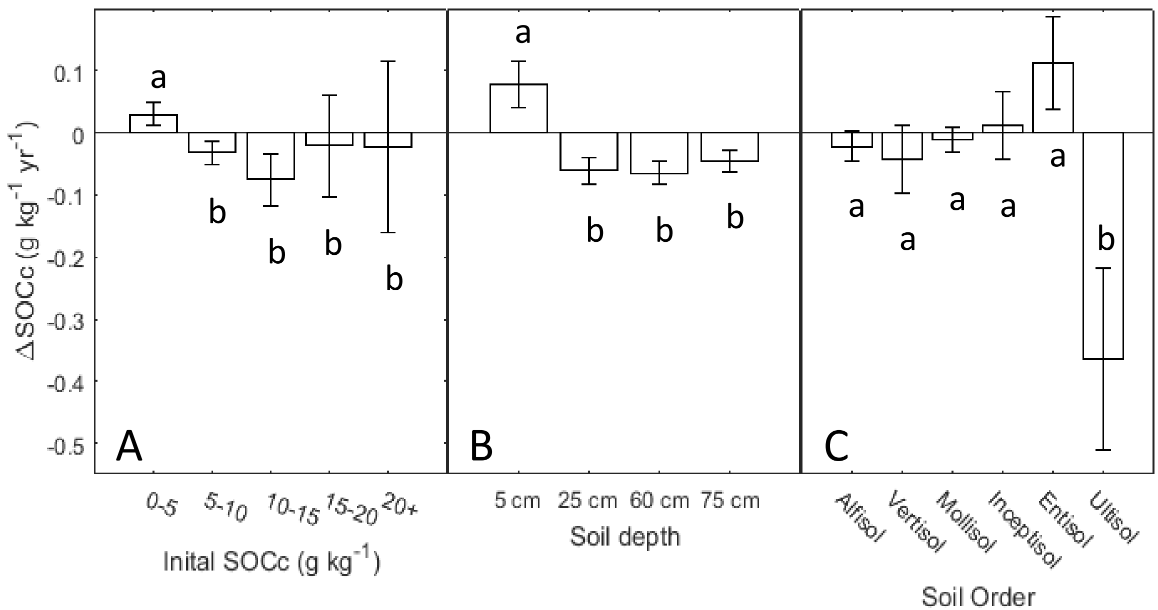


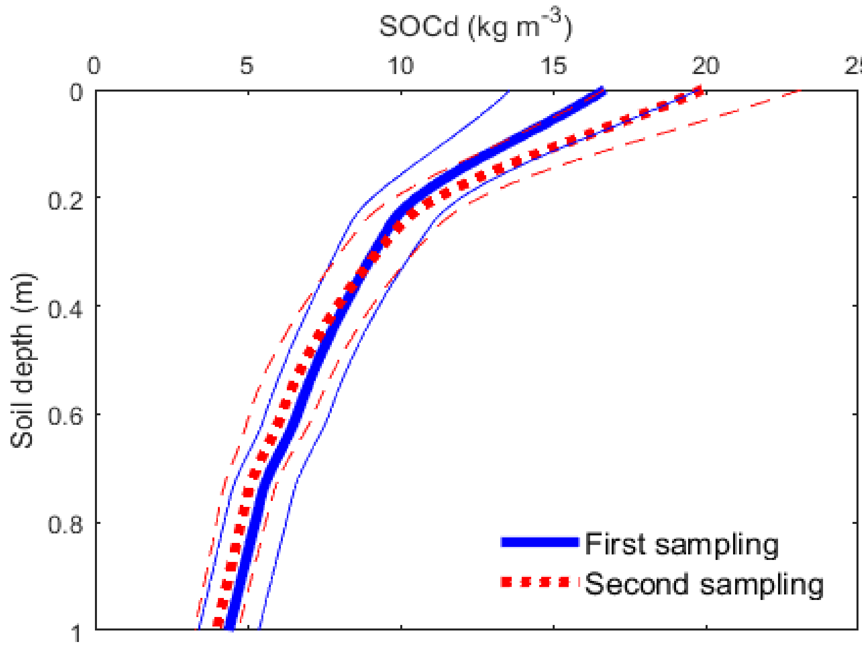
Fig. 3.2. The relationship between the ΔSOCc over the study period and the A.) initial SOCc , B.) depth of soil sample, and C.) soil order. Bars represent the mean ΔSOCc for each group. Error bars indicate the standard error of the mean ΔSOCc. Groups with the same letter are not significantly different from one another with in each panel (Fisher's LSD, α = 0.05). Soils with initial SOCc between 0 and 5 g kg $^{-1}$ have significantly more positive ΔSOCc compared to soils with higher initial SOCc. Likewise, the ΔSOCc is significantly more positive in soils at 5 cm compared to those at 25, 60, and 75-cm. Ultisol soils had a more negative ΔSOCc compared to the other soil orders, however only two Ultisol sites were included in this study.

Figure 3.3 shows the distribution of the average SOCd with depth across the 32 sites with complete data for the first and second sampling. The change in SOCd with depth between the two sampling times is consistent with the results in Figure 3.2B; SOC is increasing at the surface and decreasing at depth. A similar pattern of results is recorded in studies evaluating the effect of no-till management on cropland SOC distribution, in which gains in SOC at the surface are potentially counteracted by losses of SOC at depth (Yang and Wander, 1999; Baker et al., 2007).

From Figure 3.4, we observe a slight narrowing of the distribution of SOCs from the first to the second sampling, with the majority of sites showing small gains in SOCs. Of the 32 sites in which SOCs was calculated, 22 sites experienced an increase in SOCs, while 10 sites experienced a decrease in SOCs. The mean change in grassland SOCs across the state was 0.0096 kg m $^{-2}$ year $^{-1}$

and was not significantly different from zero (p = 0.534). The significance of SOCs change at individual locations could not be determined with the available data.

Fig. 3.3. Distribution of the average SOCd with depth across all sites in which storage was calculated (n = 32) at the first and second sampling. The blue, thick solid line is the average SOCd at the first sampling, with blue thin lines representing the 95% confidence interval of the mean. The red, thick dashed line is the average SOCd at the second sampling, with red, thin dashed lines representing the 95% confidence interval of the mean.



A reduced version of a Pearson correlation between ΔSOCs and potential predictor variables is shown in Table 3.3. Initial SOCs and percent clay content at 5 cm both have a significant negative relationship with ΔSOCs (p = 0.011 and p = 0.030, respectively). However, the clay content at 5 cm is significantly correlated to the initial SOCs (p = 0.010, r = 0.445), potentially indicating that sites with higher clay content at 5 cm had lower ΔSOCs because their initial SOCs was higher than that of other sites. Surprisingly, there were no significant correlations between ΔSOCs and any climate or soil-climate variables, or the changes thereof. The significance of the inverse relationship between initial SOCs and ΔSOCs is consistent with Figure 3.2A and results from previous studies.

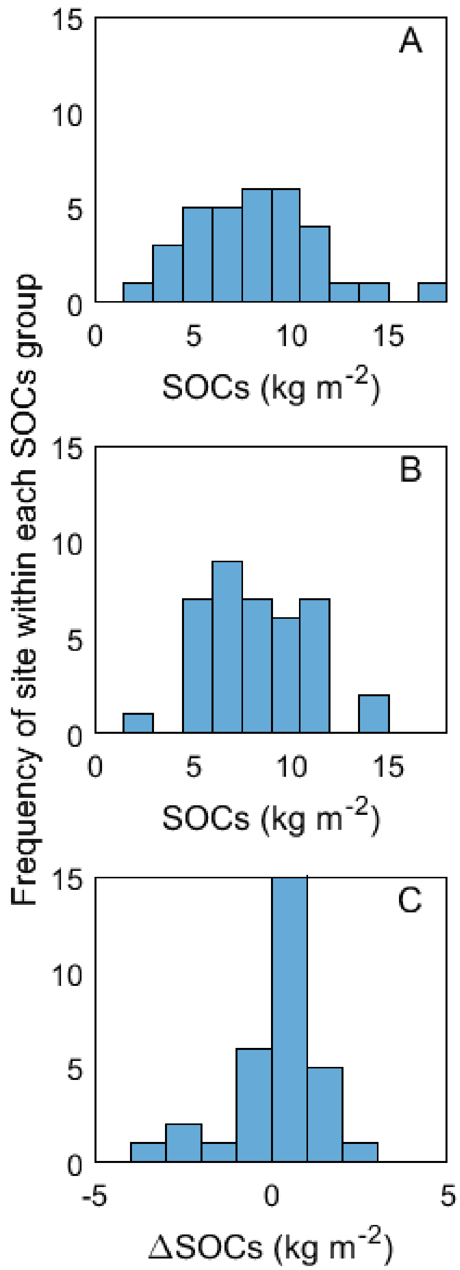


Fig. 3.4. Set of three histograms of the distribution of A.) SOCs at the first sampling, B.) SOCs at the second sampling, and C.) the difference in SOCs between the two samplings.

Table 3.3. Correlation coefficient (*r*) between ΔSOCs and independent variables. Independent variables with significant correlations to ΔSOCs ($\alpha = 0.05$) are bolded and denoted with an *. Initial SOCs and clay content at 5cm are the only independent variables that are significantly correlated (*p* = 0.0112 and *p* = 0.0301, respectively) to ΔSOCs.

Independent Variable	Pearson Correlation Coefficient (*r*)		
Carbon input variables			
Initial SOCs (kg m^{-2})	**-0.442***		
Climate variables			
Mean annual precipitation (mm)	0.036		
Mean daily air temperature (°C)	-0.137		
Rate of change in precipitation (mm yr^{-1})	0.000		
Rate of change air temperature (°C yr^{-1})	-0.050		
Soil-climate variables	*5 cm*	*25 cm*	*60 cm*
Mean volumetric water content (cm^3 cm^{-3})	-0.108	-0.236	0.060
Mean soil temperature (°C)	-0.140	-0.160	-0.160
Rate of change in volumetric water content (cm^3 cm^{-3} yr^{-1})	0.294	0.288	0.033
Rate of change in soil temperature (°C yr^{-1})	0.058	-0.098	-0.098
Soil physical property variables	*5 cm*	*25 cm*	*60 cm*
Sand content	0.131	0.068	0.002
Clay content	**-0.384***	-0.269	-0.027
Silt content	0.020	0.062	0.025

Stratification ratio, which indicates the ratio of SOCd at the surface compared to SOCd at depth, was determined for the 32 sites in which SOCs was calculated. The stratification ratio ranged from 0.93 to 6.67 with a mean of 2.27 at the first sampling, and ranged from 1.14 to 6.23 with a mean of 2.56 at the second sampling. There was a significant increase in the stratification ratio from the first sampling to the second ($p = 0.022$), indicating a significant shift of the SOC distribution toward the surface over the study period. Of the potential predictor variables tested, the change in stratification ratio was significantly and negatively correlated to initial stratification ratio and sand content at 5 cm ($p = 0.015$ and $r = -0.43$, $p = 0.043$ and $r = -0.36$, respectively).

There was no significant correlation between ΔSOCs and the change in stratification ratio (p = 0.551), stratification ratio at the first sampling (p = 0.815) or the second sampling (p = 0.830).

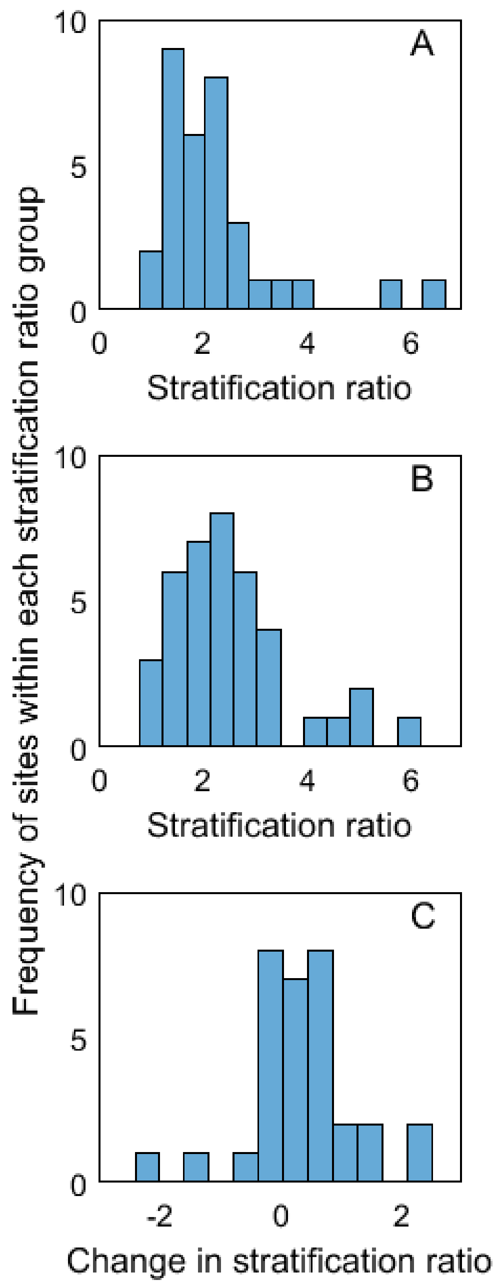


Fig. 3.5. Set of histograms showing the distribution of A.) the stratification ratio at the time of the first sampling, B.) the stratification ratio at the time of the second sampling, and C.) the change in the stratification between the two samplings.

The lack of correlation between the stratification ratio and ΔSOCs differs from the findings of de Moraes Sa and Lal (2009), who found significant correlations between stratification ratio and SOC sequestration. Percent sand content at 5 cm having a significant negative relationship to the change in stratification ratio indicates sites with coarser soil textures are experiencing a less pronounced shift in the SOC distribution toward the surface. To our knowledge, this is the first study to analyze changes in the stratification ratio of grassland SOC over time and thus the first to report increasing stratification of grassland SOC toward the soil surface.

This study has limitations which should be noted such as the fact that individual soil samples may not be a representative of the site from which they were collected because of spatial variability. These soil samples were collected by two different research groups, and some variations in sampling methods occurred. The long-term land-cover and land-use history of sites used in this study is unknown and was not considered in this study. There was a maximum of 15 years between samplings in this study, and a greater time span between samplings could ensure a more robust data set.

Despite these limitations, the results clearly show a shifting depth distribution of SOC. This unexpected discovery begs the question as to whether these sites are still recovering from historical soil disturbances, have experienced change in the dominate grass or grazing species, or perhaps are responding to climate change on a longer time scale than the study period considered here. Future research should aim to further explore the long term changes in grassland SOC stratification over time and evaluate how increasing SOC stratification may affect soil functions and SOC vulnerability.

This study utilizes two soil data sets spanning 15 years in diverse Oklahoma grasslands to better understand how SOC is changing over time. The significant inverse relationship between initial SOC and the change in SOC complement numerous studies with similar findings. Contrary to our expectations, we did not find any evidence of climate or soil-climate effects on changes in SOC during the study period. Our study did, however, shed new light on the importance of soil depth and stratification on grassland SOC changes over time, with soils at the surface gaining SOC and soils at depth losing SOC. This discovery raises a host of research questions about the causes and effects of increasing SOC stratification. These questions should be investigated using existing and new SOC data sets from grasslands around the world. Such research could lead to new insights into the relationship and feedback between grassland SOC and climate change.

CHAPTER IV

Conclusion

The objectives of the first study were to evaluate the relationship between soil organic carbon (SOC), climate, and soil-climate, and to determine if including soil-climate variables will improve SOC predictions. The main findings of the first study highlight the primary importance of soil moisture in SOC predictions. We found that SOC had a stronger correlation to soil-climate, particularly soil moisture, than to climate variables. In fact, when soil-climate data was included, precipitation and air temperature had little to no predictive power. Statistical SOC prediction models that included soil-climate data provided more accurate SOC predictions and indicate that soil moisture was the climate-related variable with the greatest influence on SOC.

The second study focused on changes in grassland SOC over a span of 15 years. The objectives of this study were to evaluate how SOC changed over time and how environmental factors correlated to those changes. The key results of the second study highlighted the importance of initial SOC and soil depth on changes in SOC and revealed that the distribution of SOC in these grassland soils changed during the study period. We found a significant inverse relationship between initial SOC and the rate of change in SOC at all depths. There was also a significant difference in the rate of SOC change based on soil depth, with soil at the surface gaining SOC while soils at depth lost SOC. The vertical distribution of SOC in these soil profiles became more stratified, with the SOC in the top 5 cm increasing in relation to SOC at deeper depths.

These studies add to the growing body of knowledge on grassland SOC storage and dynamics. Improved understanding of environmental factors influencing SOC could improve modeling and prediction of the temporal and spatial distribution of SOC. The results shown here highlight the need of more widespread use of soil moisture information to better predict SOC spatial distribution. Future studies should also focus on discovering the causes and implications of increasing grassland SOC stratification.

REFERENCES

Alvarez, R., and R.S. Lavado. 1998. Climate, organic matter and clay content relationships in the Pampa and Chaco soils, Argentina. Geoderma 83(1–2): 127–141. doi: 10.1016/S0016-7061(97)00141-9.

Baker, J.M., T.E. Ochsner, R.T. Venterea, and T.J. Griffis. 2007. Tillage and soil carbon sequestration-What do we really know? Agric. Ecosyst. Environ. doi: 10.1016/j.agee.2006.05.014.

Batjes, N.H. 1996. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. 47: 151–163. doi: 10.1016/j.envres.2018.05.014.

Bellamy, P.H., P.J. Loveland, R.I. Bradley, R.M. Lark, and G.J.D. Kirk. 2005. Carbon losses from all soils across England and Wales 1978-2003. Nature 437: 245–248. doi: 10.1038/nature04038.

Bishop, T.F.A. 1999. Modelling soil attribute depth functions with equal-area quadratic smoothing splines. Geoderma 91: 27–45. https://doi.org/10.1016/S0016-7061(99)00003-8.

Burke, I.C., C.M. Yonker, W.J. Parton, C. V. Cole, D.S. Schimel, et al. 1989. Texture, Climate, and Cultivation Effects on Soil Organic Matter Content in U.S. Grassland Soils. Soil Sci. Soc. Am. J. 53(3): 800. doi: 10.2136/sssaj1989.03615995005300030029x.

Chen, L., X. Jing, D.F.B. Flynn, Y. Shi, P. Kühn, et al. 2017. Changes of carbon stocks in apline grassland soils from 2002 to 2011 on the Tibetan Plateau and their climatic causes. Geoderma 288: 166–174. doi: 10.1016/j.geoderma.2016.11.016.

Ciais, P., W. Cramer, P. Jarvis, H. Kheshgi, C. Nore, et al. 2000. Land Use, Land-Use Change, and Forestry. In: Linder, S. and Joos, F., editors, IPCC Special Report: Land Use, Land-Use Change, and Forestry. Cambridge University Press, UK, Cambridge, UK. p. 181–281

Clarke, W.C., editor. 1982. Carbon Dioxide Review: 1982. Oxford Univeristy Press.

Crowther, T.W., K.E.O. Todd-Brown, C.W. Rowe, W.R. Wieder, J.C. Carey, et al. 2016. Quantifying global soil carbon losses in response to warming. Nature 540: 104–108. doi: 10.1038/nature20150.

Davidson, E.A., S.E. Trumbore, and R. Amundson. 2000. Soil warming and organic carbon content. Nature 408(December): 789–790.

Doetterl, S., A. Stevens, J. Six, R. Merckx, K. Van Oost, et al. 2015. Soil carbon storage controlled by interactions between geochemistry and climate. Nat. Geosci. 8(10): 780–783. doi: 10.1038/ngeo2516.

Evans, S.E., I.C. Burke, and W.K. Lauenroth. 2011. Controls on soil organic carbon and nitrogen in Inner Mongolia, China: A cross-continental comparison of temperate grasslands. Global Biogeochem. Cycles 25(3). doi: 10.1029/2010GB003945.

Fang, C., P. Smith, J.B. Moncrieff, and J.U. Smith. 2005. Similar response of labile and resistant soil organic matter pools to changes in temperature. Nature 433: 57–59. doi: 10.1130/G20750.

Franzluebbers, A.J. 2002. Soil organic matter stratification ratio as an indicator of soil quality.

Soil Tillage Res. 66: 95–106.

Gavlak, R., R. Horneck, and R.O. Miller. 2005. Soil, Plant and Water Reference Methods for the Western Region. 3rd ed. NATP.

Giardina, C.P., and M.G. Ryan. 2005. Evidence that decomposition rate of organic carbon in mineral soil do not vary with temperature. Nature 404(April): 1–4. doi: 10.1038/35009076.

Gray, J.M., and T.F.A. Bishop. 2016. Change in Soil Organic Carbon Stocks under 12 Climate Change Projections over New South Wales, Australia. Soil Sci. Soc. Am. J. 80(5): 1296. doi: 10.2136/sssaj2016.02.0038.

Hoagland, B. 2008. Vegetation of Oklahoma. In: Johnson, K. and Luza, K., editors, Earth Sciences and Mineral Resources of Oklahoma. Oklahoma Geological Survey. p. 17

Homann, P.S., J.S. Kapchinske, and A. Boyce. 2007. Relations of mineral-soil C and N to climate and texture: Regional differences within the conterminous USA. Biogeochemistry 85(3): 303–316. doi: 10.1007/s10533-007-9139-6.

ICH Expert Working Group. 1994. Validation of analytical procedures: Text and Methodology. Ich-Q2B. International Conference on Harmonization (ICH) of Technical Requirements for the Registration of Pharmaceuticals for Human Use. p. 13

Illston, B.G., J.B. Basara, D.K. Fisher, R. Elliott, C.A. Fiebrich, et al. 2008. Mesoscale monitoring of soil moisture across a statewide network. J. Atmos. Ocean. Technol. 25(2): 167–182. doi: 10.1175/2007JTECHA993.1.

Illston, B.G., C.A. Fiebrich, D.L. Grimsley, and J.B. Basara. 2013. Evaluation of a Heat Dissipation Sensor for In Situ Measurement of Soil Temperature. Soil Sci. Soc. Am. J. 77(3): 741. doi: 10.2136/sssaj2012.0189.

Jay, A., C.W. Avery, D. Barrie, A. Dave, B. DeAngelo, et al. 2018. Overview. In: Reidmiller, D.R., Avery, C.W., Easterling, D.R., Kunkel, K.E., Lewis, K.L.M., et al., editors, In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment. U.S. Global Change Research Program, Washington, DC, USA. p. 33–71

Jobbagy, E.G., and R.B. Jackson. 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol. Appl. 10(2): 423–436. doi: 10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2.

Johnson, H.L. 2008. Climate of Oklahoma. In: Johnson, K. and Luza, K., editors, Earth Sciences and Mineral Resources of Oklahoma. Oklahoma Geological Survey. p. 18–19

Knorr, W., I.C. Prentice, J.I. House, and E.A. Holland. 2005. Long-term sensitivity of soil carbon turnover to warming. Nature 433(7023): 298–301. doi: 10.1023/B:RUCO.0000037435.99654.0a.

Li, Y., X. Wang, Y. Chen, Y. Luo, J. Lian, et al. 2019. Changes in surface soil organic carbon in semiarid degraded Horqin Grassland of northeastern China between the 1980s and the 2010s. Catena 174: 217–226. doi: 10.1016/j.catena.2018.11.021.

Luo, Y., and et al. 2016. Towards more realistics projects of soil carbon dynamics by Earth system models. Glob. Biogeochem. Cycles 30(February): 40–56. doi: 10.1002/2015GB005239.

Luo, Z., W. Feng, Y. Luo, J. Baldock, and E. Wang. 2017. Soil organic carbon dynamics jointly controlled by climate, carbon inputs, soil properties and soil carbon fractions. Glob. Chang. Biol. 23: 4430–4439. doi: 10.1111/gcb.13767.

Malone, B.P., A.B. Mcbratney, B. Minasny, and G.M. Laslett. 2009. Mapping continuous depth functions of soil carbon storage and available water capacity. Geoderma 154: 138–152. doi:

10.1016/j.geoderma.2009.10.007.

McPherson, R.A., C.A. Fiebrich, K.C. Crawford, R.L. Elliott, J.R. Kilby, et al. 2007. Statewide monitoring of the mesoscale environment: A technical update on the Oklahoma Mesonet. J. Atmos. Ocean. Technol. 24(3): 301–321. doi: 10.1175/JTECH1976.1.

De Moraes Sa, J.C., and R. Lal. 2009. Soil & Tillage Research Stratification ratio of soil organic matter pools as an indicator of carbon sequestration in a tillage chronosequence on a Brazilian Oxisol. Soil Tillage Res. 103: 46–56. doi: 10.1016/j.still.2008.09.003.

Nichols, J.D. 1984. Relation of Organic Carbon to Soil Properties and Climate in the Southern Great Plains. Soil Sci. Soc. Am. J. 48(6): 1382. doi: 10.2136/sssaj1984.03615995004800060037x.

NOAA ESRL. Trends in Atmospheric Carbon Dioxide: Mauna Loa, Hawaii Data. Moauna Loa CO2 Mon. mean data. https://www.esrl.noaa.gov/gmd/ccgg/trends/data.html (accessed 4 July 2019).

Ochsner, T.E., M.H. Coshb, R.H. Cuencac, W.A. Dorigod, C.S. Drapere, et al. 2013. State of the Art in Large-Scale Soil Moisture Monitoring. Soil Sci. Soc. Am. J. 77(6): 1888–1919. doi: 10.2136/sssaj2013.03.0093.

Ogle, S.M., F. Jay Breidt, M. Easter, S. Williams, K. Killian, et al. 2010. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Glob. Chang. Biol. 16(2): 810–822. doi: 10.1111/j.1365-2486.2009.01951.x.

Oreskes, N. 2005. The Scientific Consensus on Climate Change. Essays Sci. Soc. 306(5702): 1686. doi: 10.1126/science.1103618.

Percival, H.J., R.L. Parfitt, and N.A. Scott. 2000. Factors controlling soil carbon levels in New

Zealand grasslands: is clay content important? Soil Sci. Soc. Am. J. 64: 1623–1630. doi: 10.2136/sssaj2000.6451623x.

Ramírez, P.B., F.J. Calderón, S.J. Fonte, and C.A. Bonilla. 2019. Environmental controls and long-term changes on carbon stocks under agricultural lands. Soil Tillage Res. 186: 310–321. doi: 10.1016/j.still.2018.10.018.

Scharlemann, J.P.W., E.V.J. Tanner, R. Hiederer, and V. Kapos. 2014. Global soil carbon : understanding and managing the largest terrestrial carbon pool. 5(1): 81–91. doi: 10.4155/cmt.13.77.

Schlesinger, W.H., and J.A. Andrews. 1992. Soil respiration and the global carbon cycle. Biogeochemistry 48(1): 572. doi: 10.1023/A:1006247623877.

Scott, B.L., T.E. Ochsner, B.G. Illston, J.B. Basara, and A.J. Sutherland. 2013. New soil property database improves oklahoma mesonet soil moisture estimates. J. Atmos. Ocean. Technol. 30(11): 2585–2595. doi: 10.1175/JTECH-D-13-00084.1.

Scurlock, J.M.., and D.O. Hall. 1998. The global carbon sink : a grassland perspective. Glob. Chang. Biol. (4): 229–233.

Sherrod, L.A., G. Dunn, G.A. Peterson, and R.L. Kolberg. 2002. Inorganic Carbon Analysis by Modified Pressure-Calcimeter Method. Soil Sci. Soc. Am. J. 66(1): 299. doi: 10.2136/sssaj2002.2990.

Soil Survey Staff. 1999. Natural Resources Conservation Service, United States Department of Agriculture. Offical Soil Series Descriptions. Available online. https://www.nrcs.usda.gov/Internet/FSE_MEDIA/stelprdb1237749.pdf (accessed 2 January 2019).

Virto, I., P. Barré, A. Burlot, and C. Chenu. 2012. Carbon input differences as the main factor explaining the variability in soil organic C storage in no-tilled compared to inversion tilled agrosystems. Biogeochemistry 108: 17–26. doi: 10.1007/s10533-011-9600-4.

Yang, X., and M.M. Wander. 1999. Tillage effects on soil organic carbon distribution and storage in a silt loam soil in Illinois. Soil Tillage Res. 52: 1–9.

Zou, H., T. Hastie, and R. Tibshirani. 2007. On the "degrees of freedom" of the LASSO. Ann. Stat. 35(5): 2173–2192. doi: 10.1214/009053607000000127.

VITA

Destiny D. Kerr

Candidate for the Degree of

Master of Science

Thesis: EVALUATING ENVIRONMENTAL INFLUENCES ON GRASSLAND SOIL ORGANIC CARBON TEMPORAL AND SPATIAL DISTRIBUTION

Major Field: Plant and Soil Sciences

Biographical:

Education:

Completed the requirements for the Master of Science in Plant and Soil Sciences at Oklahoma State University, Stillwater, Oklahoma in July, 2019.

Completed the requirements for the Bachelor of Science in Environmental Science at Oklahoma State University, Stillwater, Oklahoma in 2017.

Experience:

Graduate Teaching Assistant in the Environmental Science Program at Oklahoma State University, Stillwater, Oklahoma from August 2017 to present.

Undergraduate Research Assistant in the department of Plant and Soil Sciences at Oklahoma State University, Stillwater, Oklahoma from January, 2015 to August, 2017.

Professional Memberships:

Soil Science Society of America, June 2018 to present