Spatiotemporal Scaling of Soil Organic Carbon using Soil Survey, Ecological Site Concepts, and Land Use Land Cover Data in the Southern Coastal Plain (MLRA 133A)

by

RAJNEESH SHARMA

(Under the Direction of Matthew R. Levi)

ABSTRACT

Soil organic carbon (SOC) is the largest terrestrial carbon stock, but it is susceptible to management changes that make regular monitoring of SOC stock crucial. This study presents the Dynamic Soil Properties (DSP) Scale approach to predict SOC in space and time using soil survey, ecological site concepts, and land cover. We used 1441 point measurements of SOC taken between 2000 and 2018 to predict SOC stock in the upper 20 cm (SOC20) for four time periods between 2001 and 2016 in the Southern US Coastal Plain region. Our random forest model explained 68.5% of the variation for the training dataset. Total SOC20 stock in 2016 was estimated at 1305 Tg. Mean annual precipitation, elevation, erosional classes, and land cover classes were the most important predictors of SOC20 variability. The ability to monitor SOC in space and time will assist to maintain soil health and SOC stocks at regional scale.

INDEX WORDS: Soil, Soil Organic Carbon, Soil Survey, Scaling, Soil Taxonomy, Dynamic Soil Properties, Digital Soil Mapping.

Spatiotemporal Scaling of Soil Organic Carbon using Soil Survey, Ecological Site Concepts, and Land Use Land Cover Data in the Southern Coastal Plain (MLRA 133A)

by

RAJNEESH SHARMA

BS, Punjab Agricultural University, India, 2019

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2021

Spatiotemporal Scaling of Soil Organic Carbon using Soil Survey, Ecological Site Concepts, and Land Use Land Cover Data in the Southern Coastal Plain (MLRA 133A)

by

RAJNEESH SHARMA

Major Professor: Matthew R. Levi
Committee: Aaron Thompson
Elizabeth G. King

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
August 2021

DEDICATION

To all my teachers, friends, and family for being there for me and helping me at every stage and challenge in my journey.

ACKNOWLEDGEMENTS

I would like to sincerely thank my major advisor Dr. Matthew R. Levi, for the help and guidance throughout my master's degree. He is the best mentor I could have asked for who has consistently directed me towards growth and learning while also giving me independence of self-learning. I remember working late nights and emailing about something and getting quick responses. I couldn't have done this without his support. I thank him for being a role-model for passion and commitment to growth.

I also want to thank my committee members Dr. Aaron Thompson and Dr. Elizabeth King for being patient and understanding, especially in the last year of global lockdown and the pandemic. Thanks for the comments and suggestions in the preparation of this manuscript. Especially thanks for the quick replies and response even at short notices.

I also want to acknowledge our data collaborators Dr. Matthew Ricker, Dr. Kevin Robertson, and Mr. Frank Cochran. Soil organic carbon point measurements taken by them really helped the study to be more comprehensive. I also want to thank Dr. Jeff Hepinstall-Cymerman for the awesome course for ArcMap, which was immensely useful for the completion of this research.

I also want to acknowledge the help of my labmates, Derrick Platero, Dr. Grant Snitker, Jill Mullican, Chandler Gruener for being my support system. Derrick has helped me throughout my master's degree from cups of morning tea to late-night drinks. Grant helped me during my starting days with ArcMap and R. Jill Mullican was such a good friend and made me feel like home.

At last but not least, I am grateful to my family, for being a consistent source of support and inspiration. Thanks, dad for being a role model and inspiration for hard work and compassion. Thanks, mom for all the support and love. Thanks to my little brother who secretly cares a lot about me.

Finally, I want to thanks all my teachers and friends who helped me at every stage and challenge in my journey, I couldn’t have done it without y’all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1. Importance of Soil Organic Carbon

Soil organic matter (SOM) and soil organic carbon (SOC) are important soil chemical properties that affect other physical, chemical, and biological properties of soil including soil structure, water retention, nutrient cycling, and soil microbial activity (Brady & Weil, 2004; Domke et al., 2017). SOM and SOC are often used interchangeably, but it is important to recognize that SOC is only the carbon portion and represents approximately 58% of the total SOM (Pribyl, 2010).

SOC is also an essential indicator of soil health. Soil health refers to the ability of soils to support biological productivity and environmental functions (Bini et al., 2013). Liebig (1840) was one of the first to outline the importance of SOM for soil health in his classic book Organic Chemistry in its Application to Agriculture and Physiology. He stated that biomass decomposes to humus, which is a source of carbonic acid. Carbonic acid can be absorbed directly or can release nitrogen, potassium, and other nutrients from soils for absorption by plants (Liebig, 1840; Johnston et al., 2009). SOM is a major source of cation exchange capacity and water holding capacity that plays an important role in nutrient and water absorption for plant growth. SOM is essential for plant growth, which makes it a very important soil property for soil productivity and to ensure food security for the future.

SOC is not only beneficial for plant growth, but also plays a huge role in global and regional carbon budgets as the largest stock of the total terrestrial carbon pool (Batjes, 2014; Han et al., 2007; Lal & Kimble, 2000). Carbon stocks and fluxes are receiving increasing attention because of rapid increases in CO_2 concentration in the atmosphere (Scharlemann et al., 2014). Soils store around 1500 Pg of carbon as SOC globally and an estimated 214 ±67 Pg of carbon has been depleted because of deforestation since the early industrial revolution (Scharlemann et al., 2014; Zomer et al., 2017). Soil can be both a sink or a source of carbon depending upon the management and land-use changes. Land uptake is the biggest sink for CO_2 sequestration of anthropogenic CO_2 emissions (~3.4 GtC per year) and land-use change leads to approximately 1.6 GtC per year of CO_2 emissions (Friedlingstein et al., 2019).

The combined carbon stocks of the southeastern and south-central United States are estimated to be 16,535 Tg which makes 78% of the total terrestrial carbon pool in the region (Han et al., 2007). SOC stock is highly responsive to rapid land use and management changes (Worsham et al., 2010; Gebremedhin et al., 2018). Causarano et al. (2008) showed that in the Southern Piedmont and Coastal Plain physiographic regions 41.6% of the variability in SOC could be explained by land management. There was an intensive conversion of forests to croplands and pastures in the southeastern United States from the 1700s to the 1930s and after that this trend was reversed because of timber demand (Trail et al., 2013). The dynamic nature of SOC across the Southeast is strongly controlled by spatial and temporal patterns of land use and land cover; therefore, it is important to study the quantitative relationships between SOC and land management at multiple spatial scales.

The SOC stocks in the southeastern United States have a high potential to be increased, which could help to sequester large amounts of atmospheric CO_2 and help to mitigate climatic and environmental risks (Liu et al., 2004; Worsham et al., 2010). Because of the economic and environmental importance of SOC, researchers are interested in quantifying carbon stocks and improving predictions of how management might change SOC stocks. One major constraint in the prediction of SOC has been rapid changes in the stocks due to its management-dependent nature (Gebremedhin et al., 2018). For this reason, SOC is widely recognized as an important dynamic soil property (DSP; Domke et al., 2017). DSPs are soil properties that change from natural or anthropogenic drivers across human time scales (decades to centuries) (Tugel et al., 2005; Levi et al., 2010). The magnitude of variation for a particular DSP caused by a given management change is also controlled by inherent soil properties. Inherent soil properties are defined as soil properties that are relatively stable in human time scales and governed by slower soil formation processes (Gao et al., 2017; Lutz, 1935; Xue et al., 2018). These soil properties are driven by topography, climate, parent material of soils, age of soils. The combination of inherent soil properties and dynamic changes in management results in changes in carbon stocks in soils over time. Most mapping efforts are designed to study the spatial variability of SOC for one particular time period with less attention to temporal variability. Conversely, studies focused on temporal changes are frequently designed to capture changes for selected locations and lack ideal distribution for spatial modeling. Collectively we are left with many different SOC datasets created by different methods and techniques which makes it harder to quantify the changes of SOC stock occurring over a particular region.

1.2. Scaling in Soil Science

Soil property data is collected at a very small scale (e.g., point or pedon), but its implications and predictions are needed for much larger scales (Pachepsky and Hill, 2017). Scaling soil properties is a challenging task that has been discussed for many years (Pachepsky and Hill, 2017). The primary reason that scaling is so difficult is limited sampling capabilities and spatial support for spatial techniques that require large numbers of data points for accurate predictions. To bridge this gap, researchers try to tie a much bigger area to the actual footprint of the sample. A classic example of scaling up soil information is the development of soil maps where the delineation of soil map units with similar soils is based on a relatively small number of observations and connected to the landscape through the tacit knowledge of the soil scientist (Hudson, 1992). The same data have different implications at different scales. For example, at a fine-scale, such as a farmer's field, SOC variations have different meanings like that a particular field may need an application of organic manure. In other scenarios, such as at the state-level, fluctuation in SOC may be due to deforestations or high erosion due to larger areas with bare soils. Therefore, scaling is a topic that should be given thought before starting the mapping process.

In the environmental sciences, numerous scaling hierarchies have been developed to explain the complexities of ecological systems (O’Neill et al., 1989). All of them have their particular purposes such as ecological hierarchy focused on numerical quantities from organisms to ecosystems and hydrological hierarchy focused on areas of interest from local to regional scales. Common spatial hierarchies to classify land resources are Environmental Protection Agency (EPA) ecoregions National Resources Conservation Services (NRCS) resource areas (Soil and Ecological), and USFS ecological units (McMahon et al., 2001; Salley et al., 2016b). There is some overlap between all these hierarchies (Salley et al., 2016 b) and each serves the purpose of their corresponding regulating agencies. The common hierarchy in soil science is more focused on soil process scales rather than policy-making and spatial scaling of soil properties. Scaling in soil science systems can be summarized from fine to coarse as follows: peds or aggregates, horizon, pedon, polypedon, catena, soil region (Hoosbeek and Bryant, 1992). For soil resources and conservation purposes, NRCS uses the land resource hierarchy (LRH), which compiles aspects of ecology, hydrology, and soils to organize areas with similar potential (Salley et al., 2016 b).

The LRH is designed to classify land resources according to their capabilities, potentials, and limitations for use that helps to plan ecological services and regulate natural resource conservation (Salley et al., 2016 a). It classifies spatial land resource areas from small to large as soil map units (SMU), land resource units (LRU), major land resource areas (MLRA), and land resource regions (LRR). Land resource areas (LRU, MLRA, LRR) are based on aggregations of soil properties using taxonomic classification (Austin, 1965; Salley, et al., 2016 a). The LRH is an ideal method for scaling inherent soil properties because it is a taxonomic-based scaling hierarchy, but the static nature of soil taxonomy limits predictions of temporal fluctuations related to management-based changes in DSPs. A recent initiative from NRCS to bind

Ecological sites (ES) site concepts with scaling hierarchy (Fig. 1.1) provides an opportunity to incorporate DSPs which may change in human time scales.

1.3. Ecological Site (ES) concepts and State and Transition Models (STM)

ESs are areas with the same potential to support vegetation and ecosystem functions due to consistency in climate, soils, and topographic positions (Bestelmeyer et al., 2017). Each ES has a conceptual representation of ecosystem dynamics represented as a state and transition model (STM) (Bestelmeyer et al., 2009). The first publication on ES and STMs was highly appreciated and started a new era of scientific management of land resources (Westoby et al., 1989). The ES concept was originally developed from the range condition model used in the rangelands of the western United States as an ecological potential-based landscape classification system. The commendable success of using ES and STM concepts in western rangelands resulted in a formalized agreement between NRCS, the Bureau of Land Management (BLM), and the United States Forest Services (USFS) that ESs be recognized units for land management and soil conservation applications in 2010 (Salley et al., 2016 b). Since that time, NRCS has been working to expand the ES concept to more humid and forested regions like the Southern Coastal Plain (Johanson & Brown, 2012; Salley et al., 2016 b). As of 2020, soil map units in the majority of the eastern U.S. (i.e., east of the Mississippi River) lack an assigned ES (Fig. 1.2 a or 1.2 b). Currently, most of the ESs in the Southern Coastal Plain are in the provisional stage (Fig. 1.3).

By definition, ESs delineate areas with distinct abilities to support similar types and amounts of vegetation based on landforms, geology, climate, and soils (Paolucci and Stolt, 2018;

Salley et al., 2016 b; Wills et al., 2017). Variations in management or environmental drivers for a given ES are described and explained with a complimentary State and Transition Model (STM, Caudle et al., 2013; Wills et al., 2017). For each STM, conditions are represented by vegetative or ecological states that represent the relatively stable state of an ecosystem that can withstand small changes and tend to be in homeostasis considered a ‘stable state’ (i.e., ecosystem resilience) (Bestelmeyer et al., 2017). A transition can then be defined as the factors responsible for changes from one stable state to another relatively stable state. A threshold is essential to be crossed to change from one state to another (Stringham et al., 2003). In intensively managed soils of the Southeast, state changes are often imposed by management decisions as opposed to natural drivers.

Changing states within an ES over time creates variability in management-dependent soil properties or DSPs. One of the major shortcomings of STMs is that these are conceptual models that are not spatially defined, but the states in the STM are naturally related to land management and land cover. The relationship between ecological states and landcover can be used to define state or land cover changes spatially by using the National Land Cover Database (NLCD) (Homer and Fry, 2012; Mount et al., 2020). This spatial link can be used to study changes in DSPs like SOC due to land cover changes. For example, the states mentioned in Fig. 1.4 can be related to the land cover classes described in the NLCD. State 5 (pasture) and State 6 (cropland) are both present in the 2016 NLCD as two separate classes. States 1 – 4 are mainly some type of forest or plantations and all these can be represented by Deciduous, Evergreen, and Mixed forest classes of NLCD.

1.4. National land cover dataset as a tool for assessing land management and soil change

The NLCD is a land use and land cover (LULC) database for the United States derived from the Landsat remote sensing missions (Homer and Fry, 2012). The standard product is freely available at www.mrlc.gov for select dates between 2001–2016 with a 30 m spatial resolution and classifies each pixel as one of several land cover classes (croplands, pastures, shrublands, evergreen forests, mixed forests, deciduous forests, urban areas, etc.) (Homer et al., 2020). A similar database is available for land cover in 1992 (NLCD (1992)) representing the same spatial resolution and extent, however there are some differences between the methods, legends, and imageries of the databases (Fry, 2008). These differences can be resolved by modifying the legends from both the databases and creating a new legend that will be more consistent with land cover types emphasized in this research.

It is well established that LULC changes have a significant effect on soil properties including soil health, soil physical properties, and the larger ecosystem (Liu et al., 2014). However, most of the natural systems are too complex and categories of land cover classes are unable to capture them. The regions with high management intensity commonly decrease the heterogeneity of vegetation communities which often results in increased accuracy of land cover classification (Hall et al., 2020). As mentioned in earlier sections, between the 1700s and 1930s there was an intensive conversion of forests to croplands and pastures, but this trend was reversed after the 1930s because of an increase in demand for timber (Trail et al., 2013). These land cover changes effectively reduced the spatial variation of land use in the region; therefore, NLCD can represent more recent changes in management in this region. LULC change can capture anthropogenic changes at landscape scales (Teferi et al., 2016). NLCD and its potential to represent management changes can be utilized to explain variations in DSPs like SOC.

1.5. Soil Organic Carbon Prediction Modeling

Carbon stock in soils is controlled by combination of environmental factors like climate, topography, parent material, and vegetation. SOC is highly responsive to changes in these factors and is considered a dynamic soil property (DSP). The major part of the fluctuation of SOC is attributed to landcover changes. But the amplitude of these management-driven changes in SOC is controlled by inherent soil properties such as topography, climate, soil texture, and parent material. Some combination of inherent soil properties and land cover changes affect the distribution of SOC stock spatially and temporarily. Teasing apart the contributions of each driver requires the integration of both spatial and non-spatial information to effectively map SOC for large areas over time.

Digital soil mapping caught up pace in the late 1990s to quantify SOC stock in soils, but predicting SOC based on the models is not recent and has been done for several decades. Jenny et al. (1968) was one of the first to develop a climate covariable-based SOC predicting model, based on his famous “clorpt” approach (Jenny, 1941). McBratney et al. (2003) updated Jenny’s equation with a new conceptual model known as “scorpan” where they predicted soil properties spatially using covariables based on soils (s), climate (c), organisms (o), topography (r), parent material (p), age and time (a), and spatial position (n). Most studies used these broad factors to study the spatial distribution of SOC over a region until the late 1990s. Then with advances in remote sensing, visible and infrared reflectance was found to be highly related to SOC. The Normalized Difference Vegetation Index (NDVI) is the most common spectral index for vegetation as it measures greenness across a landscape (Taghizadeh-Mehrjardi et al., 2016; Schillaci et al., 2017). It's now well established that spectral, environmental and climatic covariables can be used to predict SOC stocks over a region and Minasny et al. (2013) provides a review of various digital soil mapping-based studies globally.

Several efforts have focused on SOC predictions in the southeastern U.S. Coastal Plain such as Ross et al. (2020), Xiong et al. (2014), Causarano et al. (2008b), however all these studies focus on predicting SOC for a specific time period and don't give much information about temporal changes in SOC stock.

1.6. Summary

SOC is essential for soil health and plant growth, it is also an essential part of the global carbon budget. SOC is susceptible to management changes, i.e. why monitoring of SOC stock is crucial. The Southern Coastal Plain stores large quantities of SOC and has a long history of management changes and soil erosion. Scaling SOC is a challenging task because limited sampling capabilities make it difficult to accurately predict SOC over a spatial extent. NRCS uses the LRH to classify land resources based on their potential to support vegetation and the ecosystem. The ecological site concept is also based on the land resource potential-based classification. ES and STM is a framework that captures the control of inherent soil properties and land management changes on an ecosystem over a region. This framework can be used to study soil variability in space and time. SOC has high spatiotemporal variation and the ES and STM frameworks can help make sense of this variation. However, STMs are conceptual models and thus is not defined spatially. STMs have a natural connection to land cover as both describe land management and this relationship can be used to develop spatially defined STMs by using land cover changes over a period of time. Studying the effect of soil type and management changes on SOC is crucial for better characterization of SOC stocks and soil health management.

1.7. References

Adhikari, K., A.E. Hartemink, B. Minasny, R. Bou Kheir, M.B. Greve, et al. 2014. Digital mapping of soil organic carbon contents and stocks in Denmark. PLoS One. doi: 10.1371/journal.pone.0105519.

Aksoy, E., Y. Yigini, and L. Montanarella. 2016. Combining soil databases for topsoil organic carbon mapping in Europe. PLoS One. doi: 10.1371/journal.pone.0152098.

Amano, M., R.A. Sedjo, and Resources for the future. 2006. Forest Sequestration – Performance in Selected Countries in the Kyoto Period and the Potential Role of Sequestration in Post-Kyoto Agreements. (May): 65.

Andrew J. Paolucci and Mark H. Stolt. 2018. Assessing Dynamic Soil Properties in Southern New England Forests within an Ecological Site Framework. https://acsess.onlinelibrary.wiley.com/doi/epdf/10.2136/sssaj2018.01.0047 (accessed 20 April 2021).

Austin, M.E. 1965. Land resource regions and major land resource areas of the United States (exclusive of Alaska and Hawaii) /. Washington, D.C. :

Batjes, N.H. 2014. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. doi: 10.1111/ejss.12114_2.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013a. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013b. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Bestelmeyer, B.T., A. Ash, J.R. Brown, B. Densambuu, M. Fernández-Giménez, et al. 2017. State and Transition Models: Theory, Applications, and Challenges

Bestelmeyer, B.T., A.J. Tugel, G.L. Peacock, D.G. Robinett, P.L. Shaver, et al. 2009. State-and-transition models for heterogeneous landscapes: A strategy for development and application. Rangel. Ecol. Manag. 62(1): 1–15. doi: 10.2111/08-146.

Bhandari, J., and Y. Zhang. 2019. Effect of altitude and soil properties on biomass and plant richness in the grasslands of Tibet, China, and Manang District, Nepal. Ecosphere 10(11): e02915. doi: 10.1002/ecs2.2915.

Bini, D., C. Alcantara, D. Santos, K. Banhos Do Carmo, N. Kishino, et al. 2013. Effects of land use on soil organic carbon and microbial processes associated with soil health in southern Brazil. doi: 10.1016/j.ejsobi.2012.12.010.

Breiman, L. 2001. Random forests. Mach. Learn. 45(1): 5–32. doi: 10.1023/A:1010933404324.

Caudle, D., J. Dibenedetto, M. Karl, H. Sanchez, and C. Talbot. 2013. Interagency ecological site handbook for rangelands. (January): 109.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008a. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2006.0274.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008b. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. 72(1): 221–230. doi: 10.2136/sssaj2006.0274.

Cochran, J.F. 2010. Management-Dependent Soil Variability and Surface Hydraulic Properties of Southeastern U.S. Coastal Plain Plinthic Kandiudults.

Conant, R.T., J. Six, and K. Paustian. 2004. Land use effects on soil carbon fractions in the southeastern United States. II. Changes in soil carbon fractions along a forest to pasture chronosequence. Biol. Fertil. Soils. doi: 10.1007/s00374-004-0754-2.

Data | Multi-Resolution Land Characteristics (MRLC) Consortium. https://www.mrlc.gov/data?f%5B0%5D=category%3Aland cover (accessed 27 July 2020).

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.

Domke, G.M., C.H. Perry, B.F. Walters, L.E. Nave, C.W. Woodall, et al. 2017. Toward inventory-based estimates of soil organic carbon in forests of the United States.

Ecological site descriptions. https://edit.jornada.nmsu.edu/catalogs/esd (accessed 16 October 2020).

Ekwue, E.I. 1990. Organic-matter effects on soil strength properties. Soil Tillage Res. 16(3): 289–297. doi: 10.1016/0167-1987(90)90102-J.

ESRI. 2019. ArcMap 10.7.

Fox, T.R., E.J. Jokela, and H.L. Allen. 2007. The development of pine plantation silviculture in the Southern United States. J. For. 105(7): 337–347. doi: 10.1093/jof/105.7.337.

Franzmeier, D.P., G.D. Lemme, and R.J. Miles. 1985. Organic Carbon in Soils of North Central United States. Soil Sci. Soc. Am. J. 49(3): 702–708. doi: 10.2136/sssaj1985.03615995004900030035x.

Friedlingstein, P., M.W. Jones, M. O'Sullivan, R.M. Andrew, J. Hauck, et al. 2019. Global carbon budget 2019. Earth Syst. Sci. Data 11(4): 1783–1838. doi: 10.5194/essd-11-1783-2019.

Fry, J.A. et al. 2008. Completion of the National Land Cover Database (NLCD) 1992-2001 Land Cover Change Retrofit Product.

Galik, C.S., B.C. Murray, and D.E. Mercer. 2013. Where is the carbon? carbon sequestration potential from private forestland in the southern United States. J. For. 111(1): 17–25. doi: 10.5849/jof.12-055.

Gao, L., M.A. Bowker, M. Xu, H. Sun, D. Tuo, et al. 2017. Biological soil crusts decrease erodibility by modifying inherent soil properties on the Loess Plateau, China. Soil Biol. Biochem. 105: 49–58. doi: 10.1016/j.soilbio.2016.11.009.

Gebremedhin, H., G. Gebresamual, N. Abadi, M. Hailemariam, K. Teka, et al. 2018. Conversion of communal grazing land into arable land and its impacts on soil properties and vegetation cover. Arid L. Res. Manag. doi: 10.1080/15324982.2017.1406412.

Glanemann, N., S.N. Willner, and A. Levermann. 2020. Paris Climate Agreement passes the cost-benefit test. Nat. Commun. 11(1): 1–11. doi: 10.1038/s41467-019-13961-1.

Gomes, L.C., R.M. Faria, E. de Souza, G.V. Veloso, C.E.G.R. Schaefer, et al. 2019. Modelling and mapping soil organic carbon stocks in Brazil. Geoderma 340: 337–350. doi: 10.1016/J.Geoderma.2019.01.007.

Grinand, C., G. Le Maire, G. Vieilledent, H. Razakamanarivo, T. Razafimbelo, et al. 2017. Estimating temporal changes in soil carbon stocks at ecoregional scale in Madagascar using remote-sensing. Int. J. Appl. Earth Obs. Geoinf. doi: 10.1016/j.jag.2016.09.002.

Del Grosso, S., W. Parton, T. Stohlgren, D. Zheng, D. Bachelet, et al. 2008. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology 89(8): 2117–2126. doi: 10.1890/07-0850.1.

Grunwald, S. 2009. Multi-criteria characterization of recent digital soil mapping and modeling approaches. Geoderma 152(3–4): 195–207. doi: 10.1016/j.geoderma.2009.06.003.

Guo, Y., R. Amundson, P. Gong, and Q. Yu. 2006. Quantity and Spatial Variability of Soil Carbon in the Conterminous United States. Soil Sci. Soc. Am. J. 70(2): 590–600. doi: 10.2136/sssaj2005.0162.

H. Jenny, A.E. Salem, J.R.W. 1968. Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil Fertility. Pontif. Acad. https://scholar.google.com/scholar_lookup?title=Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil

Fertility. Pontif. Acad&publication_year=1968&author=H. Jenny&author=A.E. Sal (accessed 12 June 2021).

Hall, R.M., N. Penke, M. Kriechbaum, S. Kratschmer, V. Jung, et al. 2020. Vegetation management intensity and landscape diversity alter plant species richness, functional traits and community composition across European vineyards. Agric. Syst. 177: 102706. doi: 10.1016/j.agsy.2019.102706.

Hamzehpour, N., H. Shafizadeh-Moghadam, and R. Valavi. 2019. Exploring the driving forces and digital mapping of soil organic carbon using remote sensing and soil texture. Catena. doi: 10.1016/j.catena.2019.104141.

Han, F.X., M.J. Plodinec, Y. Su, D.L. Monts, and Z. Li. 2007. Terrestrial carbon pools in southeast and south-central United States. Clim. Change. doi: 10.1007/s10584-007-9244-5.

Han, L., Z. Wan, Y. Guo, C. Song, S. Jin, et al. 2020. Estimation of soil organic carbon storage in Palustrine Wetlands, China. Int. J. Environ. Res. Public Health 17(13). doi: 10.3390/ijerph17134646.

Heuvelink, G.B.M., M.E. Angelini, L. Poggio, Z. Bai, N.H. Batjes, et al. 2020. Machine learning in space and time for modelling soil organic carbon change. Eur. J. Soil Sci. doi: 10.1111/ejss.12998.

Homer, C., J. Dewitz, S. Jin, G. Xian, C. Costello, et al. 2020. Conterminous United States land cover change patterns 2001–2016 from the 2016 National Land Cover Database. ISPRS J. Photogramm. Remote Sens. 162: 184–199. doi: 10.1016/j.isprsjprs.2020.02.019.

Homer, C., and J. Fry. 2012. The National Land Cover Database. US Geol. Surv. Fact Sheet.

Hoosbeek, M.R., and R.B. Bryant. 1992. Towards the quantitative modeling of pedogenesis-a review.

Hudson, B.D. 1992. The Soil Survey as Paradigm-based Science.

Lutz, J.F 1935. The Relation Of Soil Erosion To Certain Inherent Soil Proper... : Soil Science. https://journals.lww.com/soilsci/Citation/1935/12000/the_Relation_of_Soil_Erosion_To_Certain_Inherent.2.aspx (accessed 19 April 2021).

Jenny, H. 1941. Factors of Soil Formation: A System of Quantitative Pedology. Science (80-.). 349(6250). http://scholar.google.com/scholar_lookup?title=Global+cancer+statistics&author=A.+Jemal&author=F.+Bray&author=M.+M.+Center&author=J.+Ferlay&author=E.+Ward&author=D.+Forman&publication_year=2011%0Ahttps://anthrosource.onlinelibrary.wiley.com/servlet/linkou.

Jobba´gy, Esteban G; Jackson, R.B. 2000. The Vertical Distribution Of Soil Organic Carbon And Its Relation To Climate And Vegetation - Jobbágy - 2000 - Ecological Applications - Wiley Online Library. https://esajournals.onlinelibrary.wiley.com/doi/full/10.1890/1051-0761%282000%29010%5B0423%3ATVDOSO%5D2.0.CO%3B2 (accessed 28 June 2021).

Johanson, J., and J. Brown. 2012. Ecological site development: Accelerating the effort. Rangelands 34(2): 29–31. doi: 10.2111/RANGELANDS-D-11-00068.1.

Johnston, A.E., P.R. Poulton, and K. Coleman. 2009. Chapter 1 Soil Organic Matter. Its Importance in Sustainable Agriculture and Carbon Dioxide Fluxes. Adv. Agron. 101: 1–57. doi: 10.1016/S0065-2113(08)00801-8.

Kern, J.S. 1994a. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Kern, J.S. 1994b. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Konen, M.E., P.M. Jacobs, C.L. Burras, B.J. Talaga, and J.A. Mason. 2002. Equations for Predicting Soil Organic Carbon Using Loss-on-Ignition for North Central U.S. Soils. Soil Sci. Soc. Am. J. 66(6): 1878–1881. doi: 10.2136/sssaj2002.1878.

Kuhn, M., and K. Johnson. 2013. Applied predictive modeling. Springer New York.

Lal, R. 2008. Carbon sequestration. Philos. Trans. R. Soc. B Biol. Sci. 363(1492): 815–830. doi: 10.1098/rstb.2007.2185.

Lal, R., and J.M. Kimble. 2000. Pedogenic carbonates and the global carbon cycle. Global Climate Change And Pedogenic Carbonates

LaRowe, D.E., and P. Van Cappellen. 2011. Degradation of natural organic matter: A thermodynamic analysis. GeCoA 75(8): 2030–2042. doi: 10.1016/J.GCA.2011.01.020.

Levi, M.R. 2007. Management Dependent Soil Properties of Cultivated Versus Non-Cultivated Southeastern Coastal Plain Ecosystems.

Levi, M.R., J.N. Shaw, C.W. Wood, S.M. Hermann, E.A. Carter, et al. 2010. Land Management Effects on Near-Surface Soil Properties of Southeastern U.S. Coastal Plain Kandiudults. Soil Sci. Soc. Am. J. 74(1): 258–271. doi: 10.2136/sssaj2009.0015.

Liebig, J. 1840. Die organische Chemie in ihrer Anwendung auf Agricultur und Physiologie. Braunschweig,.

Liu, S., T.R. Loveland, and R.M. Kurtz. 2004. Contemporary carbon dynamics in terrestrial ecosystems in the Southeastern Plains of the United States. Environ. Manage. 33(SUPPL. 1): 442–456. doi: 10.1007/s00267-003-9152-z.

Liu, Z., Z. Yao, H. Huang, S. Wu, and G. Liu. 2014. Land use and climate changes and their impacts on runoff in the Yarlung Zangbo river basin, China. L. Degrad. Dev. doi: 10.1002/ldr.1159.

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. Geoderma 117(1–2): 3–52. doi: 10.1016/S0016-7061(03)00223-4.

McMahon, G., S.M. Gregonis, S.W. Waltman, J.M. Omernik, T.D. Thorson, et al. 2001. Developing a spatial framework of common ecological regions for the conterminous United States. Environ. Manage. 28(3): 293–316. doi: 10.1007/s0026702429.

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013a. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013b. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Mishra, U., R. Lal, B. Slater, F. Calhoun, D. Liu, et al. 2009. Predicting Soil Organic Carbon Stock Using Profile Depth Distribution Functions and Ordinary Kriging. Soil Sci. Soc. Am. J. 73(2): 614–621. doi: 10.2136/sssaj2007.0410.

Mount, R., N. Carolina, and S. Carolina. 2020. Ecological site F133AY007NC Atlantic Coastal Plain Wet Longleaf Pine Woodland , Wet - PROVISIONAL.

Natural, Resources, Conservation, and Service. 2009. Part 630 Hydrology National Engineering

Handbook.

Nave, L.E., E.D. Vance, C.W. Swanston, and P.S. Curtis. 2009. Harvest impacts on soil carbon storage in temperate forests. doi: 10.1016/j.foreco.2009.12.009.

NRCS. SSM - Ch. 2. Landscapes, Geomorphology, and Site Description | NRCS North Carolina. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/nc/soils/?cid=nrcs142p2_054252 (accessed 24 June 2021).

NRCS NSSC KSSL, U. 2014. Kellog Soil Survey Laboratory Methods Manual; Soil Survey Investigations Report No. 42; Version 5.0 (2014).

O'Neill, R. V., A.R. Johnson, and A.W. King. 1989. A hierarchical framework for the analysis of scale. Landsc. Ecol. 3(3–4): 193–205. doi: 10.1007/BF00131538.

Olson, J.S., J.A. Watts, and L.L.A. 1985. Major World Ecosystem Complexes Ranked by Carbon in Live Vegetation: A Database (NDP-017) (2001 version of original 1985 data) (Dataset) | OSTI.GOV. https://www.osti.gov/biblio/1389497 (accessed 24 June 2021).

Olson, K.R., M. Al-Kaisi, R. Lal, and L. Cihacek. 2016. Impact of soil erosion on soil organic carbon stocks. J. Soil Water Conserv. 71(3): 61A-67A. doi: 10.2489/jswc.71.3.61A.

Ontl, T. A. & Schulte, L.A. 2012. Soil Carbon Storage | Learn Science at Scitable. https://www.nature.com/scitable/knowledge/library/soil-carbon-storage-84223790/ (accessed 11 June 2021).

Pachepsky, Y., and R.L. Hill. 2017. Scale and scaling in soils. Geoderma 287: 4–30. doi: 10.1016/j.geoderma.2016.08.017.

PII: S0167-1987(97)00044-5 | Elsevier Enhanced Reader.

https://reader.elsevier.com/reader/sd/pii/S0167198797000445?token=BD3D01F7AD56DB80C79A51C2BC0B9CA7D37A7237E9517245EDD279B413F6D531CADB217F8DBAF1AA104A7BD6ADA87C89&originRegion=eu-west-1&originCreation=20210419154615 (accessed 19 April 2021).

Pribyl, D.W. 2010. A critical review of the conventional SOC to SOM conversion factor. Geoderma 156: 75–83. doi: 10.1016/j.geoderma.2010.02.003.

PRISM Climate Group, Oregon State U. https://prism.oregonstate.edu/normals/ (accessed 7 July 2020).

R Core Team. 2020. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ramcharan, A., T. Hengl, D. Beaudette, and S. Wills. 2017. A Soil Bulk Density Pedotransfer Function Based on Machine Learning: A Case Study with the NCSS Soil Characterization Database. Soil Sci. Soc. Am. J. 81(6): 1279–1287. doi: 10.2136/sssaj2016.12.0421.

Rapid Carbon Assessment (RaCA) | Ag Data Commons. https://data.nal.usda.gov/dataset/rapid-carbon-assessment-raca (accessed 5 July 2020).

Rasmussen, C. 2006. Distribution of Soil Organic and Inorganic Carbon Pools by Biome and Soil Taxa in Arizona. Soil Sci. Soc. Am. J. 70(1): 256–265. doi: 10.2136/sssaj2005.0118.

Rasmussen, C., K. Heckman, W.R. Wieder, M. Keiluweit, C.R. Lawrence, et al. 2018. Beyond clay: towards an improved set of variables for predicting soil organic matter content. Biogeochemistry 137(3): 297–306. doi: 10.1007/S10533-018-0424-3.

Ricker, M.C., and B.G. Lockaby. 2015. Soil Organic Carbon Stocks in a Large Eutrophic

Floodplain Forest of the Southeastern Atlantic Coastal Plain, USA. Wetlands 35(2): 291–301. doi: 10.1007/s13157-014-0618-y.

Robertson, G.P., K.M. Klingensmith, M.J. Klug, E.A. Paul, J.R. Crum, et al. 1997. SOIL Resources, Microbial Activity, And Primary Production Across An Agricultural Ecosystem.

Ross, C.W. 2017. A Region-Wide Analysis Of Terrestrial Carbon Cycling Across "The Land Of Pines."

Ross, C.W., S. Grunwald, J.G. Vogel, D. Markewitz, E.J. Jokela, et al. 2020. Accounting for two-billion tons of stabilized soil carbon. Sci. Total Environ. 703: 134615. doi: 10.1016/j.scitotenv.2019.134615.

Salley, S.W., H. Curtis Monger, and J.R. Brown. 2016a. Completing the Land Resource Hierarchy. Rangelands 38(6): 313–317. doi: 10.1016/j.rala.2016.10.003.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016b. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016c. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Scharlemann, J.P., E.V. Tanner, R. Hiederer, and V. Kapos. 2014. Carbon Management Global soil carbon: understanding and managing the largest terrestrial carbon pool. doi: 10.4155/cmt.13.77.

Schillaci, C., M. Acutis, L. Lombardo, A. Lipani, M. Fantappiè, et al. 2017. Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: The role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling. Sci. Total Environ. doi: 10.1016/j.scitotenv.2017.05.239.

Sevastas, S., D. Gasparatos, D. Botsis, I. Siarkos, K.I. Diamantaras, et al. 2018. Predicting bulk density using pedotransfer functions for soils in the Upper Anthemountas basin, Greece. Geoderma Reg. 14: e00169. doi: 10.1016/j.GEODRS.2018.e00169.

Singh, M., B. Sarkar, S. Sarkar, J. Churchman, N. Bolan, et al. 2018. Stabilization of Soil Organic Carbon as Influenced by Clay Mineralogy. Advances in Agronomy. Academic Press Inc. p. 33–84

Soil Drainage Class.

Soil Survey Staff, Natural Resources Conservation Service, U.S.D. of A. Soil Survey Geographic (SSURGO) Database.

Spash, C.L. 2010. The brave new world of carbon trading. New Polit. Econ. 15(2): 169–195. doi: 10.1080/13563460903556049.

SSM - Ch. 9. Assessing Dynamic Soil Properties and Soil Change | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/ref/?cid=nrcseprd1343021 (accessed 19 April 2021).

Stringham, T.K., W.C. Krueger, and P.L. Shaver. 2003. State and transition modeling: An ecological process approach. J. Range Manag. doi: 10.2307/4003893.

Taghizadeh-Mehrjardi, R., K. Nabiollahi, and R. Kerry. 2016. Digital mapping of soil organic carbon at multiple depths using different data mining techniques in Baneh region, Iran.

Geoderma. doi: 10.1016/j.geoderma.2015.12.003.

Teferi, E., W. Bewket, and B. Simane. 2016. Effects of land use and land cover on selected soil quality indicators in the headwater area of the Blue Nile basin of Ethiopia. Environ. Monit. Assess. doi: 10.1007/s10661-015-5086-1.

The National Map. https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map (accessed 26 June 2021).

Trail, M., A.P. Tsimpidi, P. Liu, K. Tsigaridis, Y. Hu, et al. 2013. Potential impact of land use change on future regional climate in the Southeastern U.S.: Reforestation and crop land conversion. J. Geophys. Res. Atmos. 118(20): 11,577-11,588. doi: 10.1002/2013JD020356.

Tugel, A.J., S.A. Wills, and J.E.H. 2008. Soil change guide: Procedures for soil survey and resource inventory. Version 1. Natl. Soil Surv. Ctr., Lincoln, NE.

Tugel, A.J., J.E. Herrick, J.R. Brown, M.J. Mausbach, W. Puckett, et al. 2005. Soil Change, Soil Survey, and Natural Resources Decision Making. Soil Sci. Soc. Am. J. 69(3): 738–747. doi: 10.2136/sssaj2004.0163.

US EPA, O. 2001. Ecoregion Download Files by State - Region 4. https://www.epa.gov/eco-research/ecoregion-download-files-state-region-4 (accessed 18 August 2020).

USDA-NRCS. Soil Moisture Regimes of the Contiguous United States | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/maps/?cid=nrcs142p2_053997 (accessed 28 June 2021).

USDA:NRCS:Geospatial Data Gateway:Order Data. https://datagateway.nrcs.usda.gov/GDGOrder.aspx (accessed 31 July 2020).

USDA. 2014. Keys to soil taxonomy. Soil Conserv. Serv. 12: 410. doi: 10.1109/TIP.2005.854494.

USDA, and NRCS. 2006. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and the Pacific Basin.

Vasques, G.M., S. Grunwald, and W.G. Harris. 2010. Spectroscopic Models of Soil Organic Carbon in Florida, USA. J. Environ. Qual. 39(3): 923–934. doi: 10.2134/jeq2009.0314.

Walker, J.D., and J. Geissman. 2009. 2009 GSA Geologic Time Scale Evolution of the Teton fault View project Building Stronger Geoscience Department View project. doi: 10.1130/1052-5173-19.4-5.60.

Wang, B., C. Waters, S. Orgill, J. Gray, A. Cowie, et al. 2018. High resolution mapping of soil organic carbon stocks using remote sensing variables in the semi-arid rangelands of eastern Australia. Sci. Total Environ. doi: 10.1016/j.scitotenv.2018.02.204.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic management for rangelands not at equilibrium.

Wickham, H. 2016. ggplot2. Springer International Publishing, Cham.

Wickham, J.D., S. V. Stehman, L. Gass, J. Dewitz, J.A. Fry, et al. 2013. Accuracy assessment of NLCD 2006 land cover and impervious surface. Remote Sens. Environ. 130: 294–304. doi: 10.1016/j.rse.2012.12.001.

Wills, S., C. Williams, C. Seybold, L. Scheffe, Z. Libohova, et al. 2017. Using Soil Survey to Assess and Predict Soil Condition and Change. : 123–135. doi: 10.1007/978-3-319-43394-3_11.

Worsham, L., D. Markewitz, and N. Nibbelink. 2010. Incorporating Spatial Dependence into Estimates of Soil Carbon Contents under Different Land Covers. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2008.0412.

Xiong, X., S. Grunwald, D.B. Myers, C.W. Ross, W.G. Harris, et al. 2014. Interaction effects of climate and land use/land cover change on soil organic carbon sequestration. Sci. Total Environ. 493: 974–982. doi: 10.1016/j.scitotenv.2014.06.088.

Xue, D., R. Christenson, R. Genger, A. Gevens, and R.A. Lankau. 2018. Soil Microbial Communities Reflect both Inherent Soil Properties and Management Practices in Wisconsin Potato Fields. Am. J. Potato Res. 95(6): 696–708. doi: 10.1007/s12230-018-9677-6.

Yang, R.M., G.L. Zhang, F. Liu, Y.Y. Lu, F. Yang, et al. 2016. Comparison of boosted regression tree and random forest models for mapping topsoil organic carbon concentration in an alpine ecosystem. Ecol. Indic. doi: 10.1016/j.ecolind.2015.08.036.

Zomer, R.J., D.A. Bossio, R. Sommer, and L. V. Verchot. 2017. Global Sequestration Potential of Increased Organic Carbon in Cropland Soils. Sci. Rep. 7(1): 1–8. doi: 10.1038/s41598-017-15794-8.

1.8. Figures

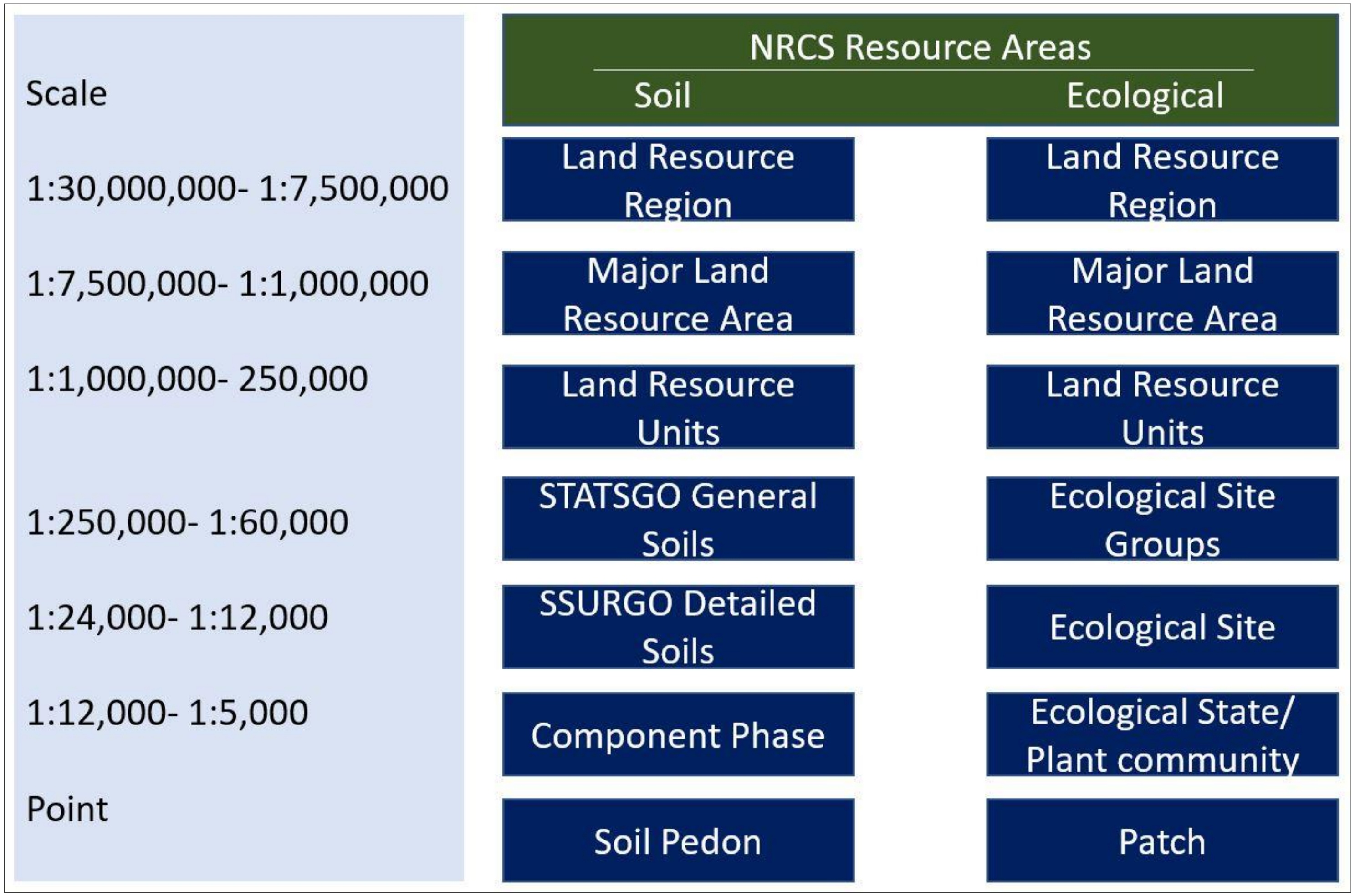

Figure 2.1 Comparison of Soil and Ecological land resource hierarchies used by USDA-NRCS (adapted from Salley et al., 2016 b).

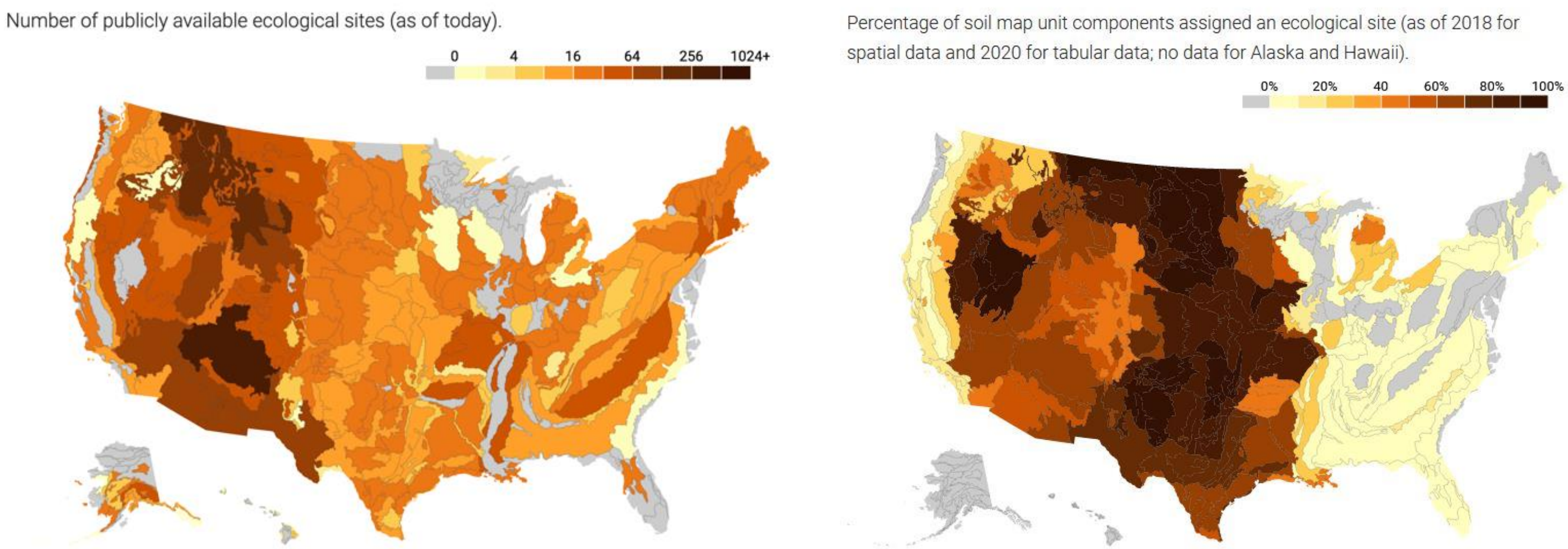

Figure 2.2 (a) The number of publicly available ES in the United States (b) Percentage of soil map units related to ES.

(Fig. 1.2(a) and 1.2(b) were taken from "Ecological site descriptions," https://edit.jornada.nmsu.edu/catalogs/esd, Accessed: 2020–10–16)

Figure 2.3 Spatial extent of the Southern Coastal Plain physiographic region (MLRA 133A).

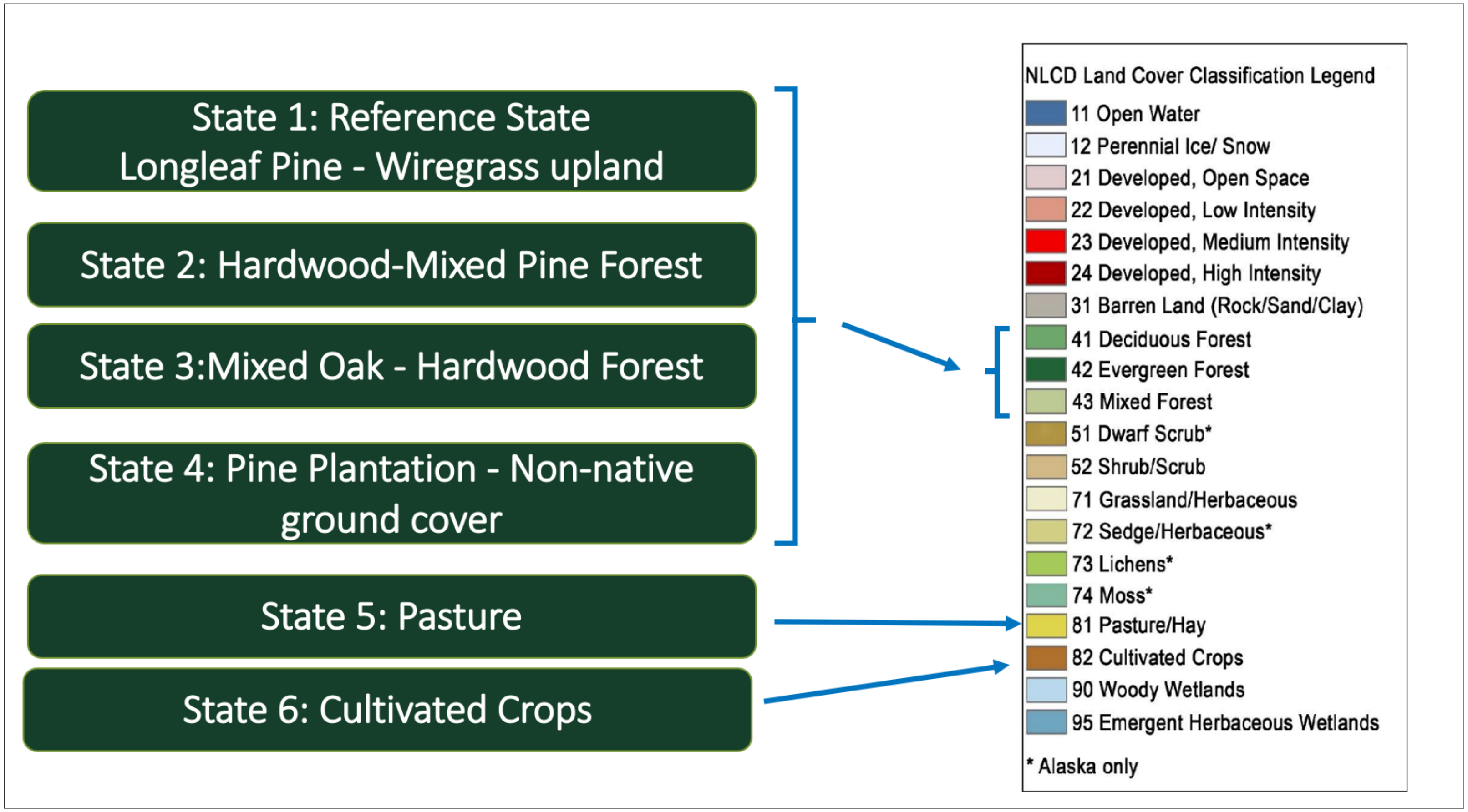

Figure 2.4 Comparison of States in the State and Transition Model for the “Atlantic Coastal Plain Upland Longleaf Pine Woodland Dry” Ecological Site and the legend of National land cover database (NLCD) (States are adapted from Mount et al. (2020)).

CHAPTER 2

SOIL TAXONOMIC GROUPINGS AND LANDSCAPE COVARIATES EXPLAIN CARBON STOCKS FOR SOILS IN THE SOUTHERN COASTAL PLAIN, USA[1]

[1]Sharma, R., Levi, M.R., King, E.G., Thompson A. To be submitted to the Soil Science Society of America Journal.

2.1. Abstract

Soil organic carbon (SOC) is very important for soil health and the global carbon budget. SOC is affected by climate, vegetation, topography, soil, and land-use factors. These factors can be used to predict SOC at multiple spatial scales. The objective of this chapter was to quantify the potential of soil taxonomic groupings and environmental covariates for explaining SOC stocks in the upper 20 cm of soil in the Southern Coastal Plain physiographic region (MLRA 133A). Point measured SOC data were compiled from the Rapid Carbon Assessment (RaCA), National Cooperative Soil Survey Database and a small collection of other projects to calculate the SOC stocks for the 0 – 20 cm mineral soil (SOC20). SOC20 was intersected with environmental covariates derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate data, National Elevation Dataset (NED), and the Soil Survey Geographic Database (SSURGO). Mean Annual Precipitation (MAP), soil taxonomy, and landcover classes were found to be significantly correlated to SOC20 for the region based on the point data collected. The largest mean SOC20 stock in MLRA 133A was found in Spodosols (492 Mg ha^{-1}), followed by Histosols (100.6 Mg ha^{-1}). The average SOC20 stock for the Ultisols that are dominant in the region was 49.2 Mg ha^{-1}. These results suggest that soil taxonomic groups are an important variable for estimating SOC at regional spatial scales. The combination of climate, soil taxonomy, and landcover covariables can be used to explain the spatial and temporal variability of SOC20 in the Southern Coastal Plain.

2.2. Introduction

Soil organic carbon (SOC) is an essential soil property dictating plant growth and soil health. Increasing concentrations of CO_2 in the atmosphere have led to a growing interest in mapping and measuring carbon stocks in soils because of their potential to sequester carbon (Minasny et al., 2013a). SOC makes up to 80% of total carbon stocks in terrestrial ecosystems (Lal, 2008; Ontl & Schulte, 2012). The estimated amount of carbon in soils globally is 1500 Pg and 214 ±67 Pg is estimated to have been lost globally because of deforestation since the industrial revolution (Scharlemann et al., 2014; Zomer et al., 2017). There is a dire need to counter this loss of carbon and encouraging accumulation of carbon in soils is a key strategy (Lal, 2008). To reduce global carbon emissions, countries have signed global climate treaties like the Kyoto Protocol and Paris climate agreement in which they commit to carbon trading also called the cap-and-trade program (Amano et al., 2006; Galik et al., 2013). Under the cap-and-trade program, countries are allocated carbon emission caps based on population and for each country carbon emissions should be under the carbon cap allocated otherwise they have to pay the other countries with lower carbon emissions (Spash, 2010; Glanemann et al., 2020). Perhaps the greatest challenge underpinning carbon trading programs is the accurate representation of carbon stocks in the soils across large spatial extents. Measurement of SOC is time and labor-intensive, therefore accurate scaling of available data is necessary to predict the variability of SOC at regional scales. Spatial associations of covariables that control SOC have great potential to improve estimates of SOC (Minasny et al., 2013). In this section, point data available across the Southern Coastal Plain of the United States are used to study the relation between SOC and climatic, topographic, and soil taxonomic covariables.

The southeastern region of the United States has a history of soil erosion because of weak soil structure, low organic matter, and highly erodible surface sand (Liu et al., 2004). Major landcover changes in the past three centuries (Trail et al., 2013) have resulted in the loss of considerable stocks of carbon due to the soil erosion and conversion of forests to croplands, but this region still holds significant forest reserves and is sometimes referred to as the "Wood Basket of the United States" (Fox et al., 2007; Trail et al., 2013). The Southern Coastal Plain acted as a carbon sink from 1973 – 2000 because of afforestation of previously cultivated and abandoned land, however the overall capacity of the region to act as a sink reduced by 63% from 1970 – 1990 due to aging forests in north and forest cutting practices in the south (Liu et al., 2004). Maintaining the carbon sink could help to sequester large amounts of atmospheric CO_2, thus reducing net carbon emissions across the region (Liu et al., 2004; Worsham et al., 2010).

Carbon stocks in soils are affected by many environmental factors like climate, topography, parent material, and vegetation. SOC is highly responsive to changes in these factors and is considered a dynamic soil property (DSP). The major part of the fluctuation of SOC is attributed to land cover changes. But the amplitude of these management-driven changes in SOC is controlled by inherent soil properties suck as topography, climate, soil texture, and parent material. Some combination of inherent soil properties and land cover changes affect the distribution of SOC stock spatially and temporarily. Elucidating the contributions of each driver requires the integration of both spatial and non-spatial information to effectively map SOC for large areas over time.

The use of modern digital soil mapping started in the 1990s to quantify SOC stock in soils, but predicting SOC based on the models is not recent and has been done for several decades. Jenny et al. (1968) was one of the first to develop a climate covariable-based SOC predicting model, based on his famous "clorpt" approach (Jenny, 1941). McBratney et al. (2003) updated Jenny's equation with a new conceptual model known as "scorpan" where they predicted soil properties spatially using covariables based on soils (s), climate (c), organisms (o), topography (r), parent material (p), age and time (a), and spatial position (n). Most studies used these broad factors to study the spatial distribution of SOC over a region until the late 1990s. Then with advances in remote sensing, visible and infrared reflectance was found to be highly related to SOC. The Normalized Difference Vegetation Index (NDVI) is a common spectral index of vegetation as it measures greenness across a landscape (Taghizadeh-Mehrjardi et al., 2016; Schillaci et al., 2017). It's now well established that spectral, environmental, and climatic covariables can be used to predict SOC stocks over a region and Minasny et al. (2013) provide a review of various digital soil mapping-based studies globally.

Another important dataset for predicting SOC is soil survey information. Rasmussen (2006) found that soil taxonomic information was helpful to study the SOC variability across Arizona, United States. Kern (1994) compared the ecology approach suggested by Olson et al. (1985) and the soil taxonomic approach with major land resource areas. He found the taxonomic approach gave reliable spatial patterns for the SOC in the contiguous United States, however he also pointed out that grouping data using soil Great Groups gave more information than groupings based on Order and Suborder. In the southeastern United States, the use of soil taxonomy for mapping SOC has been limited, though plot-level studies often compare and contrast SOC by soil type (Causarano et al., 2008; Levi et al., 2010). Ross et al. (2020) developed a SOC prediction model for the southeastern United States by using hydrological soil groups and a suite of 73 predicting covariables. Using a large number of covariables adds to the complexity of the model and model captures the spatial variability and lacks information about the changes that might occur in SOC stock with time.

The main challenge faced in mapping SOC is its spatial variability at multiple scales. Robertson et al. (1997) found 20.4% variance of SOC over a visually uniform 48 ha Michigan farm field. Conant et al. (2004) compared SOC variability at national, state, and county scale using the NCSS database and found that variability increased with larger spatial extent. The highest variance was found at the national level (63%), then for the state of Nebraska (54%), and least for Dundy County in western Nebraska (39%). The reason behind the high spatial variability of SOC is that factors affecting SOC such as temperature, precipitation, and soil physical characteristics are also highly spatially variable (Conant et al., 2004). Current and previous land management can also have lasting effects on SOC stock and SOC accumulation (Liu et al., 2014; Xiong et al., 2014). Studying soil properties within taxonomic classes can help to reduce intra-unit variability and thus allow for more effective use of a smaller number of point measurements to study soil variability over a region. Another challenge that researchers often face is a lack of soil bulk density measurements to convert SOC concentrations to SOC stocks.

There have been studies like Sevastas et al. (2018) and Ramcharan et al. (2017) which developed models to estimate bulk density using textural and geomorphological soil properties. The objective of this study was to quantify the potential of soil taxonomic groupings and environmental covariates for explaining soil organic carbon (SOC) stocks in the Southern Coastal Plain (MLRA 133A). We hypothesize that SOC will be different for various levels of soil taxonomic groups and also expect to find similar trends of SOC between climate and topographic covariables with taxonomic indicators.

2.3. Materials and Methods

2.3.1. Study site

Our study site was the Southern Coastal Plain of the United States also known as Major Land Resource Area 133A (MLRA 133A) (Fig. 2.1). (Recently MLRA 133A has been divided into two new MLRAs, MLRA 133 A, and 133 C in 2020. In this study, MLRA 133A refers to the extent before the division). It is the largest of the 278 MLRAs in the United States and spans 275,930 km^2 across 9 states (Alabama (26%), Mississippi (24%), Georgia (21%) (USDA and NRCS, 2006)).

The overall climate of this region is hot and humid. Annual precipitation in this region ranges from 1000 – 2000 mm (~ 40 – 80 inches) (PRISM Climate Group, Oregon State U, Retrieved July 7, 2020). Areas in Louisiana and southern parts of Mississippi are the wettest. The areas in Georgia, South Carolina, and North Carolina are relatively drier. The southern part of MLRA 133A is hotter than the northern part. The mean annual temperature fluctuates from 12°

Celsius (~54° Fahrenheit) to 20° Celsius (~68° Fahrenheit). Soils in this MLRA are dominated by Ultisols (highly weathered soils found in warm, humid climates), Entisols (newly formed soil with no distinct horizon development), and Inceptisols (relatively more developed than Entisols with limited horizon development) (USDA, 2014). The soils generally have siliceous or kaolinitic mineralogy, a thermic soil temperature regime (mean annual soil temperature 15 – 22 °C), and commonly have udic (humid and precipitation is more than evapotranspiration potential) and aquic (soil is saturated enough for anaerobic conditions) soil moisture regimes. The deposits in this region are from the Cretaceous period (65 – 145 million years ago) in contrast to other regions around it like the Piedmont, which were formed in the Paleozoic era (250 – 540 million years ago) (Walker and Geissman, 2009). The native vegetation found in upland landscapes of this region is oak-hickory, pine, and Southern mixed forest (US EPA, 2001). There are eight EPA ecoregions within Southern Coastal Plain: Sandhills, Southern Hilly Gulf Coastal Plain, Dougherty Plain, Tifton Upland, Coastal Plain Red Uplands, Atlantic Southern Loam Plain, Tallahassee Hills, and Southeastern Floodplain and Low Terraces (US EPA, 2001). Timber, forage, and cash-grain crops including soybeans, cotton, corn, and wheat are major products of this MLRA (USDA and NRCS, 2006). The major land cover in this MLRA is forest and wetlands with 42.5% and 20% respectively in total area coverage in 2016 according to NLCD (Data | Multi-Resolution Land Characteristics (MRLC) Consortium, Retrieved July 27, 2020).

2.3.2. SOC point data sources

Point data sources for this project are from multiple datasets and projects including the National Cooperative Soil Survey (NCSS) Soil characterization Database, the NRCS Rapid Carbon Assessment (RaCA), and individual research projects conducted in the study area (Table 2.1). The spatial distribution of the point data used in this project is shown in Fig. 2.1.

The NCSS Database is maintained by National Soil Survey Center and Kellogg Soil Survey Laboratory (KSSL) contains analytical data of soil pedons for nearly 20,000 sites in the United States and 1,100 sites in other countries. Nearly three-quarters of the data is collected over last the 20 years and overall data goes back to 40 years (NRCS NSSC KSSL, 2014). There were 174 point data measurements of SOC from the NCSS database used for analysis in MLRA 133A. The Rapid Carbon Assessment (RaCA) was started by the United States Department of Agriculture (USDA)- National Resource Conservation Services (NRCS) Soil Science Division in 2010 (Rapid Carbon Assessment (RaCA) | Ag Data Commons, Retrieved July 5, 2020). The database serves as statistically sound quantitative data for the amount and distribution of carbon stock in the United States under different land covers. The database included 144,833 samples collected from the top 1 meter of 32,084 soil pedons at 6017 randomly selected locations from all over the United States. All the measurements were taken between January 1, 2010 – December 31, 2013. Instead of exact point locations, generalized locations are included for every location because of privacy issues. There were 1155 point data measurements available in the RaCA dataset for our study area (Fig. 2.1). The data uses modeled SOC and bulk density to predict SOC stocks for various depths. In the study done by Levi (2007), 9 point measurements in Thomas county, Georgia were available. The landcover types that these points represent were Longleaf pine, planted pine, and row crops, and were classified as Kandiudults (soils with clay-rich kandic horizon with udic soil moisture regimes) (USDA, 2014). The data were collected between 2005 – 2007 to determine land use impacts on soils (Levi et al., 2010; Levi, 2007). Cochran (2010) evaluated soil data from 13 point locations in southern Alabama consisting of different land managements for Plinthic Kandiudults (kandiudults soils with 5% or more plinthite in one or more horizons) (Cochran, 2010; USDA, 2014). An additional 60 points were used from a research study done by Ricker and Locakaby (2015). This study was done in Congaree National Park in the upper Coastal Plain physiographic region of South Carolina, approximately 30 km from the city of Columbia (Ricker and Lockaby, 2015). Another dataset used was from southern Georgia and northern Florida with 222 sampled point locations between 2004 to 2019 as part of research from the Tall Timbers Research Center (hereafter Tall Timbers dataset) (K. Robertson pers. communication). Of the 222 points, only 128 had both SOC concentration and bulk density for the 0 – 20 cm depth.

A total of 1441 point locations collected between 2000 – 2018 were available to analyze the variability of SOC stocks within the study area.

2.3.3. SOC stock calculations

SOC stock was calculated for the 0 – 20 cm depth of the mineral soil for each point measurement. The variation in projects resulted in varying degrees of data completeness. SOC20 stocks for Levi, Cochran, and Ricker datasets were calculated by multiplying reported percent carbon for horizons and bulk density for complimentary depths. RaCA data had predicted SOC percent and predicted bulk densities, which were used to calculate SOC20 stocks. For the Tall Timbers dataset, only 128 points recorded SOC and bulk density and the rest were eliminated because the bulk density predicting function required soil textural information to predict bulk density which was also missing. For NCSS points, 174 had SOC concentration but did not have bulk density. For that, we used the bulk density prediction function developed by Ramcharan et al. (2017) and converted SOC percent readings to SOC20 stock. Due to the lack of SOC percent readings or other predictors required to predict bulk density, the final number of points used for this analysis was 1441.

The point data represent various depths of measurement because some were sampled by genetic soil horizon and others were sampled for specified depths. For getting SOC stock for the upper 20 cm of mineral soil, the "slab" function in the 'aqp' package of R was used (Beaudette et al., 2013a) to calculate the SOC stock for each 1 cm slice in the sampled profile and then summed for one value of SOC stock in the upper 20 cm (SOC20).

2.3.4. Spatial data sources

Soil Survey Geographic Database (SSURGO) for each state in the study area was used to get soil taxonomic data including soil Order, Suborder, and Great Group (Soil Survey Staff, Natural Resources Conservation Service accessed date 1/31/2020; *USDA:NRCS:Geospatial Data Gateway:Order Data*). Along with soil taxonomy, SSURGO was used to extract soil pH, erosional phase, drainage class, family particle size classes, and hydrologic soil groups (HSG) for map units. “Component” and “chorizon” tables available in the gSSURGO (raster version of SSURGO-grid SSURGO) were used to extract soil taxonomy and soil pH data for point SOC measurements.

SSURGO data uses erosion classes to describe the extent of erosion for soil map units. The erosional classes are “none”- an area of soil deposition, “Class 1”- with 1 – 25% of topsoil erosion, “Class 2”- with 25 – 75% of topsoil erosion, “Class 3”- with 75 – 99% of topsoil erosion, and “Class 4”- map units with all of the topsoil eroded (SSM - Ch. 2. Landscapes, Geomorphology, and Site Description, Accessed: 2021-06-24). Drainage classes represent the frequency and duration of wet periods and SSURGO classifies drainage conditions into seven classes (“Excessively Drained”, “Somewhat Excessively Drained”, “Well Drained”, “Moderately Well Drained”, “Somewhat Poorly Drained”, “Poorly Drained”, “Very Poorly Drained”) (Soil Drainage Class, Retrieved June 24, 2021). Points that did not have any erosional class record in the SSURGO data were assigned to a category labeled “unknown” for comparison and analysis.

There are four main HSGs and three additional categories for hydrologic groups that are naturally in group D but have a different rating if they are drained (e.g., A/D) (Part 630 Hydrology National Engineering Handbook et al., 2009). HSG-A has low runoff potential (more than 90% sand and less than 10% clay), HSG-B has moderately low runoff potential (50 – 90% sand and 10 – 20% clay), HSG-C has moderately high runoff potential (less than 50% sand and 20 – 40% clay), HSG-D has high runoff potential (less than 50% sand and more than 40% clay). Additionally, HSG-A/D has high runoff potential unless drained (more than 90% sand and less than 10% clay), HSG-B/D has high runoff potential unless drained (50% – 90% sand and 10-

20% clay), HSG-C/D has high runoff potential unless drained (less than 50% sand and 20 – 40% clay), HSG-D/D has high runoff potential unless drained (less than 50% sand and more than 40% clay).

The most common climatic variables used in SOC predictive models are mean annual temperature (MAT) and mean annual precipitation (MAP) (Yang et al., 2016; Han et al., 2020). Mean annual temperature (MAT) and mean annual precipitation (MAP) for the 30-year period between 1981-2010 were obtained from the Parameter-elevation Regressions on Independent Slope Model (PRISM) dataset with 4km spatial resolution (PRISM Climate Group 2021).

Elevation data was obtained from the USGS National Elevation Dataset (NED) as a 30m raster dataset (*The National Map*, Retrieved June 26, 2021). Slope percentage and aspect were derived from elevation using ArcGIS version 10.7 (ESRI, 2019). The aspect was further converted in a linear aspect also called "Southwestness" where the southwest direction (225°) had a value of 1 and northeast (45°) had a value of -1 using the following equation:

$$\text{Southwestness} = - (\cos (\text{Aspect} (\text{degrees} - 45°) *\pi/180)$$

Landcover data was obtained from Multi-Resolution Land Characteristics (MRLC) Consortium which is a Landsat-based 30 m database released at 5-year intervals from 2001 to 2016. NLCD 1992 was also used which is also 30 m Landsat-based data provided by MRLC with some differences in legend from NLCD after 2001. To match the NLCD 1992 classification system to NLCD 2001 and so on, Fry, (2008) was referenced which gives a detailed comparison of both classification systems. Landcover was extracted for two years for each point SOC data, first when the point was sampled and second land cover 10 years before the point was sampled. This created a pool of points with information about land cover when the point was taken and 10-year earlier landcover history, which was further used to study its effect on SOC stock changes.

2.3.5. Covariate Data Extraction, Aggregation, and Comparison

SOC20 point measurements were imported into ArcMap 10.7 and then data from MAP, MAT, Elevation, Slope, and aspect as added to point data by using the “Extract multiple values to point” tool in ArcMap. SSURGO data was extracted by adding “mapunit” key to point data from gSSURGO using the “extract raster values to point” tool and then joining attribute table of point data to “component” table using “mapunit key”. Soil pH was extracted by joining the component and “chorizon” table by the use of the “Component key” available in the “component” table. Then the attribute tables of point files containing all the covariable were exported as Excel files for further statistical analysis in R. In R, the “aggregate” command was used to get SOC20 mean value for different classes of covariables.

The contribution of explanatory variables to SOC20 dataset was assessed visually and statistically. The SOC20 dataset was first evaluated for normality using a Shapiro Wilk test and qqplots. Results of both tests indicated a non-normal dataset so values were log transformed for comparison. Figures of untransformed data were made using the ggplot2 package in R

(Wickham, 2016). Log-transformed data were compared by levels of each factor variable using ANOVA and Tukey-HSD tests in R.

Both simple linear regression and multivariate linear regression models were fitted using the stats package in R to predict SOC20 using climate, topography, landcover, and soil type based covariables to check the predicting power of different covariables (R Core Team, 2020).

2.4. Results and Discussion

2.4.1. SOC20 and Land Cover

We found differences in the mean SOC20 stock for the landcover classes (Table 2.2). At the time of sampling, pasture/hay had the greatest mean SOC20 stock followed by urban – open space. Mixed forest sites had the least amount of carbon stored. Other forested, grassland and developed classes had intermediate mean SOC20 stocks. Interestingly, some classes represented by the NLCD indicated that soil sample locations were located in unlikely places. For example, some sites were classified as the open water class but it is not likely that subaqueous soils were included in these datasets. These sites may include wetlands or that the geographic coordinates for the sites were not correct. Another possibility could be that the land cover classification algorithm did not effectively represent open water in these areas. Another example of unusual results is seen with the barren land/abandoned land class. The mean SOC20 stock of 45.2 Mg ha^{-1} for sites in this class is nearly the same as mean values for deciduous forest and larger than the mean stock in mixed forest. This would imply that these sites must have been abandoned land and not barren land as barren land would imply degraded soil that would likely not have high organic matter present. Furthermore, in the region, there are much fewer chances of land being classified as barren land compared to abandoned land because most of the barren land is likely in and around mine areas such as the kaolin mines found across the upper Coastal Plain in Georgia (Ekwue, 1990). The classification of these areas of barren/abandoned land could also be forest-cutting or uncultivated lands which were classified by the land cover as barren/abandoned land as the regions go through practices of forest-cutting (Liu et al., 2004). These sorts of anthropogenic changes on the landscape complicate the ability of the remotely-sensed land cover to correctly assign classes, but the NLCD still has an almost 80% prediction accuracy. Wickham et al. (2013) found 79% and 78% prediction accuracy for the years 2001 and 2006 respectively.

The impact of landcover changes on carbon stocks is well established. Nave et al. (2009) estimated an almost consistent 30 ± 6% reduction in carbon storage of forest floor after harvest. Ross, (2017) also emphasized on time after harvest was important for SOC20 fluctuations in the southeast region. Current and previous landcover can affect the temporal distribution of SOC20, especially in the regions prone to intense management changes like the southeastern United States.

2.4.2. SOC Relation with Climatic Covariates

We did not observe any meaningful relationships between SOC20 stock mean annual temperature (MAT, Fig. 2.2). The relationship between SOC20 and MAT was not significant with a negligible R^2 value. The Southern Coastal Plain region is overall hot and humid. The average temperature ranges from 12° C to 20° C. The overall temperature is mild for the region with hot, humid summers and mild winters. Temperature controls processes like microbial activity which affects SOC. Higher temperature accelerates the decomposition of SOC, reducing the retention of SOC in soils.

We found small but significant correlation values between SOC20 and precipitation (R^2 value = 0.021and p-value = < 0.01) and plot between SOC20 and MAP. Precipitation dictates the moisture level in soils which also affects the decomposition of organic matter. Higher precipitation creates favorable conditions for more biomass production and saturated conditions promote accumulation of SOC. The average annual precipitation ranges from 1000 – 2000 mm with higher amounts more common in the southern parts of the study area. Because of the already high precipitation, there was just a slight increase in the SOC20 stock with increasing precipitation (Fig. 2.3).

Our results for MAT and MAP are similar to other studies done in the region that have indicated temperature and precipitation have a limited effect on SOC for this region (Ross et al., 2020). For example, Del Grosso et al. (2008) reported weak relationships between global MAP and net primary production for forested areas ($R^2 = 0.20$) and non-forested areas ($R^2 = 0.10$). Doetterl et al. (2015) found that climate predictors explained some variance in SOC for a 4,000 km long transect across Chile and Antarctica, but not as much as geochemical properties. Ross et al. (2020) also found MAT and MAP useful predictors for SOC20 predictions and reported that MAP was a relatively better predictor for SOC20 in the southeast United States, similar to our results.

2.4.3. SOC20 relation with Topography

Topographic variables are commonly used for SOC predictive models. Usually, SOC is inversely related to elevation because of less deposition of SOC in uplands (Bhandari and Zhang, 2019) and we found similar results for our dataset. However, our study indicated weak correlations between SOC20 and topographic covariables ($R^2 = 0.008$ and p-value = 0.0003) likely because the study area is characterized by low relief. The elevation for SOC20 point measurements ranges from 0 to 243 m, 75% of data is in the range of 0 – 106 m elevation, with a mean of 76.2 m and median at 68.7 m (Fig. 2.4). SOC20 stock decreased with increasing elevation, with an average decrease of 0.15 Mg ha^{-1} of SOC20 stock with a 1 m increase in elevation.

Slope and aspect are commonly used as covariables for SOC mapping along with elevation (Adhikari et al., 2014; Aksoy et al., 2016). We did not find a significant correlation between SOC20 stock and slope with an R-value of 0.001 and p-value = 0.9 (Fig. 2.5). Similarly, the correlation between linear aspect (southwestness) and SOC20 was negligible indicating that these topographic attributes were not useful for SOC20 predictions in this flat landscape (Fig. 2.6). The slope for the point data used ranged from 0 to 30.5% but 75% of the values are in the range of 0 to 5.1% slope. The mean and median slope for our data are 3.7% and 2.5% respectively.

Ross et al. (2020) also found topographic factors to be of lower importance for SOC20 in the Southeast region. However, international studies like Adhikari et al. (2014); Aksoy et al. (2016); Taghizadeh-Mehrjardi et al. (2016) found DEM-based variables such as slope, aspect, elevation, compound topographic index (CTI), and saga wetness index to be significant predictors for SOC. This could be because there is not much variability in elevation in the Southern Coastal Plain and because of that other factors have larger control on SOC20 distribution.

2.4.4. SOC20 relation with Soil factors

Soil Taxonomy

We used SSURGO data to get soil taxonomic data and other soil properties like soil pH. We found a significantly larger mean SOC20 stock in Spodosols than other soil Orders (mean SOC20 492 Mg ha^{-1}) (Figs 2.7 and 2.8). The largest mean SOC20 stocks at the Suborder level were found in Aquods and Saprists, respectively (Fig 2.9). Likewise, Ross et al. (2020) found higher amounts of SOC20 in Aquods along with other Suborders including Humods, Udepts, and Aquults. Unlike Ross et al., data used for comparison in this study didn't have representative values for Humods, Udepts, Aquults. At the Great Group level, Alaquods had the largest SOC20 stock (Fig. 2.10), which supports the idea that Spodosols generally have higher SOC stock as they have more than 85% of spodic material (illuvial accumulated organic matter and aluminum, with or without iron) accumulation in Ap horizon (USDA, 2014). The second highest mean SOC20 stock was found in Histosols with a mean SOC20 of 100.6 Mg ha^{-1}. Soils in the Saprists Suborder were reported in the data points used in this study, however Histosols were not reported by Ross et al. (2020) in the region. The Southern Coastal Plain is dominated by Ultisols and the mean SOC20 in Ultisols was 49.2 Mg ha^{-1}. Kern, (1994b) reported a mean of 70 Mg ha^{-1} for

Ultisols that included all the Ultisols in the United States. Vertisols had the smallest mean SOC20 stock with 18 Mg ha^{-1}. The effect of soil taxonomy was apparent on the spatial variability of SOC in the region.

Hydrological soil properties

Erosion plays a big role in SOC distribution. Severely eroded places can lose a significant amount of SOC whereas SOC increases with deposition (Olson et al., 2016). Fig. 2.11 shows the variability of SOC20 stock in different erosional classes. Erosional classes no-deposition, 1, and 2 had similar mean and median values of SOC20 stock in the region. For class 3, however the median SOC20 stock was lower than all other classes despite some outliers that increased the mean SOC20 stock. However, none of the pairwise differences were significant based on the Tukey HSD test (Fig. 2.12) for erosional class versus the log of SOC20.

Drainage classes represent seasonal variations in seasonal high-water tables and the general moisture content of soils. Well-drained soils usually have less SOC than poorly drained soils because wetter soils tend to accumulate organic matter. This is largely controlled by the microbial communities present where oxic environments support more efficient aerobic C decomposition and in anoxic environments anaerobic metabolism is a less-efficient for many forms of organic matter (although not all) (LaRowe and Van Cappellen, 2011). ‘Very poorly drained’ soils had the largest mean SOC20 stock and together with ‘poorly drained’ soils had significantly larger mean SOC20 stocks than several other classes (Fig. 2.13, Fig 2.14). This pattern was hypothesized given the controls of wet soil conditions on organic matter decomposition. Interestingly, ‘excessively drained’ and ‘somewhat excessively drained’ soils also had significantly larger mean SOC20 stocks than classes with intermediate drainage classes. This could be caused by other factors like landcover differences.

Some hydrologic soil groups (HSG) SOC20 stocks were significantly different from others (Figs 2.15 and 2.16). We anticipated that HSGs would explain differences in SOC because they account for differences in both soil texture and drainage, both of which exert control on SOC dynamics. The mean SOC20 stock was significantly larger in group A/D than all other groups. Group A had a significantly larger mean SOC20 stock than groups C and D. This pattern of HSG supports the findings of the drainage class where very wet soils have a larger mean SOC stock and also the more sandy soils with less runoff and lower water tables have significantly larger mean SOC stocks. HSGs are one of the lesser-used covariables to explain SOC, however Ross et al. (2020) found hydrological classes to be an as important explainer of SOC20 in the southeastern United States.

Soil particle sizes and soil pH

Soil texture plays an important role in the variability of SOC. The presence of more clay is generally coupled with higher SOC because clay provides physical protection of SOC from decomposition (Singh et al., 2018). However, particle size for our data with sandy family particle size classes had the largest SOC20 stock of 491.8 Mg ha^{-1} (Fig. 2.17). Fine, fine-loamy and fine-silty soils had the smallest mean SOC20 stock. One possible explanation for the pattern of soils with sandy textures having the largest SOC20 stocks is that we evaluated family particle size classes that are not focused on the surface soils, rather they are in the particle size control section (purposefully deeper in the soil profile to prevent soil taxa from changing over human time scales). Therefore, the particle size classes represented in our groupings of soils may not reflect a one-to-one comparison of soil texture to SOC in the 0 – 20 cm depth. To test this hypothesis, we plotted SOC concentration in the top layer (A-horizon) against clay and sand proportions for 343 of the NCSS data points with complete data and found the expected relationships (Figs. 2.18 and Fig. 2.19). A significant correlation was found in clay proportion and SOC percentage with R^2 of 0.11 with a p-value of <0.001. There was an average increase of 0.08% carbon with a 1% increase in clay proportion. A significant negative correlation was found for sand proportion and SOC percentage with R^2 of 0.14 with a p-value of <0.001. On average with an increase of 1% sand, SOC percentage decreased by 0.06%. Ross et al. (2017) also found that soil texture explained the spatial distribution of SOC, however didn't have a substantial effect on temporal changes.

We found a negative correlation between soil pH and SOC20 stock (Fig. 2.20). The correlation was small but significant with a correlation coefficient of -0.13 and a p-value of <0.001. The is an average decrease of 20.6 Mg ha^{-1} for a unit increase in soil pH. This is similar to findings of (Rasmussen et al., 2018) who attributed this negative relationship between soil pH and SOC to the presence of short range order minerals and organo-metal complexation most common at low pH ranges (e.g., <5.5). The highest value of SOC20 stock was around a soil pH of 5. This relationship may also help explain why the sandy family particle size classes had the largest mean SOC20 stock because Spodosols tend to have coarser textures throughout the upper portion of the soil profile promoting more leaching (i.e., lower pH).

2.4.5 Multi-variate linear regression model

Linear regression model based on climate (MAT and MAP), topography (elevation, slope, and linear aspect), land cover classes, soil taxonomy, and soil pH explained 35% of the variation. Covariables like MAP, elevation, linear aspect which were had week individual correlation with SOC20 were significantly improving the predictability of linear model (p-value <0.01). This suggests that these covariables have a greater cumulative effect on SOC20. Other covariables like erosion classes, drainage classes, and hydrological soil groups also had significant importance to predict SOC20 for linear model (p-value <0.01). Similarly soil type and soil pH were also important predictors of SOC20.

2.5. Conclusions

It is well established that the "cloprt" set of soil forming factors control SOC variation in space and time. We analyzed covariables derived from climate, topography, soil taxonomy, and landcover to explore their influence on SOC20 in the Southern Coastal Plain, we found that soil taxonomy and landcover are major drivers for SOC20 in this region. Soil taxonomy can be highly useful to account for the spatial variability of SOC over the region which in turn increases the predictability and understanding of spatial SOC fluctuation. Soil properties derived from soil surveys like erosion classes and hydrologic groups are less commonly used to explain the variability of SOC, but we found they can have a significant effect on spatial SOC20 distribution. The mean climate influence was minimal, but MAP was found to be better related to SOC20 than MAT for SOC20. Topographic-based covariables such as elevation, slope, and aspect were found to have negligible control over SOC20 in the region likely because of the low relief across the area. The temporal variability of SOC20 was influenced by land cover and landcover history. Soil survey provides a valuable collection of spatial and non-spatial information that can overcome shortcomings of coarse-scaled environmental covariables for predicting dynamic soil properties such as SOC. A combination of climate, topography, soil taxonomy, and land cover-based covariables can be used to explain the spatial and temporal variability of SOC in the Southern Coastal Plain which can contribute to improved interpretations of SOC dynamics and spatial predictions.

2.6. References

Adhikari, K., A.E. Hartemink, B. Minasny, R. Bou Kheir, M.B. Greve, et al. 2014. Digital mapping of soil organic carbon contents and stocks in Denmark. PLoS One. doi: 10.1371/journal.pone.0105519.

Aksoy, E., Y. Yigini, and L. Montanarella. 2016. Combining soil databases for topsoil organic carbon mapping in Europe. PLoS One. doi: 10.1371/journal.pone.0152098.

Amano, M., R.A. Sedjo, and Resources for the future. 2006. Forest Sequestration – Performance in Selected Countries in the Kyoto Period and the Potential Role of Sequestration in Post-Kyoto Agreements. (May): 65.

Andrew J. Paolucci and Mark H. Stolt. 2018. Assessing Dynamic Soil Properties in Southern

New England Forests within an Ecological Site Framework. https://acsess.onlinelibrary.wiley.com/doi/epdf/10.2136/sssaj2018.01.0047 (accessed 20 April 2021).

Austin, M.E. 1965. Land resource regions and major land resource areas of the United States (exclusive of Alaska and Hawaii) /. Washington, D.C. :

Batjes, N.H. 2014. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. doi: 10.1111/ejss.12114_2.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013a. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013b. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Bestelmeyer, B.T., A. Ash, J.R. Brown, B. Densambuu, M. Fernández-Giménez, et al. 2017. State and Transition Models: Theory, Applications, and Challenges

Bestelmeyer, B.T., A.J. Tugel, G.L. Peacock, D.G. Robinett, P.L. Shaver, et al. 2009. State-and-transition models for heterogeneous landscapes: A strategy for development and application. Rangel. Ecol. Manag. 62(1): 1–15. doi: 10.2111/08-146.

Bhandari, J., and Y. Zhang. 2019. Effect of altitude and soil properties on biomass and plant richness in the grasslands of Tibet, China, and Manang District, Nepal. Ecosphere 10(11): e02915. doi: 10.1002/ecs2.2915.

Bini, D., C. Alcantara, D. Santos, K. Banhos Do Carmo, N. Kishino, et al. 2013. Effects of land use on soil organic carbon and microbial processes associated with soil health in southern

Brazil. doi: 10.1016/j.ejsobi.2012.12.010.

Breiman, L. 2001. Random forests. Mach. Learn. 45(1): 5–32. doi: 10.1023/A:1010933404324.

Caudle, D., J. Dibenedetto, M. Karl, H. Sanchez, and C. Talbot. 2013. Interagency ecological site handbook for rangelands. (January): 109.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008a. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2006.0274.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008b. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. 72(1): 221–230. doi: 10.2136/sssaj2006.0274.

Cochran, J.F. 2010. Management-Dependent Soil Variability and Surface Hydraulic Properties of Southeastern U.S. Coastal Plain Plinthic Kandiudults.

Conant, R.T., J. Six, and K. Paustian. 2004. Land use effects on soil carbon fractions in the southeastern United States. II. Changes in soil carbon fractions along a forest to pasture chronosequence. Biol. Fertil. Soils. doi: 10.1007/s00374-004-0754-2.

Data | Multi-Resolution Land Characteristics (MRLC) Consortium. https://www.mrlc.gov/data?f%5B0%5D=category%3Aland cover (accessed 27 July 2020).

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.

Domke, G.M., C.H. Perry, B.F. Walters, L.E. Nave, C.W. Woodall, et al. 2017. Toward inventory-based estimates of soil organic carbon in forests of the United States.

Ecological site descriptions. https://edit.jornada.nmsu.edu/catalogs/esd (accessed 16 October 2020).

Ekwue, E.I. 1990. Organic-matter effects on soil strength properties. Soil Tillage Res. 16(3): 289–297. doi: 10.1016/0167-1987(90)90102-J.

ESRI. 2019. ArcMap 10.7.

Fox, T.R., E.J. Jokela, and H.L. Allen. 2007. The development of pine plantation silviculture in the Southern United States. J. For. 105(7): 337–347. doi: 10.1093/jof/105.7.337.

Franzmeier, D.P., G.D. Lemme, and R.J. Miles. 1985. Organic Carbon in Soils of North Central United States. Soil Sci. Soc. Am. J. 49(3): 702–708. doi: 10.2136/sssaj1985.03615995004900030035x.

Friedlingstein, P., M.W. Jones, M. O'Sullivan, R.M. Andrew, J. Hauck, et al. 2019. Global carbon budget 2019. Earth Syst. Sci. Data 11(4): 1783–1838. doi: 10.5194/essd-11-1783-2019.

Fry, J.A. et al. 2008. Completion of the National Land Cover Database (NLCD) 1992-2001 Land Cover Change Retrofit Product.

Galik, C.S., B.C. Murray, and D.E. Mercer. 2013. Where is the carbon? carbon sequestration potential from private forestland in the southern United States. J. For. 111(1): 17–25. doi: 10.5849/jof.12-055.

Gao, L., M.A. Bowker, M. Xu, H. Sun, D. Tuo, et al. 2017. Biological soil crusts decrease erodibility by modifying inherent soil properties on the Loess Plateau, China. Soil Biol.

Biochem. 105: 49–58. doi: 10.1016/j.soilbio.2016.11.009.

Gebremedhin, H., G. Gebresamual, N. Abadi, M. Hailemariam, K. Teka, et al. 2018. Conversion of communal grazing land into arable land and its impacts on soil properties and vegetation cover. Arid L. Res. Manag. doi: 10.1080/15324982.2017.1406412.

Glanemann, N., S.N. Willner, and A. Levermann. 2020. Paris Climate Agreement passes the cost-benefit test. Nat. Commun. 11(1): 1–11. doi: 10.1038/s41467-019-13961-1.

Gomes, L.C., R.M. Faria, E. de Souza, G.V. Veloso, C.E.G.R. Schaefer, et al. 2019. Modelling and mapping soil organic carbon stocks in Brazil. Geoderma 340: 337–350. doi: 10.1016/J.GEODERMA.2019.01.007.

Grinand, C., G. Le Maire, G. Vieilledent, H. Razakamanarivo, T. Razafimbelo, et al. 2017. Estimating temporal changes in soil carbon stocks at ecoregional scale in Madagascar using remote-sensing. Int. J. Appl. Earth Obs. Geoinf. doi: 10.1016/j.jag.2016.09.002.

Del Grosso, S., W. Parton, T. Stohlgren, D. Zheng, D. Bachelet, et al. 2008. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology 89(8): 2117–2126. doi: 10.1890/07-0850.1.

Grunwald, S. 2009. Multi-criteria characterization of recent digital soil mapping and modeling approaches. Geoderma 152(3–4): 195–207. doi: 10.1016/j.geoderma.2009.06.003.

Guo, Y., R. Amundson, P. Gong, and Q. Yu. 2006. Quantity and Spatial Variability of Soil Carbon in the Conterminous United States. Soil Sci. Soc. Am. J. 70(2): 590–600. doi: 10.2136/sssaj2005.0162.

H. Jenny, A.E. Salem, J.R.W. 1968. Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil Fertility. Pontif. Acad. https://scholar.google.com/scholar_lookup?title=Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil Fertility. Pontif. Acad&publication_year=1968&author=H. Jenny&author=A.E. Sal (accessed 12 June 2021).

Hall, R.M., N. Penke, M. Kriechbaum, S. Kratschmer, V. Jung, et al. 2020. Vegetation management intensity and landscape diversity alter plant species richness, functional traits and community composition across European vineyards. Agric. Syst. 177: 102706. doi: 10.1016/j.agsy.2019.102706.

Hamzehpour, N., H. Shafizadeh-Moghadam, and R. Valavi. 2019. Exploring the driving forces and digital mapping of soil organic carbon using remote sensing and soil texture. Catena. doi: 10.1016/j.catena.2019.104141.

Han, F.X., M.J. Plodinec, Y. Su, D.L. Monts, and Z. Li. 2007. Terrestrial carbon pools in southeast and south-central United States. Clim. Change. doi: 10.1007/s10584-007-9244-5.

Han, L., Z. Wan, Y. Guo, C. Song, S. Jin, et al. 2020. Estimation of soil organic carbon storage in Palustrine Wetlands, China. Int. J. Environ. Res. Public Health 17(13). doi: 10.3390/ijerph17134646.

Heuvelink, G.B.M., M.E. Angelini, L. Poggio, Z. Bai, N.H. Batjes, et al. 2020. Machine learning in space and time for modelling soil organic carbon change. Eur. J. Soil Sci. doi: 10.1111/ejss.12998.

Homer, C., J. Dewitz, S. Jin, G. Xian, C. Costello, et al. 2020. Conterminous United States land cover change patterns 2001–2016 from the 2016 National Land Cover Database. ISPRS J. Photogramm. Remote Sens. 162: 184–199. doi: 10.1016/j.isprsjprs.2020.02.019.

Homer, C., and J. Fry. 2012. The National Land Cover Database. US Geol. Surv. Fact Sheet.

Hoosbeek, M.R., and R.B. Bryant. 1992. Towards the quantitative modeling of pedogenesis-a review.

Hudson, B.D. 1992. The Soil Survey as Paradigm-based Science.

Lutz J.F. 1935. The Relation Of Soil Erosion To Certain Inherent Soil Proper... : Soil Science. https://journals.lww.com/soilsci/Citation/1935/12000/the_Relation_of_Soil_Erosion_To_Certain_Inherent.2.aspx (accessed 19 April 2021).

Jenny, H. 1941. Factors of Soil Formation: A System of Quantitative Pedology. Science (80-.). 349(6250). http://scholar.google.com/scholar_lookup?title=Global+cancer+statistics&author=A.+Jemal&author=F.+Bray&author=M.+M.+Center&author=J.+Ferlay&author=E.+Ward&author=D.+Forman&publication_year=2011%0Ahttps://anthrosource.onlinelibrary.wiley.com/servlet/linkou.

Jobba´gy, Esteban G; Jackson, R.B. 2000. The Vertical Distribution Of Soil Organic Carbon And Its Relation To Climate And Vegetation - Jobbágy - 2000 - Ecological Applications - Wiley Online Library. https://esajournals.onlinelibrary.wiley.com/doi/full/10.1890/1051-0761%282000%29010%5B0423%3ATVDOSO%5D2.0.CO%3B2 (accessed 28 June 2021).

Johanson, J., and J. Brown. 2012. Ecological site development: Accelerating the effort. Rangelands 34(2): 29–31. doi: 10.2111/RANGELANDS-D-11-00068.1.

Johnston, A.E., P.R. Poulton, and K. Coleman. 2009. Chapter 1 Soil Organic Matter. Its Importance in Sustainable Agriculture and Carbon Dioxide Fluxes. Adv. Agron. 101: 1–57. doi: 10.1016/S0065-2113(08)00801-8.

Kern, J.S. 1994a. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Kern, J.S. 1994b. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Konen, M.E., P.M. Jacobs, C.L. Burras, B.J. Talaga, and J.A. Mason. 2002. Equations for Predicting Soil Organic Carbon Using Loss-on-Ignition for North Central U.S. Soils. Soil Sci. Soc. Am. J. 66(6): 1878–1881. doi: 10.2136/sssaj2002.1878.

Kuhn, M., and K. Johnson. 2013. Applied predictive modeling. Springer New York.

Lal, R. 2008. Carbon sequestration. Philos. Trans. R. Soc. B Biol. Sci. 363(1492): 815–830. doi: 10.1098/rstb.2007.2185.

Lal, R., and J.M. Kimble. 2000. Pedogenic carbonates and the global carbon cycle. Global Climate Change And Pedogenic Carbonates

LaRowe, D.E., and P. Van Cappellen. 2011. Degradation of natural organic matter: A thermodynamic analysis. GeCoA 75(8): 2030–2042. doi: 10.1016/J.GCA.2011.01.020.

Levi, M.R. 2007. Management Dependent Soil Properties of Cultivated Versus Non-Cultivated Southeastern Coastal Plain Ecosystems.

Levi, M.R., J.N. Shaw, C.W. Wood, S.M. Hermann, E.A. Carter, et al. 2010. Land Management Effects on Near-Surface Soil Properties of Southeastern U.S. Coastal Plain Kandiudults.

Soil Sci. Soc. Am. J. 74(1): 258–271. doi: 10.2136/sssaj2009.0015.

Liebig, J. 1840. Die organische Chemie in ihrer Anwendung auf Agricultur und Physiologie. Braunschweig,.

Liu, S., T.R. Loveland, and R.M. Kurtz. 2004. Contemporary carbon dynamics in terrestrial ecosystems in the Southeastern Plains of the United States. Environ. Manage. 33(SUPPL. 1): 442–456. doi: 10.1007/s00267-003-9152-z.

Liu, Z., Z. Yao, H. Huang, S. Wu, and G. Liu. 2014. Land use and climate changes and their impacts on runoff in the Yarlung Zangbo river basin, China. L. Degrad. Dev. doi: 10.1002/ldr.1159.

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. Geoderma 117(1–2): 3–52. doi: 10.1016/S0016-7061(03)00223-4.

McMahon, G., S.M. Gregonis, S.W. Waltman, J.M. Omernik, T.D. Thorson, et al. 2001. Developing a spatial framework of common ecological regions for the conterminous United States. Environ. Manage. 28(3): 293–316. doi: 10.1007/s0026702429.

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013a. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013b. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Mishra, U., R. Lal, B. Slater, F. Calhoun, D. Liu, et al. 2009. Predicting Soil Organic Carbon Stock Using Profile Depth Distribution Functions and Ordinary Kriging. Soil Sci. Soc. Am. J. 73(2): 614–621. doi: 10.2136/sssaj2007.0410.

Mount, R., N. Carolina, and S. Carolina. 2020. Ecological site F133AY007NC Atlantic Coastal Plain Wet Longleaf Pine Woodland , Wet - Provisional.

Natural, Resources, Conservation, and Service. 2009. Part 630 Hydrology National Engineering Handbook.

Nave, L.E., E.D. Vance, C.W. Swanston, and P.S. Curtis. 2009. Harvest impacts on soil carbon storage in temperate forests. doi: 10.1016/j.foreco.2009.12.009.

NRCS. SSM - Ch. 2. Landscapes, Geomorphology, and Site Description | NRCS North Carolina. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/nc/soils/?cid=nrcs142p2_054252 (accessed 24 June 2021).

NRCS NSSC KSSL, U. 2014. Kellog Soil Survey Laboratory Methods Manual; Soil Survey Investigations Report No. 42; Version 5.0 (2014).

O'Neill, R. V., A.R. Johnson, and A.W. King. 1989. A hierarchical framework for the analysis of scale. Landsc. Ecol. 3(3–4): 193–205. doi: 10.1007/BF00131538.

Olson, J.S., J.A. Watts, and L.L.A. 1985. Major World Ecosystem Complexes Ranked by Carbon in Live Vegetation: A Database (NDP-017) (2001 version of original 1985 data) (Dataset) | OSTI.GOV. https://www.osti.gov/biblio/1389497 (accessed 24 June 2021).

Olson, K.R., M. Al-Kaisi, R. Lal, and L. Cihacek. 2016. Impact of soil erosion on soil organic carbon stocks. J. Soil Water Conserv. 71(3): 61A-67A. doi: 10.2489/jswc.71.3.61A.

Ontl, T. A. & Schulte, L.A. 2012. Soil Carbon Storage | Learn Science at Scitable. https://www.nature.com/scitable/knowledge/library/soil-carbon-storage-84223790/ (accessed 11 June 2021).

Pachepsky, Y., and R.L. Hill. 2017. Scale and scaling in soils. Geoderma 287: 4–30. doi: 10.1016/j.geoderma.2016.08.017.

PII: S0167-1987(97)00044-5 | Elsevier Enhanced Reader. https://reader.elsevier.com/reader/sd/pii/S0167198797000445?token=BD3D01F7AD56DB80C79A51C2BC0B9CA7D37A7237E9517245EDD279B413F6D531CADB217F8DBAF1AA104A7BD6ADA87C89&originRegion=eu-west-1&originCreation=20210419154615 (accessed 19 April 2021).

Pribyl, D.W. 2010. A critical review of the conventional SOC to SOM conversion factor. Geoderma 156: 75–83. doi: 10.1016/j.geoderma.2010.02.003.

PRISM Climate Group, Oregon State U. https://prism.oregonstate.edu/normals/ (accessed 7 July 2020).

R Core Team. 2020. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ramcharan, A., T. Hengl, D. Beaudette, and S. Wills. 2017. A Soil Bulk Density Pedotransfer Function Based on Machine Learning: A Case Study with the NCSS Soil Characterization Database. Soil Sci. Soc. Am. J. 81(6): 1279–1287. doi: 10.2136/sssaj2016.12.0421.

Rapid Carbon Assessment (RaCA) | Ag Data Commons. https://data.nal.usda.gov/dataset/rapid-carbon-assessment-raca (accessed 5 July 2020).

Rasmussen, C. 2006. Distribution of Soil Organic and Inorganic Carbon Pools by Biome and Soil Taxa in Arizona. Soil Sci. Soc. Am. J. 70(1): 256–265. doi: 10.2136/sssaj2005.0118.

Rasmussen, C., K. Heckman, W.R. Wieder, M. Keiluweit, C.R. Lawrence, et al. 2018. Beyond clay: towards an improved set of variables for predicting soil organic matter content. Biogeochemistry 137(3): 297–306. doi: 10.1007/S10533-018-0424-3.

Ricker, M.C., and B.G. Lockaby. 2015. Soil Organic Carbon Stocks in a Large Eutrophic Floodplain Forest of the Southeastern Atlantic Coastal Plain, USA. Wetlands 35(2): 291–301. doi: 10.1007/s13157-014-0618-y.

Robertson, G.P., K.M. Klingensmith, M.J. Klug, E.A. Paul, J.R. Crum, et al. 1997. SOIL Resources, Microbial Activity, And Primary Production Across An Agricultural Ecosystem.

Ross, C.W. 2017. A Region-Wide Analysis Of Terrestrial Carbon Cycling Across "The Land Of Pines."

Ross, C.W., S. Grunwald, J.G. Vogel, D. Markewitz, E.J. Jokela, et al. 2020. Accounting for two-billion tons of stabilized soil carbon. Sci. Total Environ. 703: 134615. doi: 10.1016/j.scitotenv.2019.134615.

Salley, S.W., H. Curtis Monger, and J.R. Brown. 2016a. Completing the Land Resource Hierarchy. Rangelands 38(6): 313–317. doi: 10.1016/j.rala.2016.10.003.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016b. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016c. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Scharlemann, J.P., E.V. Tanner, R. Hiederer, and V. Kapos. 2014. Carbon Management Global soil carbon: understanding and managing the largest terrestrial carbon pool. doi: 10.4155/cmt.13.77.

Schillaci, C., M. Acutis, L. Lombardo, A. Lipani, M. Fantappiè, et al. 2017. Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: The role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling. Sci. Total Environ. doi: 10.1016/j.scitotenv.2017.05.239.

Sevastas, S., D. Gasparatos, D. Botsis, I. Siarkos, K.I. Diamantaras, et al. 2018. Predicting bulk density using pedotransfer functions for soils in the Upper Anthemountas basin, Greece. Geoderma Reg. 14: e00169. doi: 10.1016/j.GEODRS.2018.e00169.

Singh, M., B. Sarkar, S. Sarkar, J. Churchman, N. Bolan, et al. 2018. Stabilization of Soil Organic Carbon as Influenced by Clay Mineralogy. Advances in Agronomy. Academic Press Inc. p. 33–84

Soil Drainage Class.

Soil Survey Staff, Natural Resources Conservation Service, U.S.D. of A. Soil Survey Geographic (SSURGO) Database.

Spash, C.L. 2010. The brave new world of carbon trading. New Polit. Econ. 15(2): 169–195. doi: 10.1080/13563460903556049.

SSM - Ch. 9. Assessing Dynamic Soil Properties and Soil Change | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/ref/?cid=nrcseprd1343021 (accessed 19 April 2021).

Stringham, T.K., W.C. Krueger, and P.L. Shaver. 2003. State and transition modeling: An ecological process approach. J. Range Manag. doi: 10.2307/4003893.

Taghizadeh-Mehrjardi, R., K. Nabiollahi, and R. Kerry. 2016. Digital mapping of soil organic carbon at multiple depths using different data mining techniques in Baneh region, Iran. Geoderma. doi: 10.1016/j.geoderma.2015.12.003.

Teferi, E., W. Bewket, and B. Simane. 2016. Effects of land use and land cover on selected soil quality indicators in the headwater area of the Blue Nile basin of Ethiopia. Environ. Monit. Assess. doi: 10.1007/s10661-015-5086-1.

The National Map. https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map (accessed 26 June 2021).

Trail, M., A.P. Tsimpidi, P. Liu, K. Tsigaridis, Y. Hu, et al. 2013. Potential impact of land use change on future regional climate in the Southeastern U.S.: Reforestation and crop land conversion. J. Geophys. Res. Atmos. 118(20): 11,577-11,588. doi: 10.1002/2013JD020356.

Tugel, A.J., S.A. Wills, and J.E.H. 2008. Soil change guide: Procedures for soil survey and resource inventory. Version 1. Natl. Soil Surv. Ctr., Lincoln, NE.

Tugel, A.J., J.E. Herrick, J.R. Brown, M.J. Mausbach, W. Puckett, et al. 2005. Soil Change, Soil Survey, and Natural Resources Decision Making. Soil Sci. Soc. Am. J. 69(3): 738–747. doi: 10.2136/sssaj2004.0163.

US EPA, O. 2001. Ecoregion Download Files by State - Region 4. https://www.epa.gov/eco-research/ecoregion-download-files-state-region-4 (accessed 18 August 2020).

USDA-NRCS. Soil Moisture Regimes of the Contiguous United States | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/maps/?cid=nrcs142p2_053997 (accessed 28 June 2021).

USDA:NRCS:Geospatial Data Gateway:Order Data. https://datagateway.nrcs.usda.gov/GDGOrder.aspx (accessed 31 July 2020).

USDA. 2014. Keys to soil taxonomy. Soil Conserv. Serv. 12: 410. doi: 10.1109/TIP.2005.854494.

USDA, and NRCS. 2006. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and the Pacific Basin.

Vasques, G.M., S. Grunwald, and W.G. Harris. 2010. Spectroscopic Models of Soil Organic Carbon in Florida, USA. J. Environ. Qual. 39(3): 923–934. doi: 10.2134/jeq2009.0314.

Walker, J.D., and J. Geissman. 2009. 2009 GSA Geologic Time Scale Evolution of the Teton fault View project Building Stronger Geoscience Department View project. doi: 10.1130/1052-5173-19.4-5.60.

Wang, B., C. Waters, S. Orgill, J. Gray, A. Cowie, et al. 2018. High resolution mapping of soil organic carbon stocks using remote sensing variables in the semi-arid rangelands of eastern Australia. Sci. Total Environ. doi: 10.1016/j.scitotenv.2018.02.204.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic management for rangelands not at equilibrium.

Wickham, H. 2016. ggplot2. Springer International Publishing, Cham.

Wickham, J.D., S. V. Stehman, L. Gass, J. Dewitz, J.A. Fry, et al. 2013. Accuracy assessment of NLCD 2006 land cover and impervious surface. Remote Sens. Environ. 130: 294–304. doi: 10.1016/j.rse.2012.12.001.

Wills, S., C. Williams, C. Seybold, L. Scheffe, Z. Libohova, et al. 2017. Using Soil Survey to Assess and Predict Soil Condition and Change. : 123–135. doi: 10.1007/978-3-319-43394-3_11.

Worsham, L., D. Markewitz, and N. Nibbelink. 2010. Incorporating Spatial Dependence into Estimates of Soil Carbon Contents under Different Land Covers. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2008.0412.

Xiong, X., S. Grunwald, D.B. Myers, C.W. Ross, W.G. Harris, et al. 2014. Interaction effects of climate and land use/land cover change on soil organic carbon sequestration. Sci. Total Environ. 493: 974–982. doi: 10.1016/j.scitotenv.2014.06.088.

Xue, D., R. Christenson, R. Genger, A. Gevens, and R.A. Lankau. 2018. Soil Microbial Communities Reflect both Inherent Soil Properties and Management Practices in Wisconsin Potato Fields. Am. J. Potato Res. 95(6): 696–708. doi: 10.1007/s12230-018-9677-6.

Yang, R.M., G.L. Zhang, F. Liu, Y.Y. Lu, F. Yang, et al. 2016. Comparison of boosted regression tree and random forest models for mapping topsoil organic carbon concentration in an alpine ecosystem. Ecol. Indic. doi: 10.1016/j.ecolind.2015.08.036.

Zomer, R.J., D.A. Bossio, R. Sommer, and L. V. Verchot. 2017. Global Sequestration Potential of Increased Organic Carbon in Cropland Soils. Sci. Rep. 7(1): 1–8. doi: 10.1038/s41598-017-15794-8.

2.7. Tables

Table 3.1 Soil point data used for SOC20 assessment by source.

Data Source	Type of Data	Number of points used	Date range of Points	References
Rapid Carbon Assessment dataset (RaCA)	Predicted carbon concentrations†	1155	2010 – 2013	Rapid Carbon Assessment (RaCA) | Ag Data Commons, Retrieved July 5, 2020
National Cooperative Soil Survey (NCSS) Soil characterization Database	Carbon concentration	174	2000 – 2015	National Cooperative Soil Survey Soil Characterization Database (accessed Wednesday, June 23, 2021)
Levi et al., 2010	Carbon concentration	9	2005 – 2007	Levi et al. (2010)
Cochran, (2010)	Carbon concentration	13	2009 – 2010	Cochran, (2010)
Ricker and Locakaby, (2015)	Carbon concentration	60	2010	Ricker and Lockaby, (2015)
Tall Timbers Research Center	Carbon concentration	128	2010 – 2018	K. Robertson pers. communication

† Most carbon values were predicted with visible near-infrared spectroscopy using a subset of available data from the project to train the predictive model.

Table 3.2 Mean SOC20 stock for the landcover classes (based on National Land Cover Database (NLCD)) at the time of soil sampling.

Land Cover Class	Mean SOC20 Stock (Mg ha^{-1})
Open Water	53.6
Urban- Open Spaces	64.2
Urban- Low Residential	40.4
Barren Land/Abandoned land	45.2
Deciduous Forest	45.9
Evergreen Forest	56.8
Mixed Forest	36.4
Shrub/Scrub	53.9
Grassland/Herbaceous	50.6
Pasture/Hay	69.3

2.8 Figures

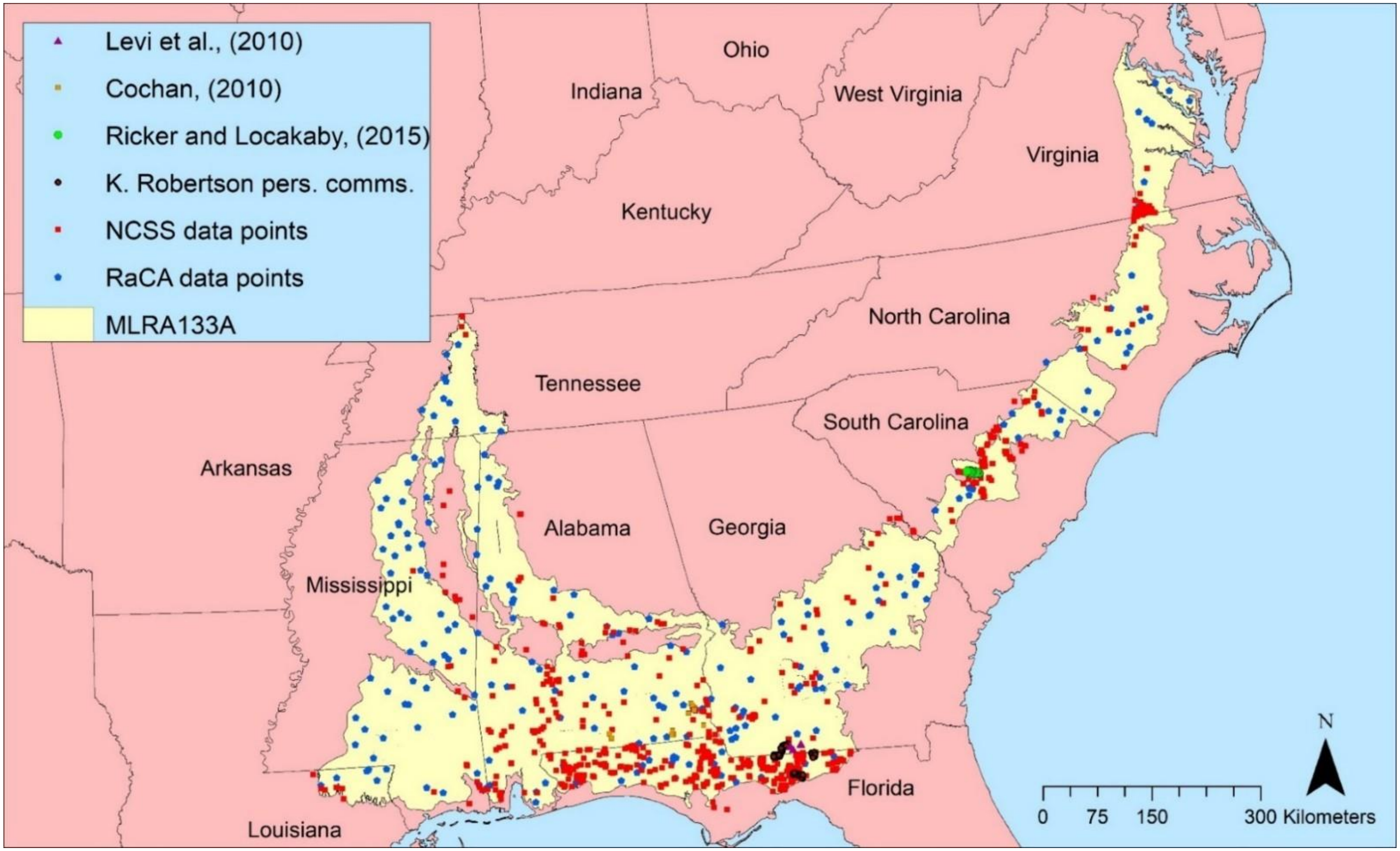

Figure 3.1 Spatial distribution of 1441 point locations in the Southern Coastal Plain (MLRA 133A) with available soil organic carbon measurements from multiple sources.

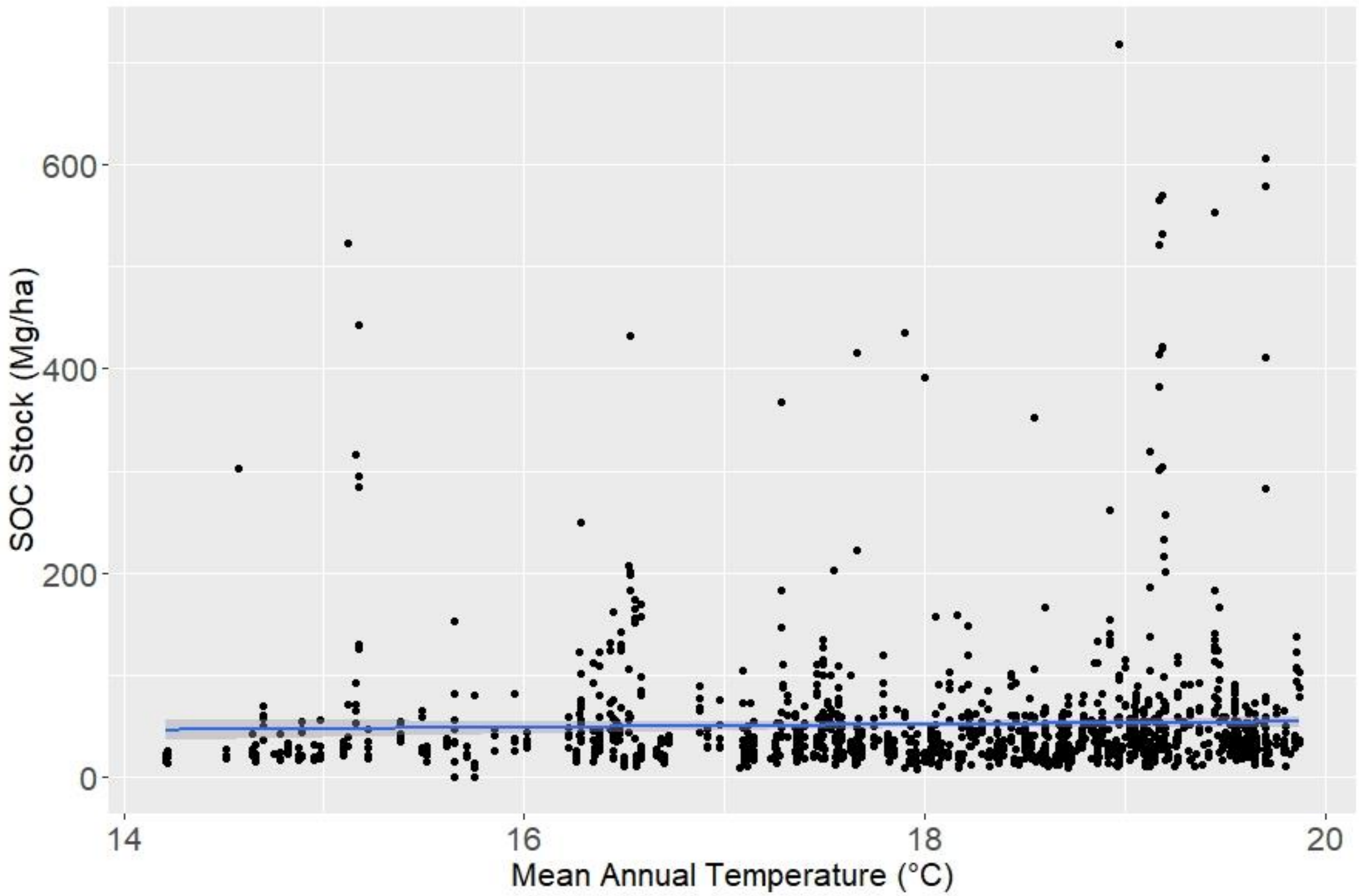

Figure 3.2 Changes in SOC20 stock with mean annual temperature (MAT) across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and MAT and grey area around it is 95% confidence interval)

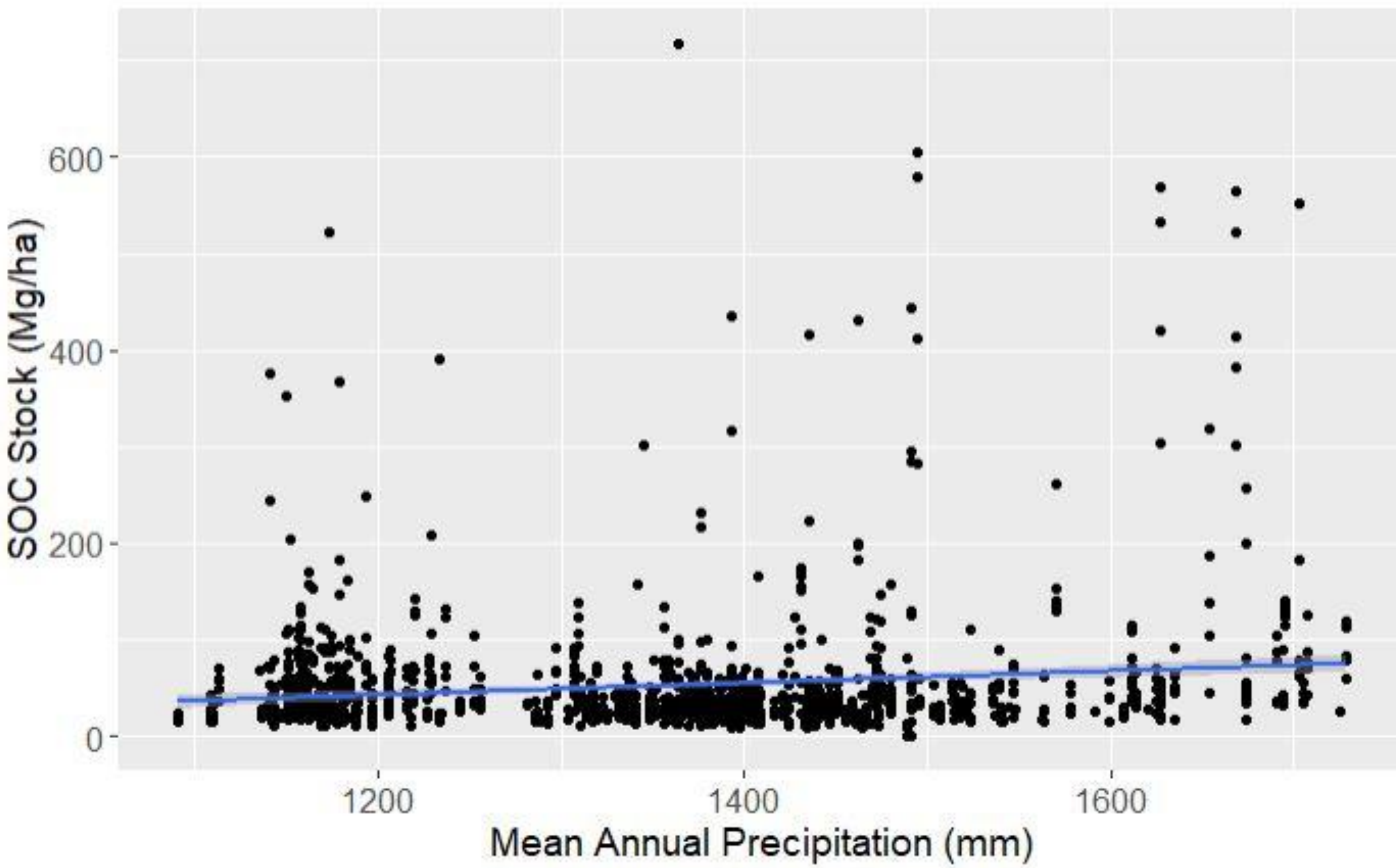

Figure 3.3 Changes in SOC20 stock with mean annual precipitation (MAP) across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and MAP and grey area around it is 95% confidence interval)

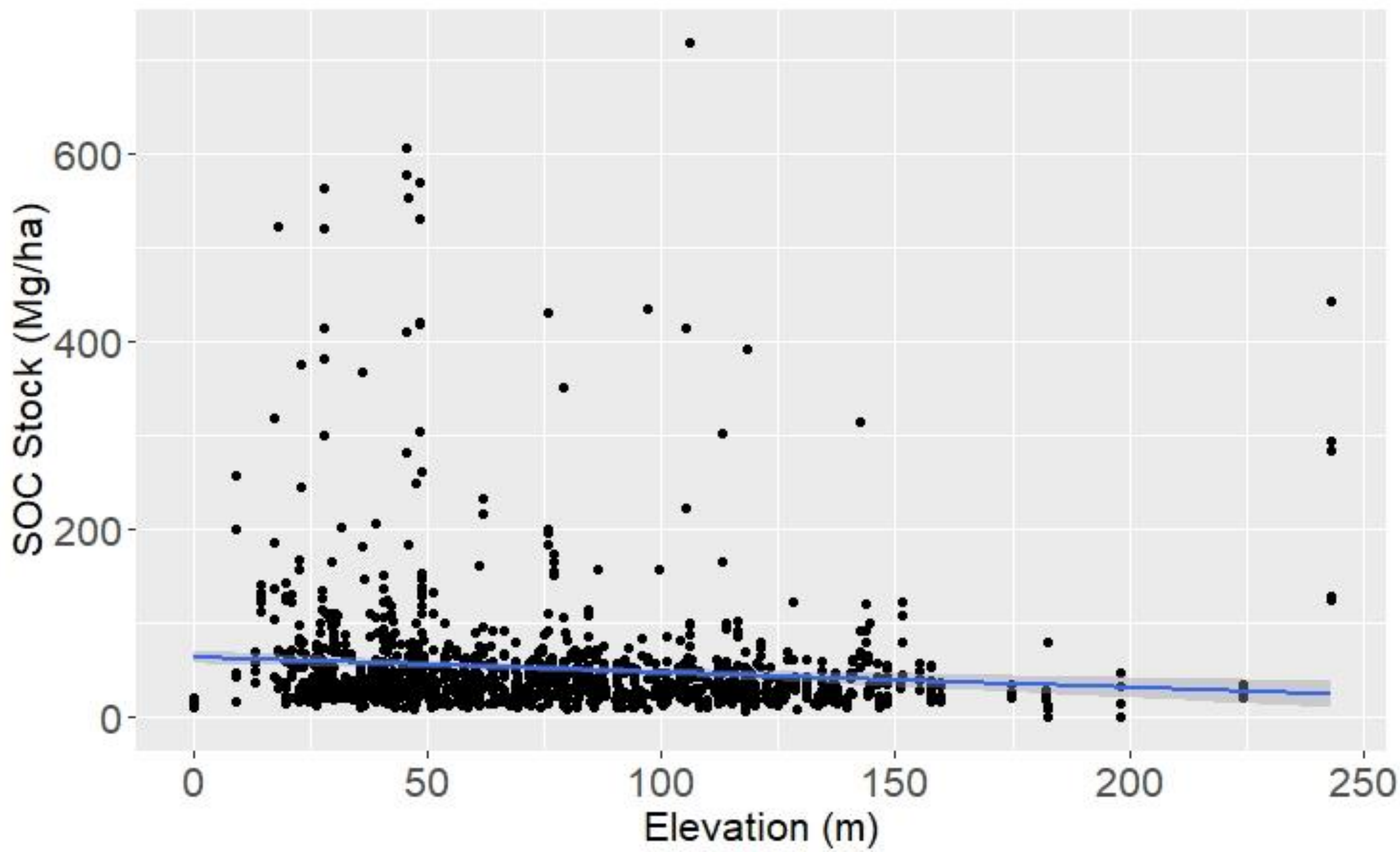

Figure 3.4 Change in SOC20 stock with increasing elevation across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and elevation and grey area around it is 95% confidence interval)

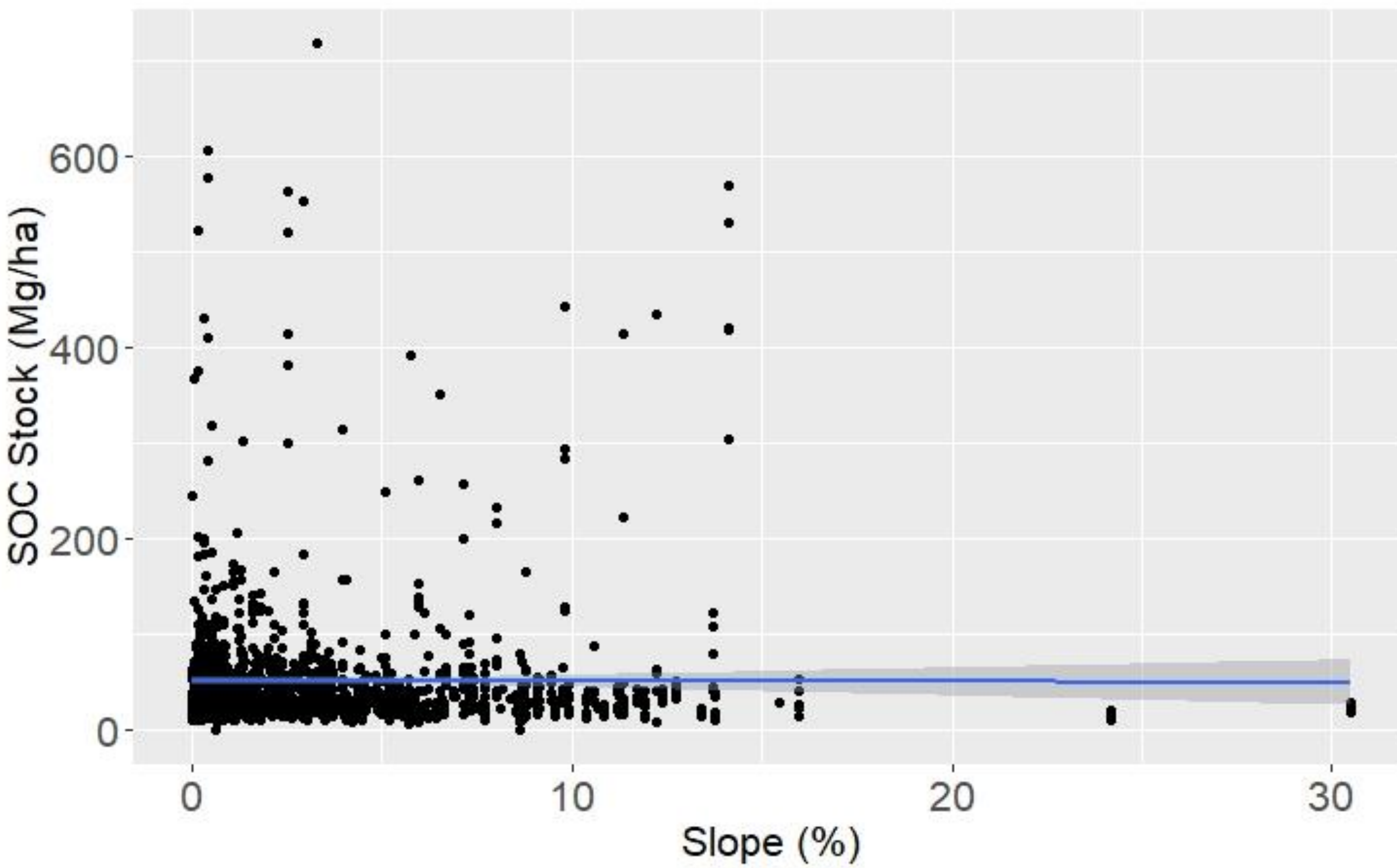

Figure 3.5 SOC20 stock compared to slope (percent) across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and slope and grey area around it is 95% confidence interval)

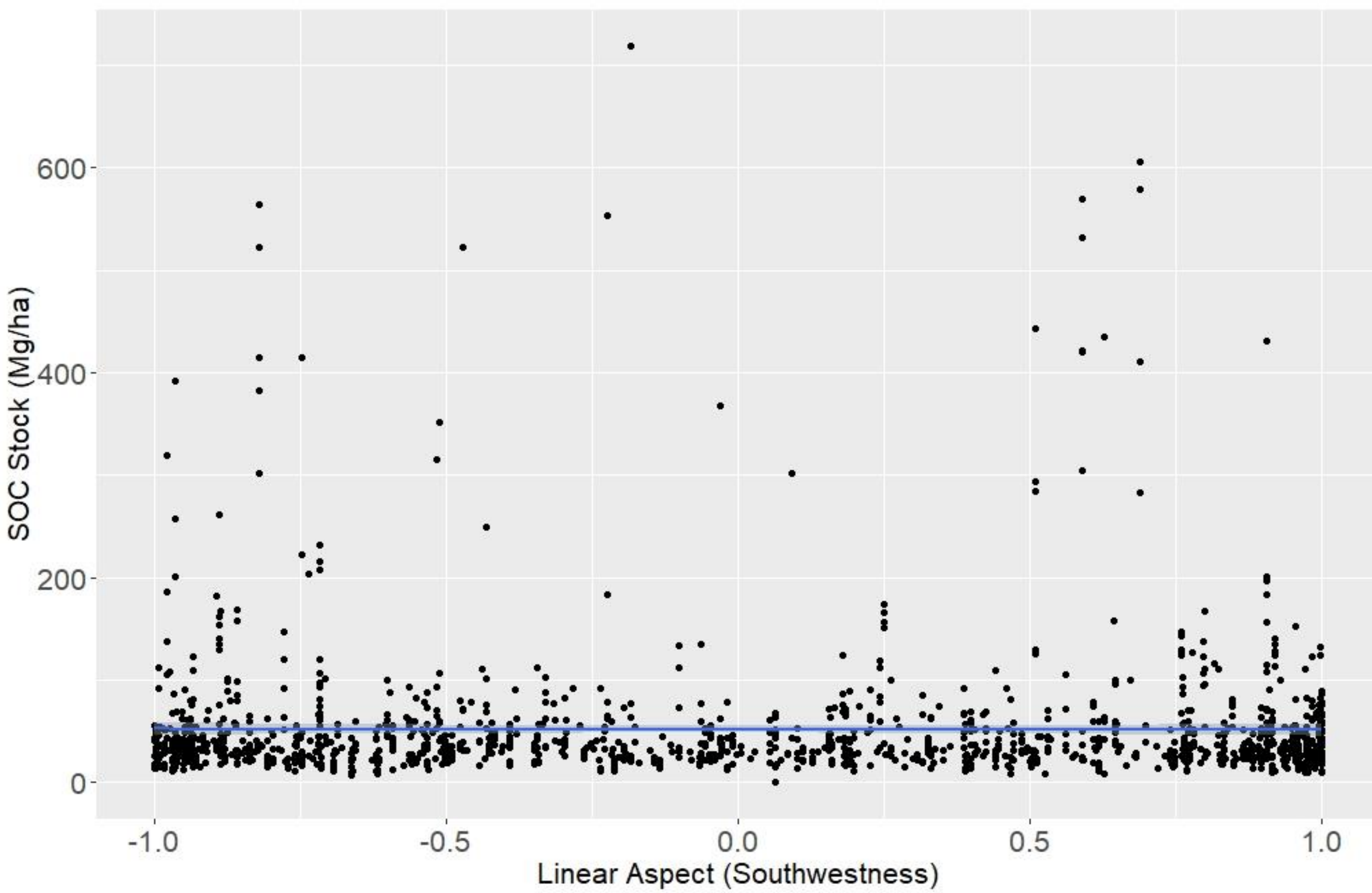

Figure 3.6 SOC20 stock compared to linear aspect (southwestness) across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and linear aspect and grey area around it is 95% confidence interval)

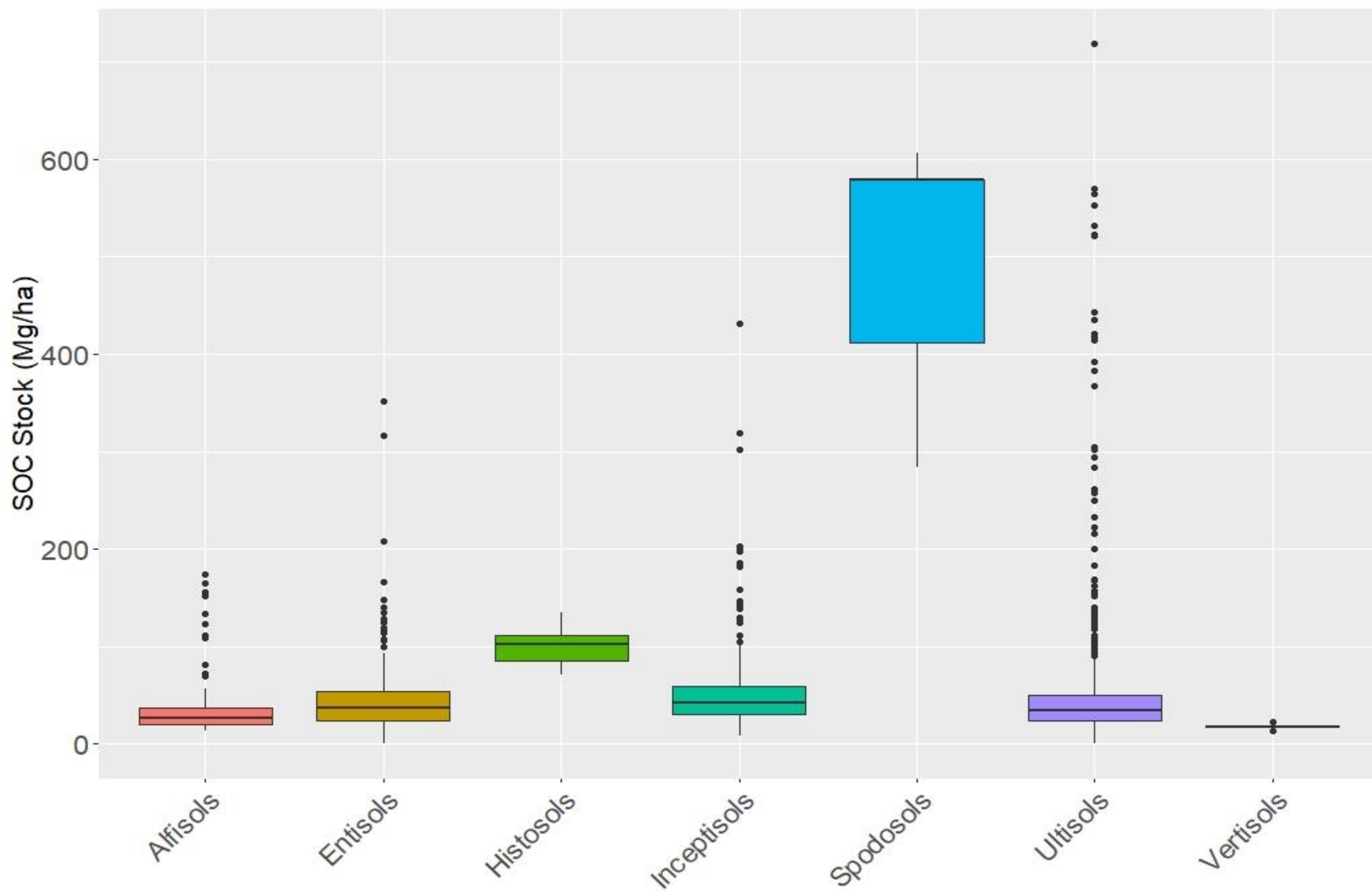

Figure 3.7 SOC20 stock (Mg ha-1) in different soil Orders across the Southern Coastal Plain.

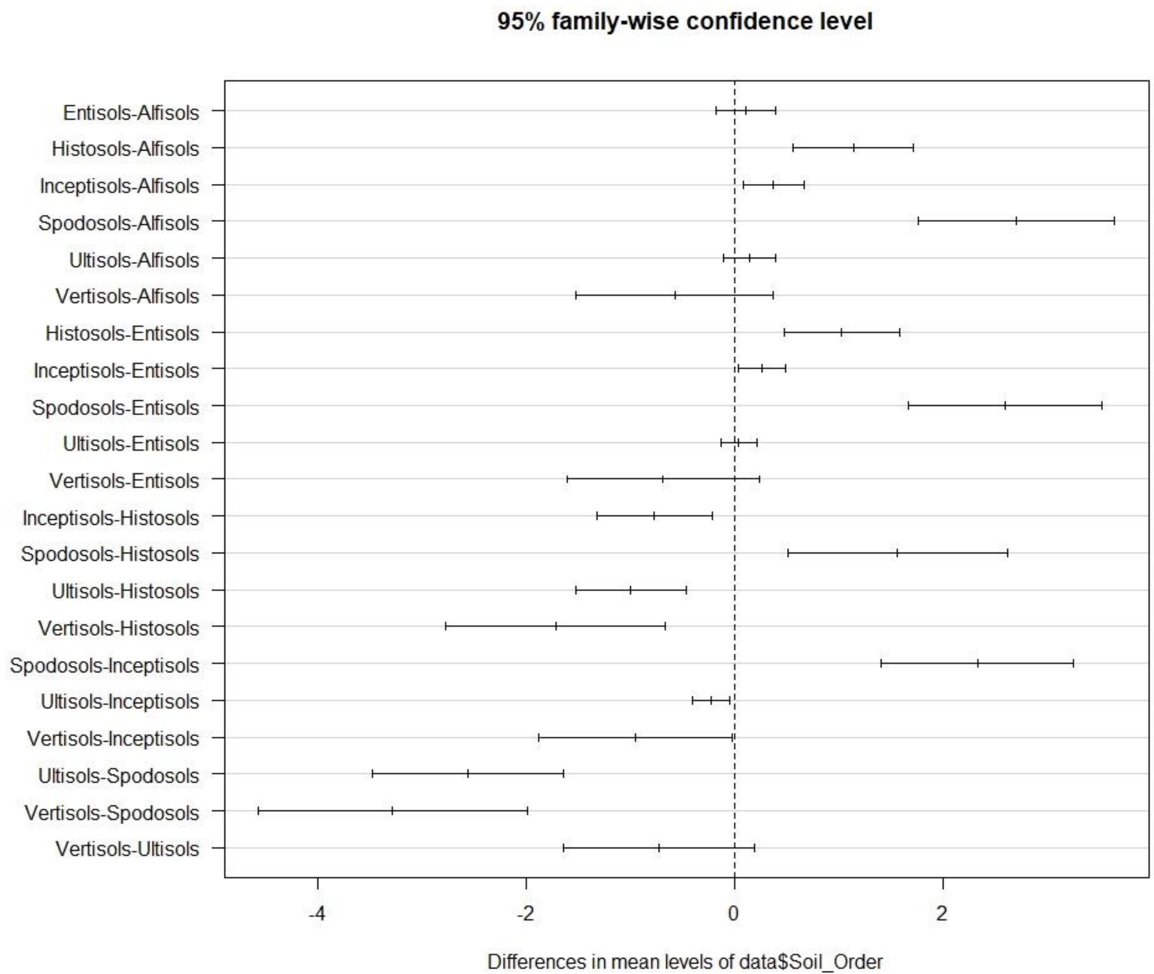

Figure 3.8 Tukey HSD test for significance between soil orders and log of SOC20 stock.

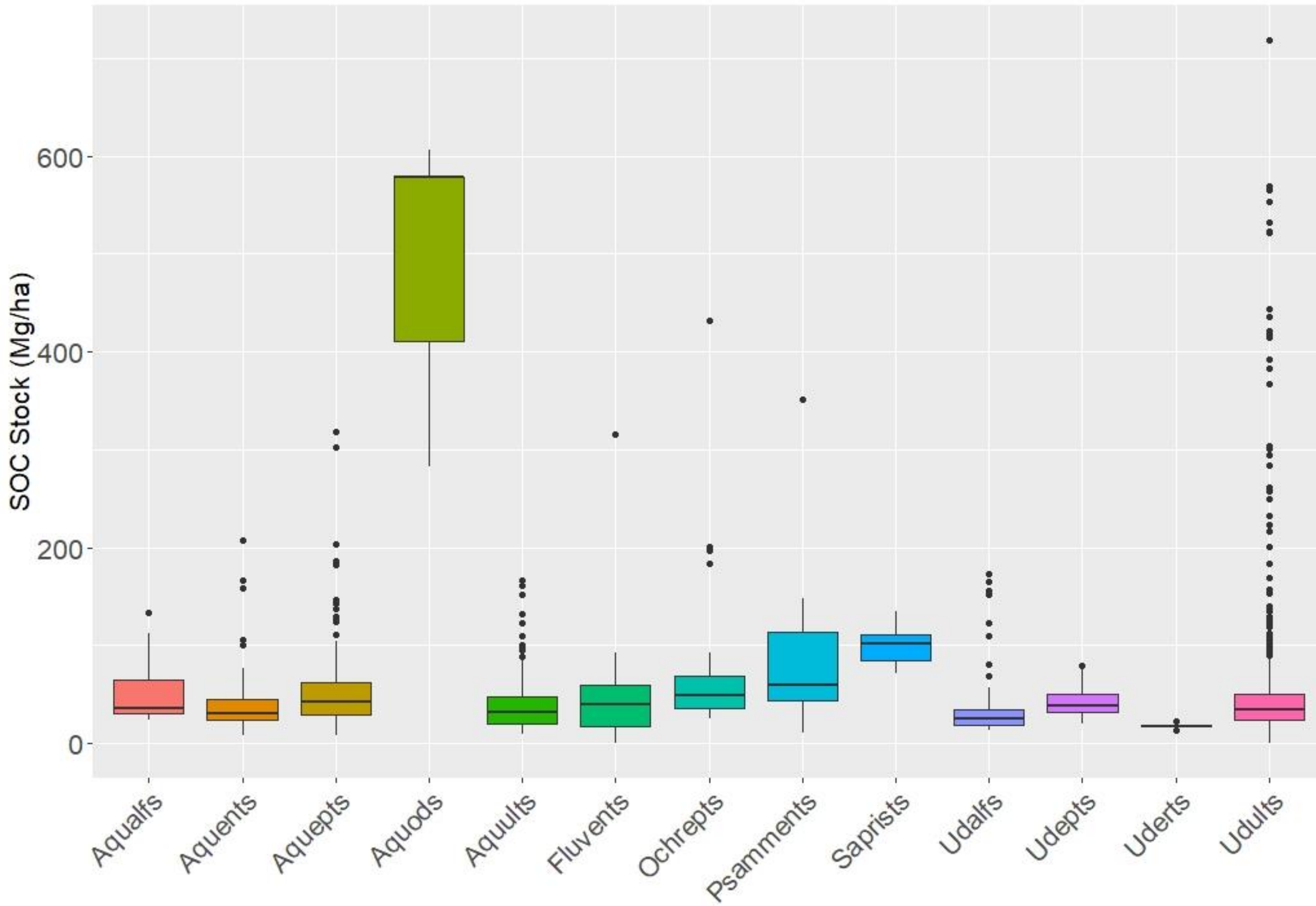

Figure 3.9 SOC20 stock (Mg ha^{-1}) in different soil Suborders across the Southern Coastal Plain.

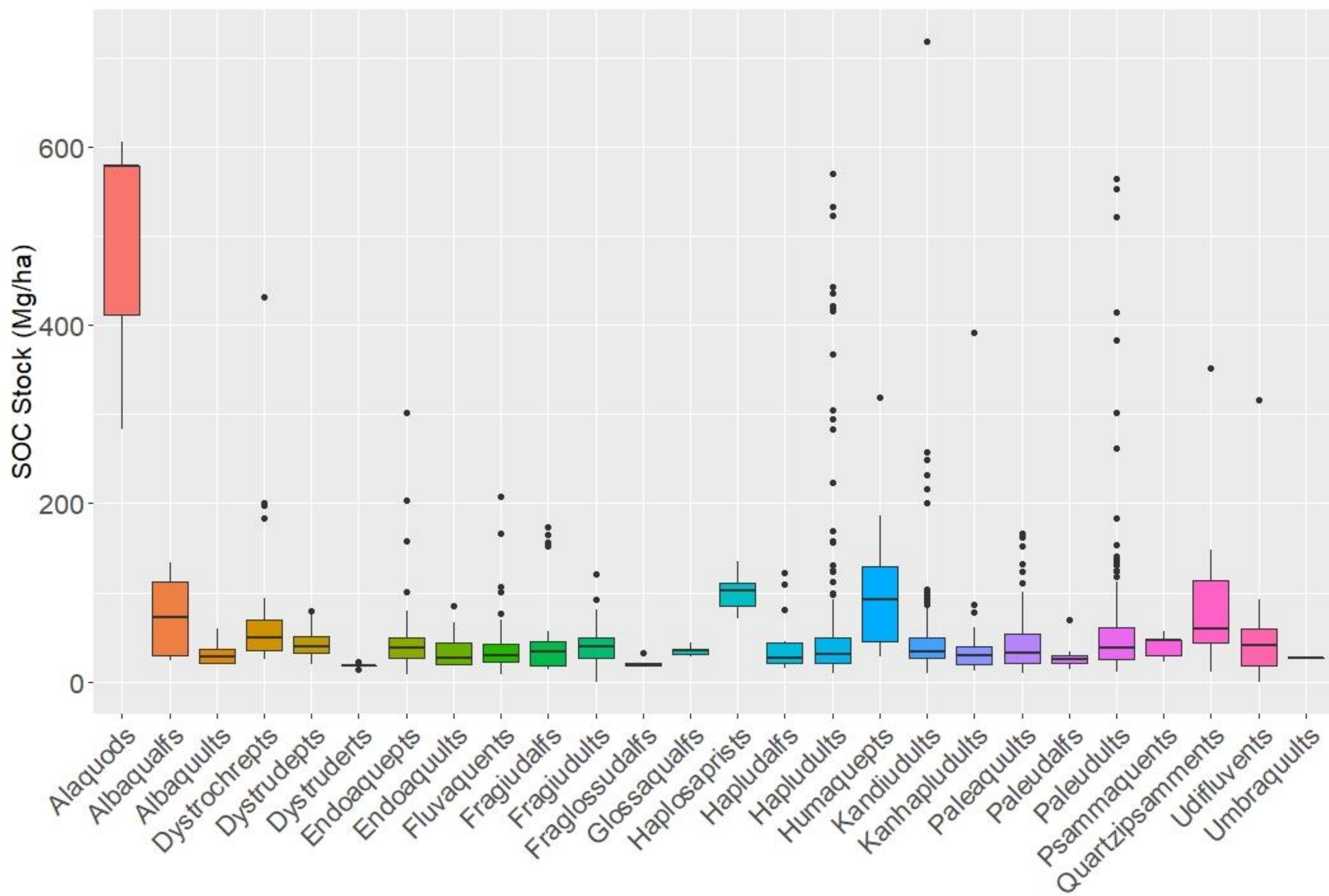

Figure 3.10 SOC20 stock (Mg ha^{-1}) in different soil Great Groups across the Southern Coastal Plain.

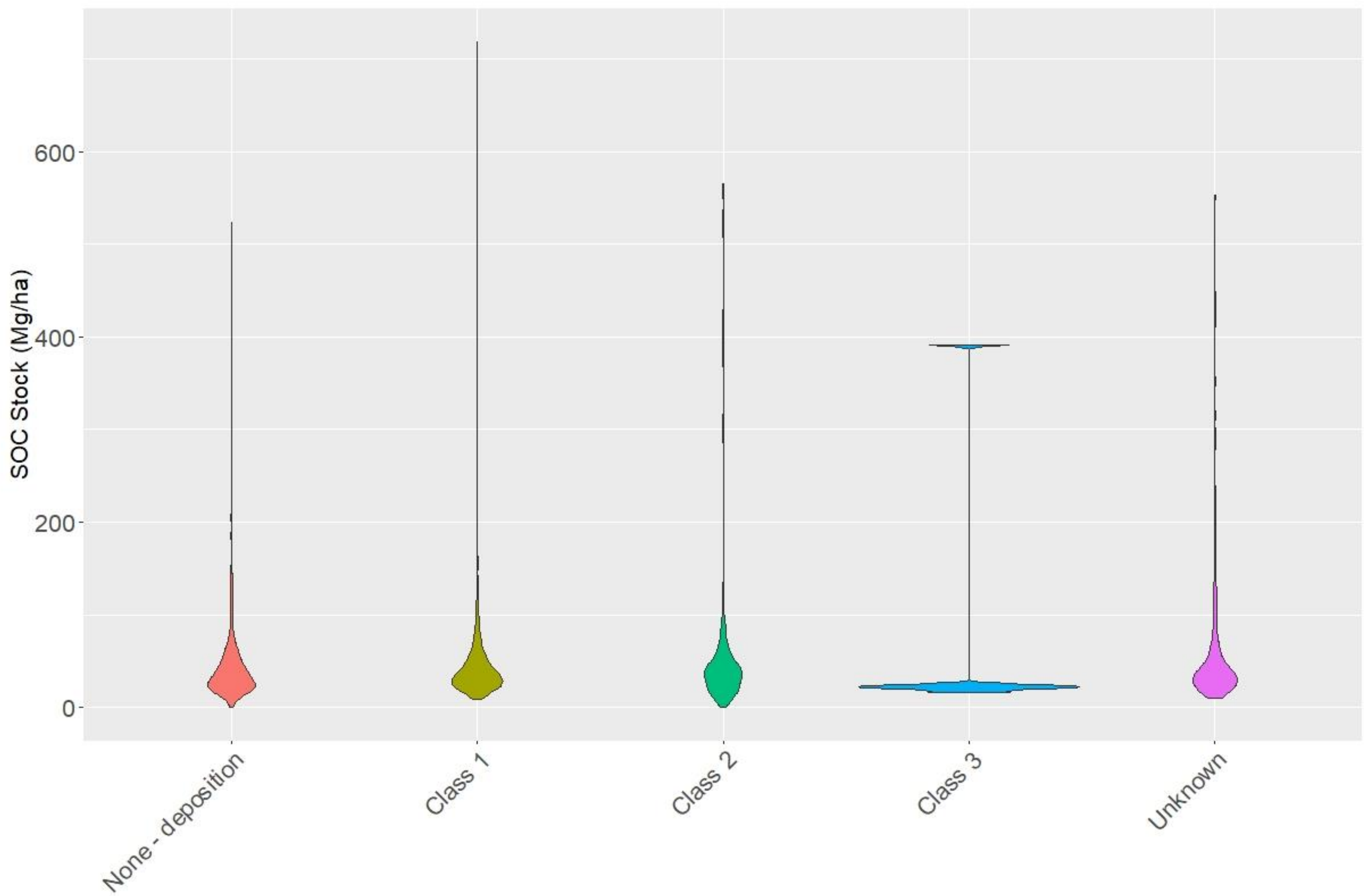

Figure 3.11 SOC20 stock (Mg ha^{-1}) in different soil erosional classes across the Southern Coastal Plain.

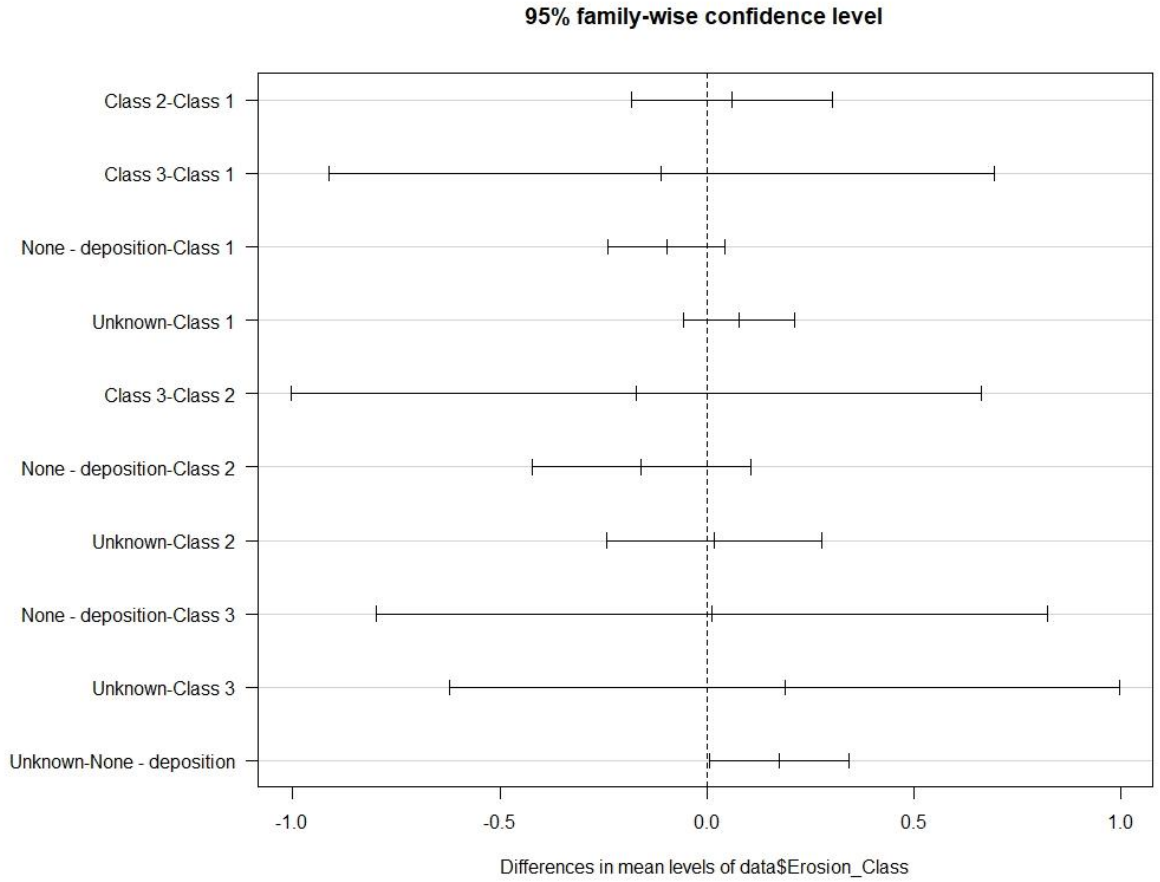

Figure 3.12 Tukey HSD test for significance between soil erosion classes and log of SOC20 stock.

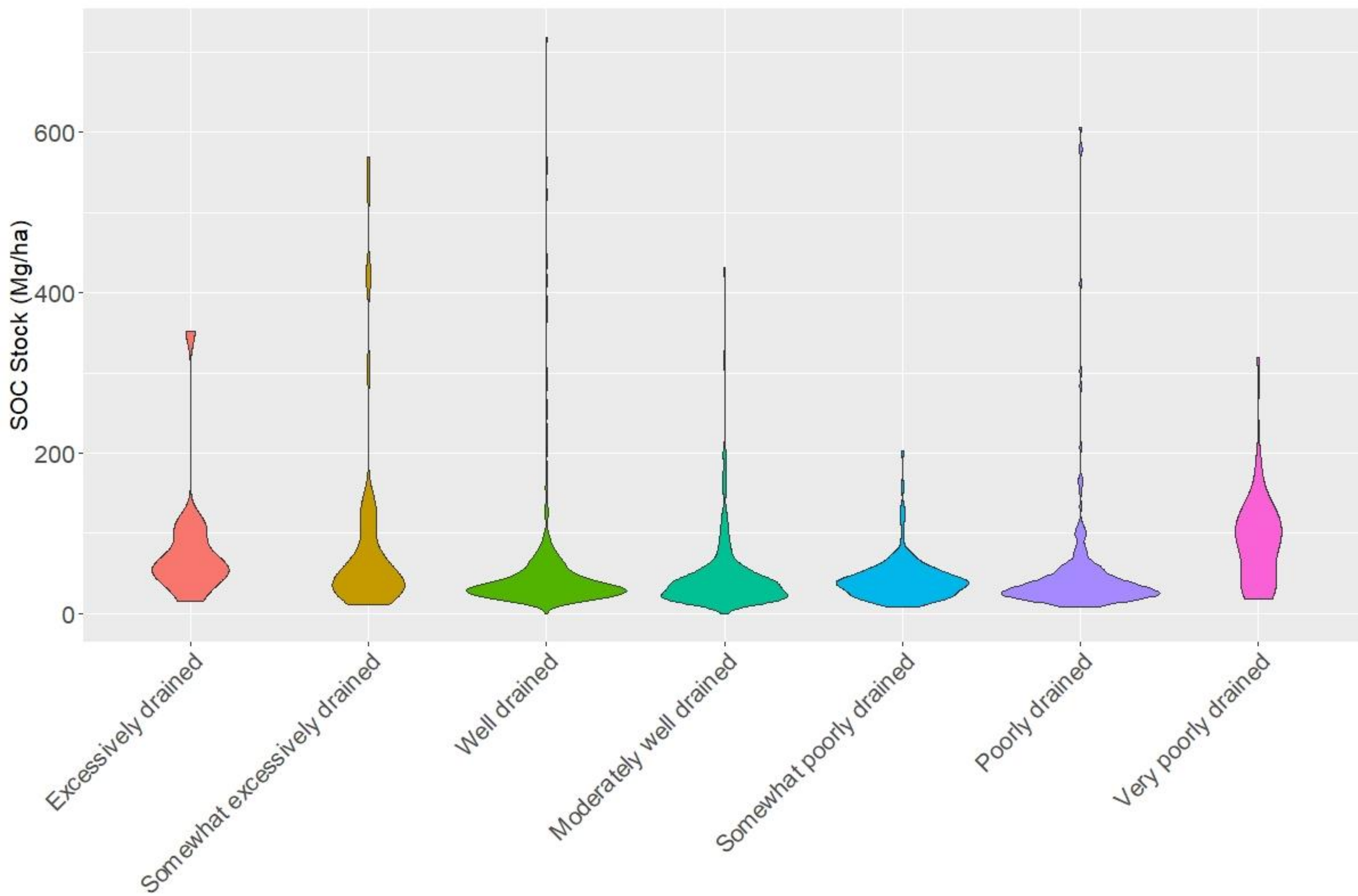

Figure 3.13 SOC20 stock (Mg ha^{-1}) in different soil drainage classes across the Southern Coastal Plain.

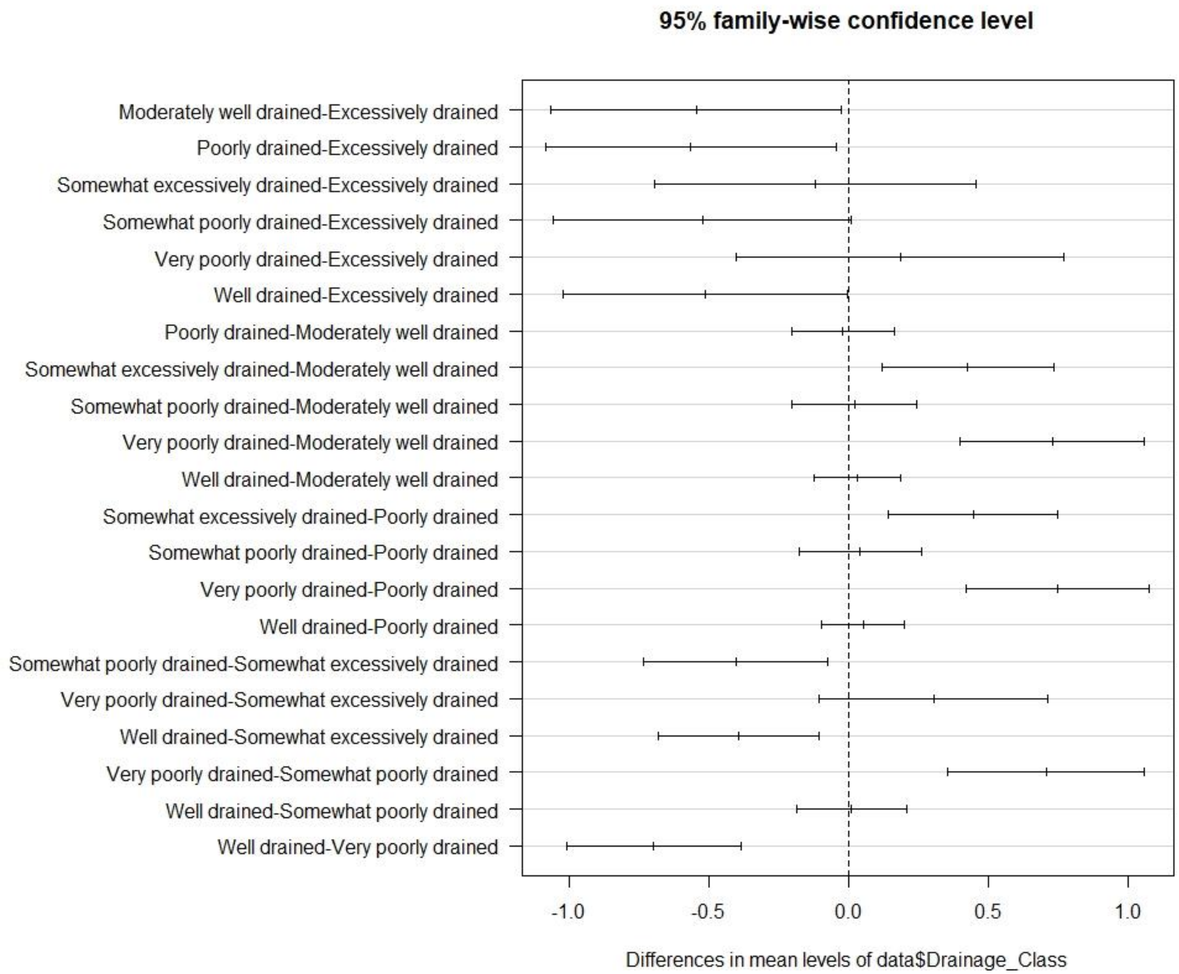

Figure 3.14 Tukey HSD test for significance between soil drainage classes and log of SOC20 stock.

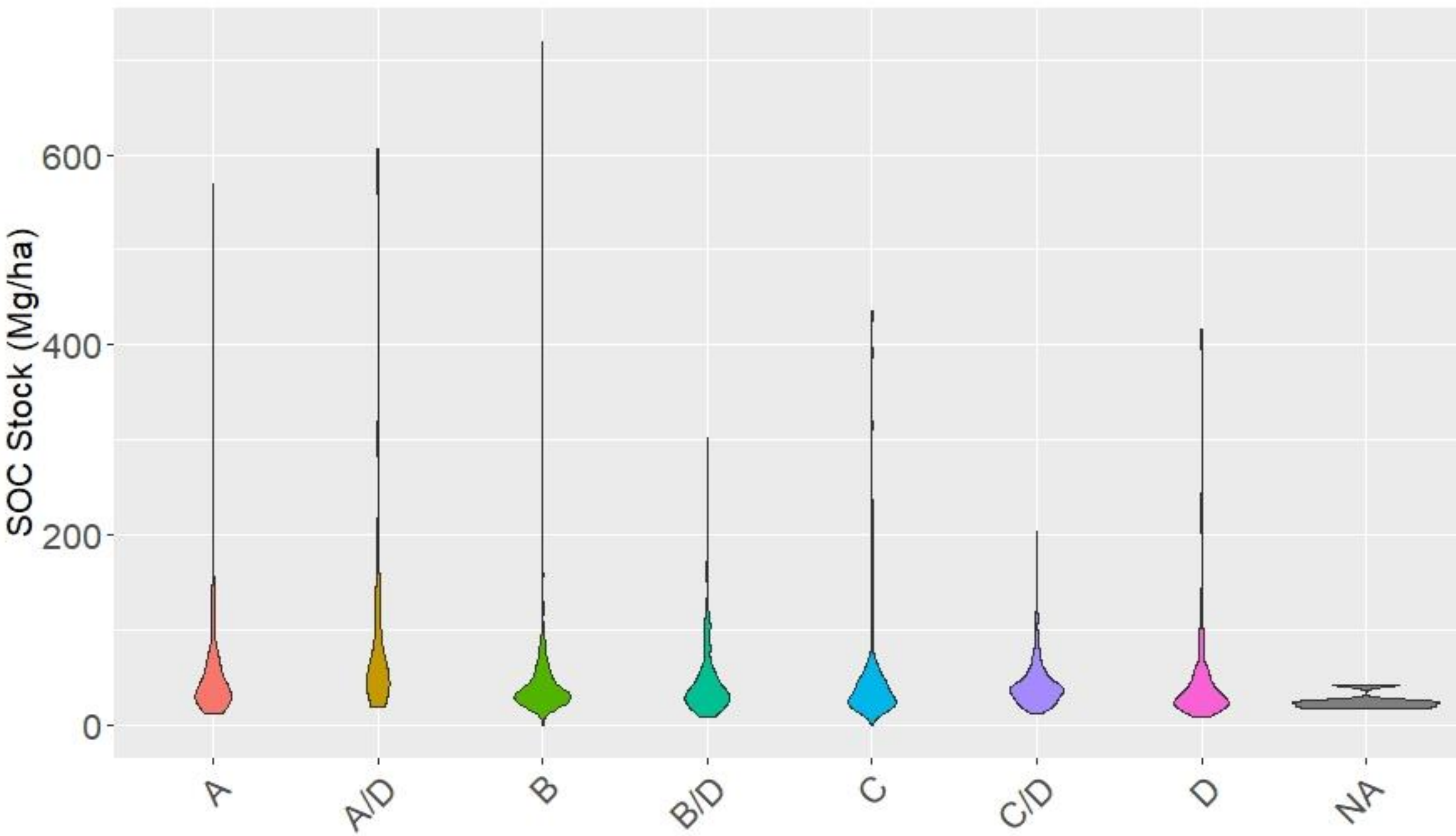

Figure 3.15 SOC20 stock (Mg ha^{-1}) in different hydrologic soil group classes across the Southern Coastal Plain.

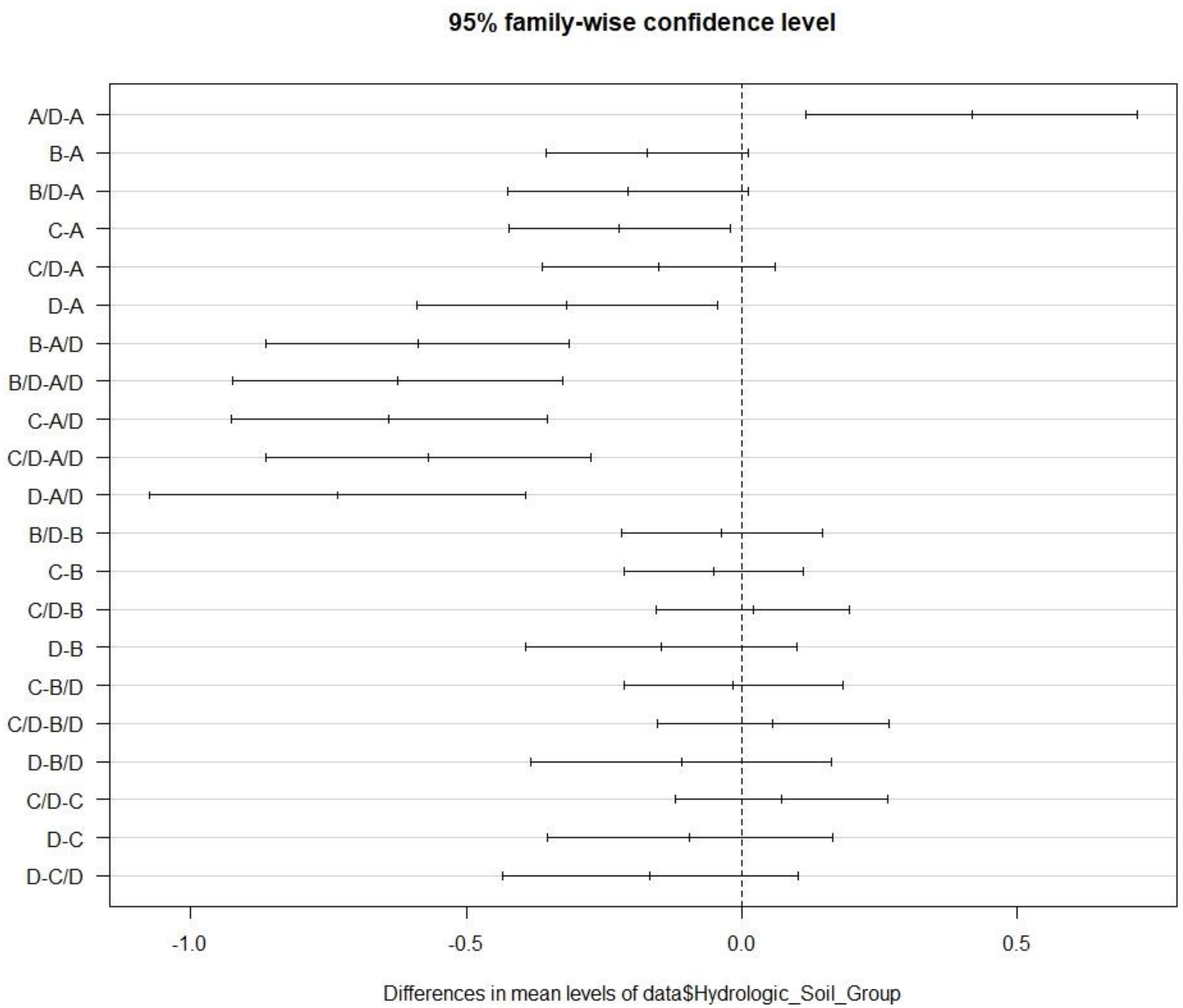

Figure 3.16 Tukey HSD test for significance between soil hydrological groups and log of SOC20 stock

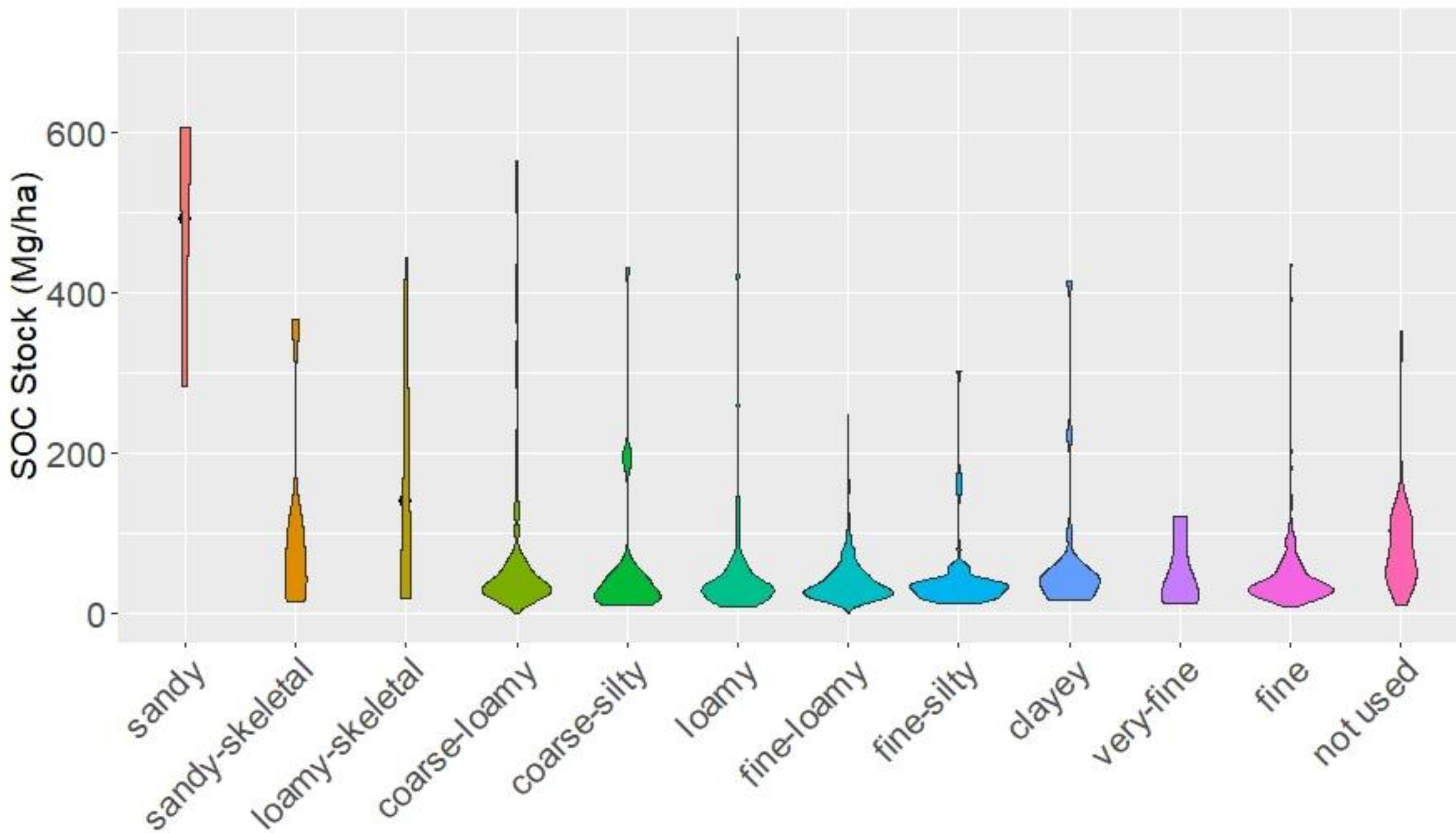

Figure 3.17 SOC20 stock (Mg ha^{-1}) in coarse to fine particle size classes across the Southern Coastal Plain.

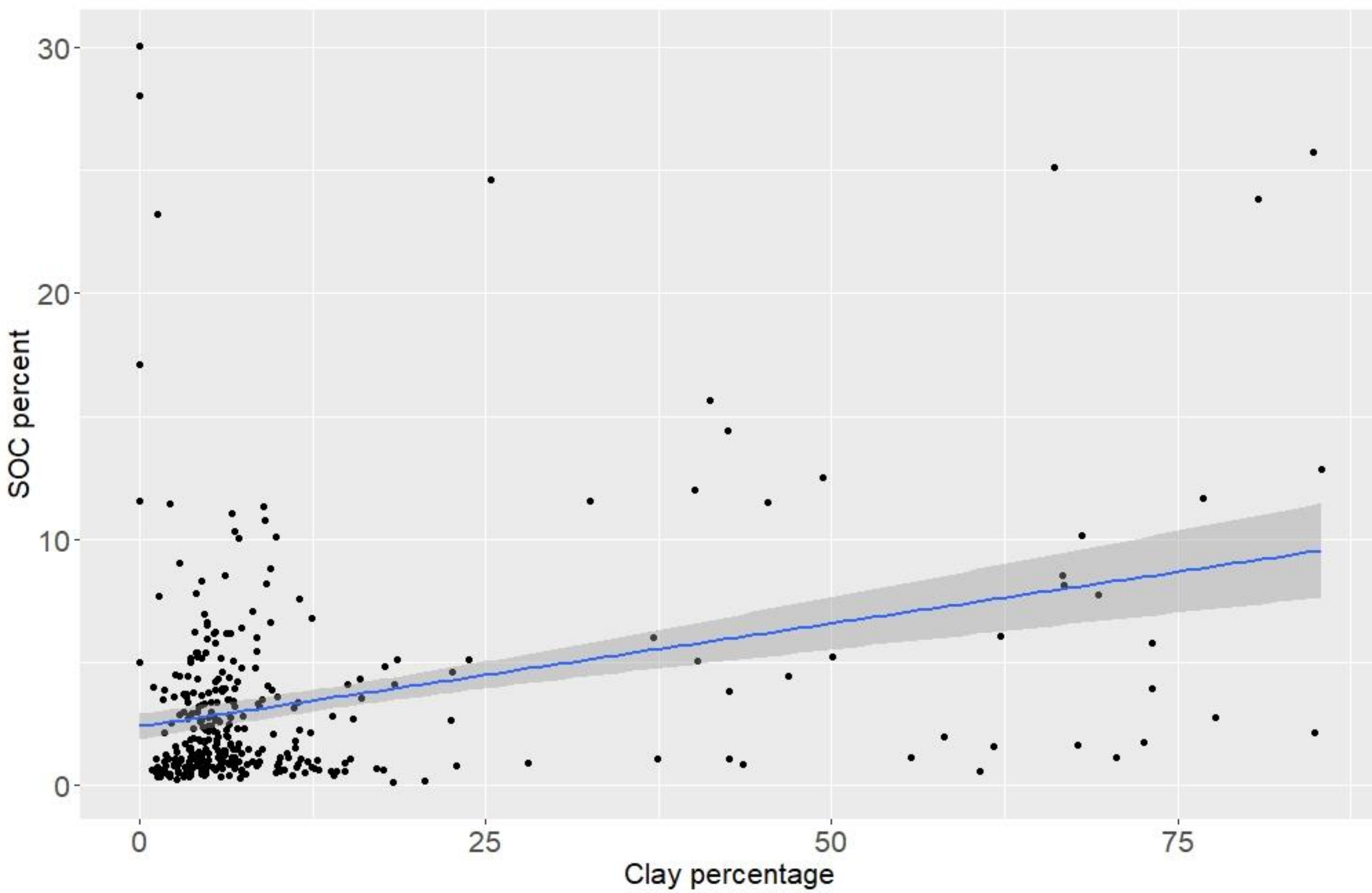

Figure 3.18 SOC percent change with clay percentage change across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 percent and clay percentage and grey area around it is 95% confidence interval)

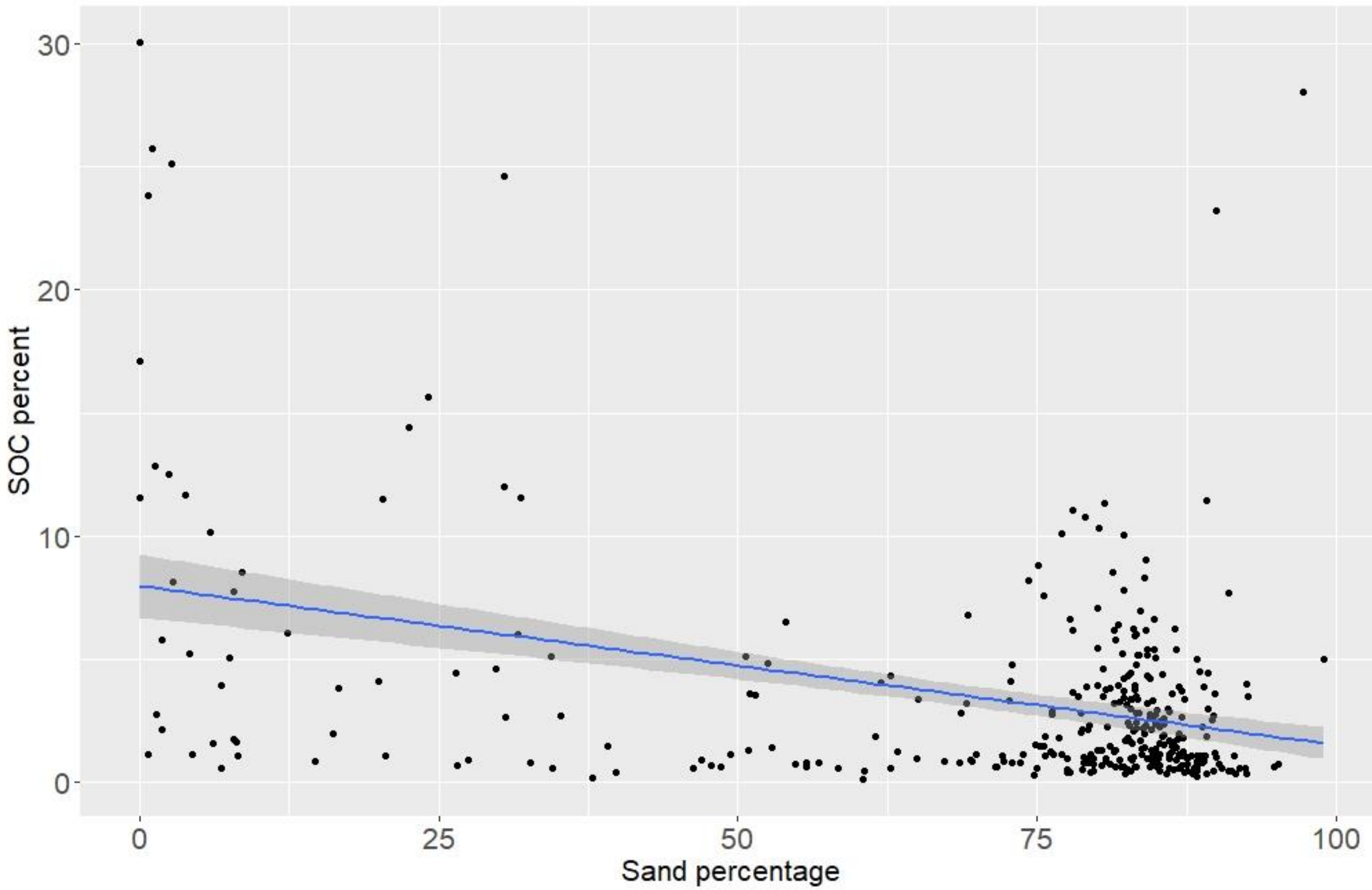

Figure 3.19 SOC percent change with sand percentage change across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 percent and sand percentage and grey area around it is 95% confidence interval)

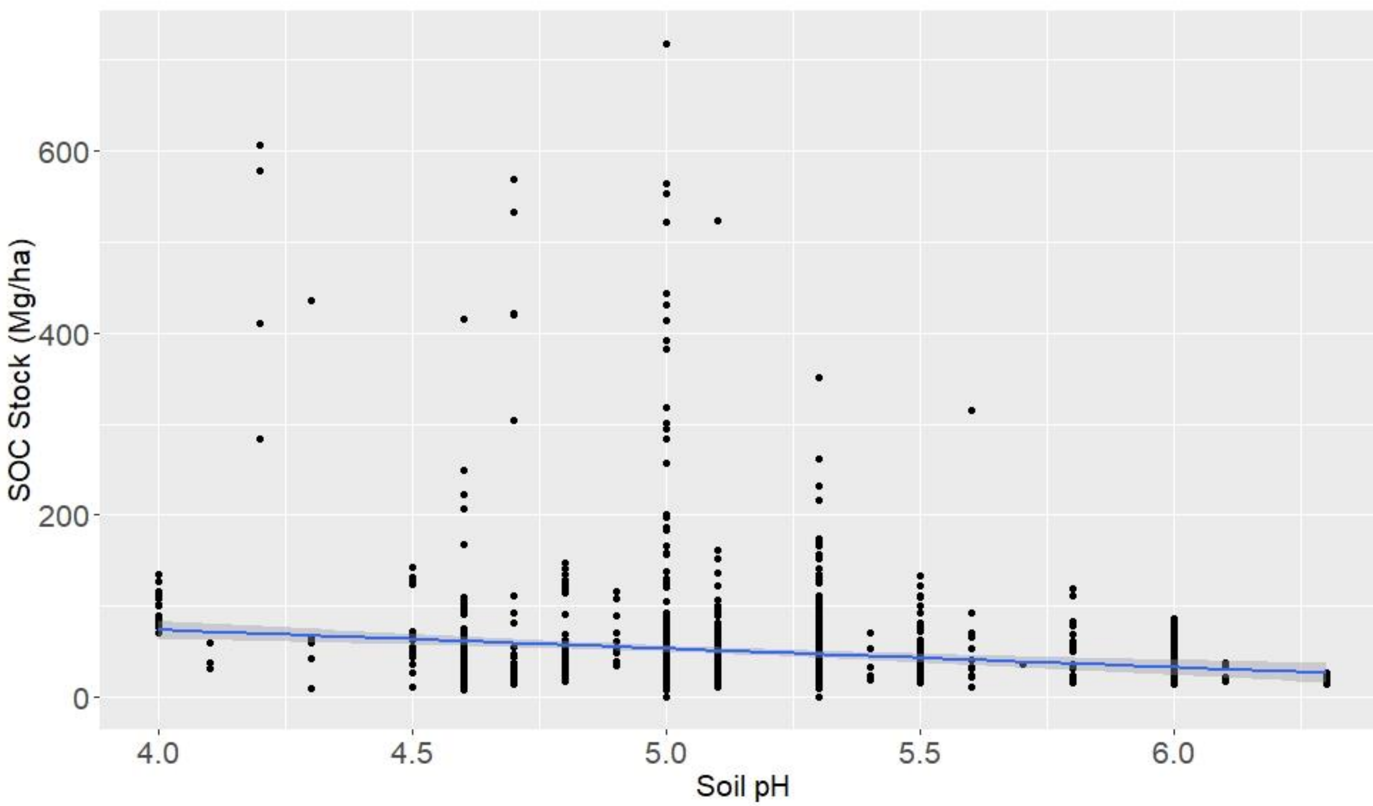

Figure 3.20 Changes in SOC20 stock for changing soil pH across the Southern Coastal Plain. (Blue line shows the linear model between SOC20 stock and soil pH and grey area around it is 95% confidence interval)

CHAPTER 3

PREDICTING SOIL ORGANIC CARBON IN TIME AND SPACE FOR THE SOUTHERN COASTAL PLAIN, UNITED STATES[1]

[1]Sharma, R., Levi, M.R., King, E.G., Thompson A. To be submitted to the Soil Science Society of America Journal.

3.1 Abstract

Increasing atmospheric carbon is attracting the attention of researchers to map terrestrial carbon stocks. Soil organic carbon (SOC) holds one of the largest shares of terrestrial carbon. However, SOC is a dynamic soil property (DSP) and is very susceptible to management changes; SOC is not only important to map in space, but also in time. We developed the DSP-Scale approach to map and monitor SOC in the top 20 cm (SOC 20) for this study. This approach uses concepts from ecological sites and state and transition models to group soils by inherent properties and applies land cover information to represent management as a way to estimate DSPs. We used 1441 SOC point data measurements from the Rapid Carbon Assessment (RaCA), National Cooperative Soil Survey (NCSS) Soil Characterization database, and other local studies to estimate SOC20 stock for four time periods (2001, 2006, 2011, and 2016) in the Southern Coastal Plain. Our random forest model used commonly available climatic, topographic, soil survey, and land cover-based covariables to predict SOC20 in space and time. For training the model, 80% of the total points were used and 20% of the total points were kept for validating the model. Our model explained 68.46% of the variation for training and 55.6% of the variation for the validation data. We estimated total SOC20 stock of 1327.4 Tg and 1305.3 Tg across 24.9 million hectares of the Southern Coastal Plain for 2001 and 2016, respectively. Ultisols with evergreen forests represented 249.9 Tg, which is the largest proportion of the carbon stock, and Histosols classified as abandoned land hold 0.004621 Tg (4621 Mg) in the region. The DSP-Scale approach can be effectively used to predict DSPs in space and time at regional scales. This approach will facilitate monitoring and management of soil health and SOC stocks.

3.2. Introduction

Carbon stocks and fluxes are receiving increasing attention because of rapid increases in CO_2 concentration in the atmosphere (Scharlemann et al., 2014). Soil can be both a sink or a source of carbon depending upon the management and land cover. The combined carbon stocks of the southeastern and south-central United States are estimated to be 16,535 Tg which makes 78% of the total terrestrial carbon pool in the region (Han et al., 2007). Because of the importance of SOC for multiple soils and ecosystem functions, attempts to accurately predict SOC stocks have long been a focus of research activities. Early attempts started with understanding the factors controlling spatial variability of SOC over the region. Studies such as Jenny et al. (1968), Franzmeier et al. (1985), and Kern, (1994) tried to predict the spatial variability of carbon by exploring correlations with climate, topography, and soil factors.

More recent approaches commonly used at regional scales consider a suite of environmental covariables to predict SOC (Adhikari et al., 2014; Aksoy et al., 2016; Taghizadeh-Mehrjardi et al., 2016; Yang et al., 2016; Grinand et al., 2017; Wang et al., 2018; Hamzehpour et al., 2019). Regional-scale models commonly use environmental, climate, topographic, soil types, and land cover-based covariables to represent SOC stocks for various depth slices of the soil and aid in the development of semi-3D continuous depth functions and predictions of temporal changes in SOC (see review by Minasny et al., 2013). There have been numerous studies about the importance of covariables for terrestrial SOC modeling, and prediction accuracies of models vary from region to region. Land cover and land use exert significant control over the SOC stock distribution, which suggests land cover has a significant effect on SOC (Liu et al., 2004). Xiong et al. (2014) studied the effect of land cover changes on SOC accumulation for Florida which also included portions of the Coastal Plain physiographic region. They found significant differences in SOC accumulation in different land cover using a linear model based on land cover, mean annual precipitation, and mean annual temperature. Ross et al. (2020) used a comprehensive random forest-based SOC predicting model for the forest land covers in the southeastern United States including the southern Coastal Plain and adjacent physiographic regions. They used gamma-ray, topographic variables, parent material, land cover, spectral, and soil property-based covariables.

Earlier SOC predicting models were linear or polynomial-based models, but with advances in computer science and statistics, the nature of SOC forcasting has also changed. To predict SOC many studies prepare regression models like Konen et al. (2002) who made linear models for predicting SOC for MLRA's 65, 75, 95B, 103, and 108. Mishra et al. (2009) used ordinary kriging to visualize SOC distribution over the state of Indiana. Advances in artificial intelligence (AI) have brought new machine learning-based SOC predicting models. There are several machine learning-based models, and their efficiency depends on the site conditions and data types. Some commonly used models are k-nearest neighbor, random forest, extreme gradient boosting, support vector machine, and cubist (Kuhn and Johnson, 2013). All of these models and ways to predict SOC have improved spatial prediction of SOC, however now the focus is changing to emphasize temporal variation of SOC stocks (Heuvelink et al., 2020). To map SOC in both space and time, the covariables used for the SOC modeling should be able to capture both spatial and temporal variability of soils, which has not been included in most recent efforts (Grunwald, 2009).

One possible approach for supporting the space-time requirements for mapping dynamic soil properties like SOC is the linkage of ecological concepts with land management and soil properties. Ecological sites (ES) are areas with similar potential to support vegetation and ecosystem functions defined based on the consistency of climate, topography, and soil factors that remain relatively static for long periods of time (Bestelmeyer et al., 2017). Each ES has a complimentary State-and-Transition Model (STM) for the conceptual representation of ecosystem dynamics with a particular focus on vegetative conditions (Bestelmeyer et al., 2009). Vegetative states represent relatively stable conditions in an ES. However, when a state is disturbed by something like a management change or significant environmental driver, it may cross a threshold and transition to a new state. These states and their transition dynamics are recorded in the STM linked to that ES (Wills et al., 2017). The ES framework relies on a many-to-one relationship between soil types and ESs that can be useful for grouping similar soils along with other static covariables that can explain the spatial variability of soils. By utilizing the concepts of STMs associated with the soil groupings in an ES, dynamic covariables such as land cover can be used to explain temporal variability in management for a given area thereby aiding in the prediction of dynamic soil properties (DSPs). DSPs are soil properties that are sensitive to ecosystem changes such as changes in land management and show changes in human time scales (Tugel et al., 2008). SOC is highly responsive to rapid land use and management changes (Worsham et al., 2010; Gebremedhin et al., 2018) and it is also closely tied to other important

DSPs (Ekwue, 1990). Causarano et al. (2008) showed that in the Southern Piedmont and Coastal Plain physiographic regions 41.6% of the variability in SOC could be explained by land management. Levi et al. (2010) found that DSPs were more similar by land management than by soil taxa for sites in the Georgia Coastal Plain. The objective of this chapter was to develop a robust, flexible model to predict SOC in both space and time using available spatial and non-spatial data for the Southern Coastal Plain. An overarching hypothesis was that existing soil information could be combined with a variety of environmental covariates including soil taxonomy to estimate SOC stocks over time using the newly created DSP-Scale model. ES and STM concepts are highly successful for land management in the rangelands of the western United States and their use for land management has now become a national priority(Johanson & Brown, 2012; Salley et al., 2016 b). Developing a tool for assessing soil property differences and potential changes with vegetative states is a critical step for developing ES/STM models for regions like the Southern Coastal Plain.

3.3 Materials and Methods

3.3.1. Study site

The Southern Coastal Plain (MLRA 133A, Fig 3.1) extends from Virginia to Louisiana with a total area of 275,930 km^2. It stretches over 9 states with 26 percent in Alabama, 24 percent in Mississippi, 21 percent in Georgia (USDA and NRCS (2006), Fig. 3.1). The climate of MLRA 133A is hot and humid for most of the year with average annual precipitation of 1000 – 2000 mm (PRISM Climate Group, Oregon State U, Retrieved July 7, 2020). Most of the soils in this region are Ultisols (highly weathered soils) with some Spodosols, Histosols, Entisols (young soils), and Inceptisols (soils with limited horizon development). The area is dominated by forest with 42.5 percent of total area in 2016 with Longleaf Pine (*Pinus palustris*) woodland as the dominant vegetation type (Data | Multi-Resolution Land Characteristics (MRLC) Consortium, Retrieved July 27, 2020). The region also has agricultural importance with about 14 percent of the total area under cropland with major crops grown soybeans, cotton, corn, and wheat. The region is susceptible to soil erosion and low productivity of soils.

3.3.2. Data Description

Point data

The major sources of our point data are the Rapid Carbon Assessment (RaCA) database (referred as RaCA data hereafter) and National Cooperative Soil Survey (NCSS) soil characterization Database (referred as NCSS data hereafter). Other data sources include select studies done in the region, including Levi et al. (2010), Cochran (2010), Ricker & Lockaby (2015), K. Robertson (pers. communication). This made a total of 1441 points with necessary data to calculate SOC stock for the upper 20 cm (SOC20) of the mineral soil surface. All the data sources mentioned above recorded SOC concentrations as percent carbon so bulk density was used to convert SOC percent to SOC20 stock when available. NCSS data lacked some bulk density readings so the bulk density prediction model given by Ramcharan et al. (2017) was used to predict bulk density. SOC20 was extracted using the slab function in the aqp package of R

(Beaudette et al., 2013b) using R version 4.0.5. The depth of 20 cm was intentionally used to maximize the number of points with SOC stock measurements.

Spatial data

A suite of spatial data representing soils, topography, climate, and land cover was collected to develop spatial models of SOC. Soil properties and interpretations were obtained from the Soil Survey Geographic Database (SSURGO) for each state in the study area to get soil taxonomic data including soil Order, Suborder, and Great Group was used (Soil Survey Staff, Natural Resources Conservation Service accessed date 1/31/2020; *USDA:NRCS:Geospatial Data Gateway:Order Data*). Along with soil taxonomy, SSURGO was used to extract soil pH, erosional phase, drainage class, family particle size classes, and hydrologic soil groups (HSG) for map units. “Component” and “chorizon” tables available in the gSSURGO (raster version of SSURGO-grid SSURGO) were used to extract soil taxonomy and soil pH data for point SOC20 measurements.

SSURGO data uses erosion classes to describe the extent of erosion for soil map units. The erosional classes are “none”- the area of soil deposition, “Class 1”- with 1 – 25% of top soil erosion, “Class 2”- with 25 – 75% of top soil erosion, “Class 3”- with 75 – 99% of top soil erosion, and “Class 4”- map units with all of the top soil eroded (SSM - Ch. 2. Landscapes, Geomorphology, and Site Description, Accessed: 2021 – 06 – 24). Drainage classes represent the frequency and duration of wet periods and SSURGO classifies drainage conditions into seven classes (“Excessively Drained”, “Somewhat Excessively Drained”, “Well Drained”, “Moderately

Well Drained", "Somewhat Poorly Drained", "Poorly Drained", "Very Poorly Drained") (Soil Drainage Class, Retrieved June 24, 2021). Points that did not have any erosional class record in the SSURGO data were assigned to a category labeled "unknown" for comparison and analysis.

There are four main HSGs and three additional categories for hydrologic groups that are naturally in group D but have a different rating if they are drained (e.g., A/D) (Part 630 Hydrology National Engineering Handbook et al., 2009). HSG-A has low runoff potential (more than 90% sand and less than 10% clay), HSG-B has moderately low runoff potential (50 – 90% sand and 10 – 20% clay), HSG-C has moderately high runoff potential (less than 50% sand and 20 – 40% clay), HSG-D has high runoff potential (less than 50% sand and more than 40% clay). Additionally, HSG-A/D has high runoff potential unless drained (more than 90% sand and less than 10% clay), HSG-B/D has high runoff potential unless drained (50 – 90% sand and 10 – 20% clay), HSG-C/D has high runoff potential unless drained (less than 50% sand and 20 – 40% clay), HSG-D/D has high runoff potential unless drained (less than 50sand and more than 40% clay).

The most common climatic variables used in SOC20 predictive models are mean annual temperature (MAT) and mean annual precipitation (MAP) (Yang et al., 2016; Han et al., 2020). Mean annual temperature (MAT) and mean annual precipitation (MAP) for the 30 years between 1981 – 2010 were obtained from the Parameter-elevation Regressions on Independent Slope Model (PRISM) dataset with 4km spatial resolution (PRISM Climate Group 2021).

Elevation data was obtained from the USGS National Elevation Dataset (NED) as a 30m raster dataset (*The National Map*, Retrieved June 26, 2021). Slope percentage and aspect were derived from elevation using ArcGIS version 10.7 (ESRI, 2019). The aspect was further converted in a linear aspect also called "Southwestness" where the southwest direction (225°) had a value of 1 and northeast (45°) had a value of -1 using the following equation:

$$\text{Southwestness} = -\left(\cos\left(\text{Aspect}\left(\text{degrees} - 45°\right) * \pi/180\right)\right.$$

Landcover data was obtained from Multi-Resolution Land Characteristics (MRLC) Consortium which is a Landsat-based 30 m database released at 5-year intervals from 2001 to 2016. NLCD 1992 was also used which is also 30 m Landsat-based data provided by MRLC with some differences in legend from NLCD after 2001. To match the NLCD 1992 classification system to NLCD 2001 and so on, Fry, (2008) was referenced which gives a detailed comparison of both classification systems. Landcover was extracted for two years for each point SOC20 data, first when the point was sampled and second land cover 10 years before the point was sampled. This created a pool of points with information about land cover when the point was taken and 10-year earlier land cover history, which was further used to study its effect on SOC20 stock changes.

3.3.3. Covariate Data Extraction and Aggregation

SOC20 point measurements were imported into ArcMap 10.7 and then data from MAP, MAT, Elevation, Slope, and aspect as added to point data by using the "Extract multiple values to point" tool in ArcMap. SSURGO data was extracted by adding "mapunit" key to point data from gSSURGO using the “extract raster values to point” tool and then joining attribute table of point data to “component” table using “mapunit key”. Soil pH was extracted by joining the component and “chorizon” table using the “Component key” available in the “component” table. Then the attribute tables of point files containing all the covariable were exported as excel files for further statistical analysis in R.

3.3.4. Model Design

The overall design of the model was based on ecological site concepts, which account for static spatial environmental, topographical, and soil factors clubbed with dynamic temporal factors that usually involve land management changes.

DSP-Scale Model

The DSP-Scale model is a spatial and temporal scaling framework that links measured values of desired soil properties at point locations to spatial representations of soil-landscape units and land use. It utilizes the structure of existing soil information stored in soil survey and taxonomic classifications to represent similar soils and combines that with the ES and STM concepts (Fig. 3.2). The spatial and temporal resolution of land management, land use, and land cover is captured from the NLCD. The central idea was to quantify the effect of management on DSPs within similar soil groups and use existing point measurements to extrapolate DSPs to a much larger area. Data in the NLCD was used as a proxy for land management (and conceptually vegetative states in an STM) to represent conditions for different periods between 1992 – 2016 to quantify the effect of management changes. Soil groups were established in multiple ways. The preferred method would have been to utilize the ES structure that has a many-to-one relationship (i.e., many soils to one ES) to aggregate inherently similar soils with the same potential to support vegetation. But ESs are in provisional stages for the southeastern United States and are not established for the Southern Coastal Plain. As ES and soil taxonomy are both based on static or inherent soil properties, we used soil taxonomy as an alternative for ESs. We grouped similar soil taxonomic factors to match with the soil factors available in the point data used for developing the DSP-Scale model.

ES concepts explain variability in vegetative states (or land cover) using STMs; however STMs are conceptual models and lack spatial scale. States represented in a given STM have a natural relationship with management and land cover of the area, e.g. states mentioned in Fig. 3.3 can be captured by land cover in the NLCD database. Land cover data of two different decades was used to represent changes in SOC20 in a long period of time due to land cover changes. The prediction of SOC stock would have required a substantial amount of point measurements, but the DSP-Scale model makes it feasible using fewer point measurements by relating SOC concentrations to soil types and land management.

Random forest model

To implement the DSP-Scale model, a random forest model was developed using the random forest package in R version 4.0.5 (Breiman, 2001; R Core Team, 2020). Random forest models are ensemble decision tree-based algorithms that have many benefits over other parametric models (Kuhn and Johnson, 2013). Random training data is chosen, and a specific number of variables (mtry) are chosen to be considered for each tree. The combination of all the predictions done by these trees are used to develop the final predictions. For our study, model tuning involved the adjustment of the number of trees and mtry to optimize performance. A combination of 500 trees and an mtry value of 8 produced the model with the lowest RMSE and we used this as the final model to develop spatial predictions of SOC20 stock. For model development and validation, an 80:20 data split was used, i.e., 80% of data was used to train the model and 20% of data was used for validation. The 80:20 data split was used to maximize number to train model but still keeping enough points for validation of the model, as this is a common approach for this type of modeling (Gomes et al., 2019). To check model performance we used two parameters, the coefficient of determination (R^2), and the second root mean square error (RMSE).

Covariates Used

As explained in section 3.3.2, we used two types of covariables representing static and dynamic predictors to explain SOC20 stock. Static variables such as climatic, topography, and soil taxonomy are relatively constant over century time scales. The inherent soil properties in soil taxonomy capture the spatial variability of multiple soil properties. The second type of covariables used was dynamic (changing in decadal-scale) and were primarily comprised of land cover from the NLCD. These dynamic covariables explain the temporal variability of soils resulting from management. Some soil Suborders and Great Groups were clubbed together to create modified soil Suborder and Great Group categories as all the variability of soils were not represented by the point data used for making models.

Two random forest models were developed from the point SOC20 data. The first model used all the original and modified versions of covariables, the complete model. The second model used only simplified versions of some covariables and left out some of the covariables used in the complete model (such as soil Suborder, soil Great Group) (Table 3.1). Table 3.2 and Table 3.3 shows the grouping process of sub-order and great group classes to form modified soil sub-order and great group classes. The groupings were made to club similar soil features by referring to (USDA, 2014). Climatic covariables (MAT, MAP) and topographic covariables (elevation, slope, linear aspect (Southwestness)), erosion class, drainage class, hydrologic soil groups, soil pH, and mineralogy were used in both models. For soil taxonomy, soil Orders, soil Suborder, modified soil Suborder, soil Great Group, modified soil great group, modified subgroup were used in a complete random forest model. Soil s Suborder and soil Great Group were not used as covariables in the simpler model. For the simpler model, we had two versions, the version with higher R^2 and lower RMSE was used to compute results, discussions, and tabular data in this chapter. However, because of the size of files associated with the model and time limitations, the figures are based on the previous version of the model with a lower R^2. There was not much overall difference between the results of the two versions of the simpler model (tabular results from another version of the model with lower R^2 and higher RMSE are mentioned in Appendix). Final SOC20 predictions were made for 3984042 pixels (250*250 m^2) which represent 24.875 million hectares in the Southern Coastal Plain.

3.4 Results

3.4.1. Model Performance

Both models (Complete and the simpler model) had similar performance, but the simpler model performed slightly better than the complete model with an R^2 of 68.46 and RMSE of 36.71 (Mg ha^{-1}) for the training dataset and an R^2 of 55.60 and RMSE of 45.68 (Mg ha^{-1}) (Table 3.4). For this reason, we used the simpler model to make spatial predictions of SOC for the region. Fig. 3.4 shows the percent increase in mean square error (MSE) (if covariable is permuted) of the 30 most important covariables and specific categories of predictors that were factors that control SOC20. MAP was found to be the most important predictor for the model. Elevation and slope were among the top five predictors that suggest that topography plays an important role in SOC20 distribution for our study area despite the relatively low slope ranges common in the study area (mean slope 3.7% for training data). Land cover factors were also among important SOC20 predictors. If a site was pasture or hay at the time of sampling, it was 7^{th} most important predictor and similarly sites which had deciduous forest 10 years before sampling represented the 11^{th} most important predictor of SOC20 (Fig 3.4). This show that landcover changes have a considerable control over SOC20 changes over time.

3.4.2. SOC20 stock distribution in space and time

Our model predicted similar SOC20 stocks for all four time periods (2001, 2006, 2011, and 2016) ranging from 1310.7 to 1335.2 Tg of carbon for the whole region (Table 3.5). However, there were considerable changes in SOC20 stock between 2001 to 2016 for each pixel

(Fig. 3.5). The predicted SOC20 stock was the largest in 2001 and the lowest in 2011 (slightly less than 2016). Our model predicted a 2% decrease over the 15 years. The total stocks for the years 2001 and 2006 were similar with 4 Tg of SOC20 change. Similarly, SOC20 stocks for 2011 and 2016 were similar to each other with an absolute difference of 0.3 Tg SOC20. The difference was noted in 2006 and 2011 of 20.5 Tg SOC20 i.e., 1.5% decrease in SOC20 stock over the region from 2006 to 2011. The biggest difference was observed in 2001 and 2011 of 24.5 Tg of SOC20.

The spatial variability of SOC20 showed similar patterns for each time period reflecting the stability of total stocks for the region (Fig. 3.5). The SOC20 stock content increased with proximity to the coast which was also observed by Ross et al. (2020). This could be because of changes in the moisture regime from Udic to Aquic as you approach the coast (USDA-NRCS, Retrieved June 28, 2021). The coastal areas also experience more precipitation than areas further inland due to tropical storms and hurricanes. We observed a pattern with higher SOC20 stock in a portion of Tennessee, shown in Fig. 3.6. Ross, (2017) also showed that pattern in the proximity of that area. We couldn’t explain pattern with confidence but it could be related to the proximity of this zone to a neighboring region (Highland Rim and Pennyroyal MLRA that is next to Nashville Basin). SOC20 stock in the portion of Tennessee was relatively stable and the change was less than 10% from 2001 to 2016 (Fig 3.7 and Fig 3.8).

The highest SOC20 stock in the region was predicted for Ultisols, 891.0 Tg SOC20 in 2001 and 873.6 Tg SOC20 in 2016 (Table 3.6). This is likely because Ultisols are the dominant soil Order in the region, however SOC20 stock was most densely packed in Spodosols (i.e a concentration of 389 Mg ha^{-1} over the years compared to 18 Mg ha^{-1} and 20 Mg ha^{-1} for Ultisols, and Entisols respectively). Histosols and Vertisols reported the smallest SOC20 stock of 3.8 Tg and 4.1 Tg for 2016, but both only represent <400,000 hectares in the region (Table 3.6). After Ultisols, Entisols and Inceptisols had the next highest SOC20 stock of 191.1 Tg and 113.0 Tg, respectively for 2016. SOC20 stock in Spodosols was much greater than Alfisols considering the area under both soil orders is 1.3% and 5.2% of total land area. The greatest fluctuation in SOC20 stock over the years was seen in Ultisols with a reduction of 17.4 Tg from 2001 to 2016. Almost no change was found in the SOC20 stock for Histosols or Spodosols.

The highest stock of SOC20 in terms of landuse was evergreen forest (42.5% of the area is forested in the region) with a total of 349.2 Tg in 2016 (Table 3.7). The second highest SOC20 stock was recorded in woody wetlands (20% of total area), 270.8 Tg of SOC20 stock in 2016. The greatest decrease of SOC20 stock over the years was found in pasture/hay with a reduction of 24.2 Tg of SOC20 stock from 2001 to 2016. The SOC20 stock was almost stable for evergreen forests over the years, however there was a decrease of 7.7 Tg SOC20 stock from 2001 to 2016 in deciduous forests and a reduction of 6.9 Tg SOC20 stock for mixed forest types. There was a reduction of 21.5 Tg of SOC20 in the forest ecosystems from 2001 to 2016 in the region. Grasslands and Shrubland gained 16.4 Tg and 3.4 Tg of SOC20 stock from 2001 to 2016. However, overall, our model predicts a loss of 24.2 Tg of SOC 20 from 2001 to 2016.

3.5 Discussion

SOC is a dynamic soil property that changes with land cover and ecosystem disturbances; therefore, regular monitoring is crucial for understanding fluxes from anthropogenic and natural drivers. The DSP-Scale approach uses easily available covariables to predict SOC stocks at a regional scale for different time periods. Most studies predicting SOC in the United States and the Southern Coastal Plain map spatial distributions of SOC for one time period (Guo et al., 2006; Vasques et al., 2010; Ross et al., 2020). The model performance of our simpler model used in this study is on par with the parsimonious model developed by Ross, (2017). DSP-Scale based model predicted 55.6% of the variation for the validation data, however parsimonious model developed by Ross, (2017) explained 52% variation for validation data.

We found a median concentration of 43.4 Mg ha^{-1} for SOC20 for the year 2001 in the Southern Coastal Plain. Guo et al. (2006) found 32.3 Mg ha^{-1} to be the median value for SOC20 stock of organic carbon for the contiguous United States. The Contiguous United States includes drier areas of the United States that have relatively lower organic carbon like rangelands in the western United States i.e., the median value is lower for the contiguous United States. Vasques et al. (2010) predicted SOC stocks for 30 cm for the Florida state by Florida Soil Characterization project data 1965 – 1996 and got 62.6 Mg ha^{-1}. Our predictions for the Southern Coastal Plain in Florida (panhandle area of Florida, Fig 3.1) were 86.2 Mg ha^{-1} for the upper 20 cm. The mean value of SOC stock for 20 cm may be higher in our study than for results of Vasques et al. because our 0 – 20 cm depth increment may have a greater concentration of SOC simply because it was not averaging the 20 – 30 cm increment which could have reduce the average values they presented. Ross et al. (2020) predicted forest land stock to be 1200 Tg in 20 cm between 2012 and 2015 for the southeastern United States. We found a total of 547.2 Tg for 2016 and 551 Tg for 2011 for the forest land cover in the Southern Coastal Plain, but our study area was smaller than that of Ross et al. (2020) who included some parts of adjacent MLRAs as far west as Texas, north to include the Piedmont and east including the Atlantic Coast Flatwoods. Importantly, the Atlantic Coast Flatwoods region is more likely to have soils mapped as Spodosols than the Coastal Plain, which has been shown to hold higher concentrations of SOC. We found the 54.2 Mg ha^{-1} SOC20 stock for the evergreen forest in 2001 for the Southern Coastal Plain, which is lower than 68.14 Mg ha^{-1}, the global average estimated by Jobba´gy and Jackson, (2000) for the temperate evergreen forest. However, the mean SOC20 stock for cropland (47.2 Mg ha^{-1} for 2001) in the Southern Coastal Plain was similar to the global average of 45.92 Mg ha^{-1} estimated by Jobba´gy and Jackson, (2000).

Over the 15 years of our study period (2001 – 2016), we found the total predicted SOC stocks over the region were nearly stable, however the changes at finer scale ranged from -80% to +450% SOC20 stock. There were 944 pixel values in the region that had more than doubled their SOC20 stock values in 15 years. Most of these soils were dominated by Ultisols (836 pixels out of 944 with a more than 100% increase of SOC20). Within these Ultisols the major landcover changes that were responsible for this increase were mainly the change from cultivated land in 2001 to pasture/hay in 2016 (471 pixels, appendix table 4.6). These changes are likely as cultivation maintains lower SOC; while conversion to pasture/hay increased SOC20. However, the second landcover change responsible for the increase in SOC20 stock in Ultisols was the conversion of evergreen forest (2001) to pasture/hay (2016). Usually, forests have higher SOC content than pasture/hay, but the increase reported here could be a result of immediate forest-cutting disturbances.

In terms of spatial trends southern regions of Mississippi, Alabama, and Georgia and the panhandle region of Florida showed the biggest changes in SOC20 over 15 years (Figs. 3.7 and 3.8 highlights areas which went through changes in SOC20 stock from 2001 to 2016). Overall there was a decrease in the SOC20 stock from 2001 to 2016 for most places at the fine-scale. There was an overall decrease of more than 10% SOC20 stock in 15 years for 509,776 pixels (3.18 million hectares or 12.78% of total predicted area) in the region compared to 216,574 pixels (1.35 million hectares or 5.4% of total predicted area) with more than 10% gain of SOC20 stock.

3.6 Conclusions

Regular mapping of SOC stocks is important for monitoring terrestrial carbon dynamics. Measuring DSPs at point locations is labor and time-intensive. Our DSP-Scaling approach facilitates mapping DSPs in space and time with a limited number of point measurements and easily available covariables. Our results indicate that MAP was the most important predictor of SOC and that soil taxonomic groups also explain a considerable amount of SOC variability. The Southern Coastal Plain holds a considerable amount of SOC stocks (> 1300 Tg of C) and regularly undergoes management changes, albeit in relatively small areas. In the 15 years studied, the total SOC stock in the upper 20 cm of mineral soil decreased by 1.7%, primarily driven by changes in land cover. The net carbon stock decreased in forest ecosystems whereas a net increase was observed in grassland/herbaceous land covers from 2001 to 2016. Ultisols hold the largest carbon stock in the region in the upper 20 cm and showed a slight decrease (15.6 Tg) from 2001 to 2016. Regular monitoring of SOC stock is crucial to improve our understanding of carbon fluxes in response to management and to inform the growing interest in carbon trading programs focused on sequestration. With advances in remote sensing and data collection techniques, the DSP-Scale approach will assist policymakers and land managers with decisions related to soil health and SOC stocks overtime at regional scales.

3.7 References

Adhikari, K., A.E. Hartemink, B. Minasny, R. Bou Kheir, M.B. Greve, et al. 2014. Digital mapping of soil organic carbon contents and stocks in Denmark. PLoS One. doi: 10.1371/journal.pone.0105519.

Aksoy, E., Y. Yigini, and L. Montanarella. 2016. Combining soil databases for topsoil organic carbon mapping in Europe. PLoS One. doi: 10.1371/journal.pone.0152098.

Amano, M., R.A. Sedjo, and Resources for the future. 2006. Forest Sequestration – Performance in Selected Countries in the Kyoto Period and the Potential Role of Sequestration in Post-Kyoto Agreements. (May): 65.

Andrew J. Paolucci and Mark H. Stolt. 2018. Assessing Dynamic Soil Properties in Southern New England Forests within an Ecological Site Framework. https://acsess.onlinelibrary.wiley.com/doi/epdf/10.2136/sssaj2018.01.0047 (accessed 20

April 2021).

Austin, M.E. 1965. Land resource regions and major land resource areas of the United States (exclusive of Alaska and Hawaii) /. Washington, D.C. :

Batjes, N.H. 2014. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. doi: 10.1111/ejss.12114_2.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013a. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Beaudette, D.E., P. Roudier, and A.T. O'Geen. 2013b. Algorithms for quantitative pedology: A toolkit for soil scientists. Comput. Geosci. 52: 258–268. doi: 10.1016/j.cageo.2012.10.020.

Bestelmeyer, B.T., A. Ash, J.R. Brown, B. Densambuu, M. Fernández-Giménez, et al. 2017. State and Transition Models: Theory, Applications, and Challenges

Bestelmeyer, B.T., A.J. Tugel, G.L. Peacock, D.G. Robinett, P.L. Shaver, et al. 2009. State-and-transition models for heterogeneous landscapes: A strategy for development and application. Rangel. Ecol. Manag. 62(1): 1–15. doi: 10.2111/08-146.

Bhandari, J., and Y. Zhang. 2019. Effect of altitude and soil properties on biomass and plant richness in the grasslands of Tibet, China, and Manang District, Nepal. Ecosphere 10(11): e02915. doi: 10.1002/ecs2.2915.

Bini, D., C. Alcantara, D. Santos, K. Banhos Do Carmo, N. Kishino, et al. 2013. Effects of land use on soil organic carbon and microbial processes associated with soil health in southern Brazil. doi: 10.1016/j.ejsobi.2012.12.010.

Breiman, L. 2001. Random forests. Mach. Learn. 45(1): 5–32. doi: 10.1023/A:1010933404324.

Caudle, D., J. Dibenedetto, M. Karl, H. Sanchez, and C. Talbot. 2013. Interagency ecological site handbook for rangelands. (January): 109.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008a. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2006.0274.

Causarano, H.J., A.J. Franzluebbers, J.N. Shaw, D.W. Reeves, R.L. Raper, et al. 2008b. Soil Organic Carbon Fractions and Aggregation in the Southern Piedmont and Coastal Plain. Soil Sci. Soc. Am. J. 72(1): 221–230. doi: 10.2136/sssaj2006.0274.

Cochran, J.F. 2010. Management-Dependent Soil Variability and Surface Hydraulic Properties of Southeastern U.S. Coastal Plain Plinthic Kandiudults.

Conant, R.T., J. Six, and K. Paustian. 2004. Land use effects on soil carbon fractions in the southeastern United States. II. Changes in soil carbon fractions along a forest to pasture chronosequence. Biol. Fertil. Soils. doi: 10.1007/s00374-004-0754-2.

Data | Multi-Resolution Land Characteristics (MRLC) Consortium. https://www.mrlc.gov/data?f%5B0%5D=category%3Aland cover (accessed 27 July 2020).

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.

Domke, G.M., C.H. Perry, B.F. Walters, L.E. Nave, C.W. Woodall, et al. 2017. Toward inventory-based estimates of soil organic carbon in forests of the United States.

Ecological site descriptions. https://edit.jornada.nmsu.edu/catalogs/esd (accessed 16 October

2020).

Ekwue, E.I. 1990. Organic-matter effects on soil strength properties. Soil Tillage Res. 16(3): 289–297. doi: 10.1016/0167-1987(90)90102-J.

ESRI. 2019. ArcMap 10.7.

Fox, T.R., E.J. Jokela, and H.L. Allen. 2007. The development of pine plantation silviculture in the Southern United States. J. For. 105(7): 337–347. doi: 10.1093/jof/105.7.337.

Franzmeier, D.P., G.D. Lemme, and R.J. Miles. 1985. Organic Carbon in Soils of North Central United States. Soil Sci. Soc. Am. J. 49(3): 702–708. doi: 10.2136/sssaj1985.03615995004900030035x.

Friedlingstein, P., M.W. Jones, M. O'Sullivan, R.M. Andrew, J. Hauck, et al. 2019. Global carbon budget 2019. Earth Syst. Sci. Data 11(4): 1783–1838. doi: 10.5194/essd-11-1783-2019.

Fry, J.A. et al. 2008. Completion of the National Land Cover Database (NLCD) 1992-2001 Land Cover Change Retrofit Product.

Galik, C.S., B.C. Murray, and D.E. Mercer. 2013. Where is the carbon? carbon sequestration potential from private forestland in the southern United States. J. For. 111(1): 17–25. doi: 10.5849/jof.12-055.

Gao, L., M.A. Bowker, M. Xu, H. Sun, D. Tuo, et al. 2017. Biological soil crusts decrease erodibility by modifying inherent soil properties on the Loess Plateau, China. Soil Biol. Biochem. 105: 49–58. doi: 10.1016/j.soilbio.2016.11.009.

Gebremedhin, H., G. Gebresamual, N. Abadi, M. Hailemariam, K. Teka, et al. 2018. Conversion of communal grazing land into arable land and its impacts on soil properties and vegetation cover. Arid L. Res. Manag. doi: 10.1080/15324982.2017.1406412.

Glanemann, N., S.N. Willner, and A. Levermann. 2020. Paris Climate Agreement passes the cost-benefit test. Nat. Commun. 11(1): 1–11. doi: 10.1038/s41467-019-13961-1.

Gomes, L.C., R.M. Faria, E. de Souza, G.V. Veloso, C.E.G.R. Schaefer, et al. 2019. Modelling and mapping soil organic carbon stocks in Brazil. Geoderma 340: 337–350. doi: 10.1016/J.GEODERMA.2019.01.007.

Grinand, C., G. Le Maire, G. Vieilledent, H. Razakamanarivo, T. Razafimbelo, et al. 2017. Estimating temporal changes in soil carbon stocks at ecoregional scale in Madagascar using remote-sensing. Int. J. Appl. Earth Obs. Geoinf. doi: 10.1016/j.jag.2016.09.002.

Del Grosso, S., W. Parton, T. Stohlgren, D. Zheng, D. Bachelet, et al. 2008. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology 89(8): 2117–2126. doi: 10.1890/07-0850.1.

Grunwald, S. 2009. Multi-criteria characterization of recent digital soil mapping and modeling approaches. Geoderma 152(3–4): 195–207. doi: 10.1016/j.geoderma.2009.06.003.

Guo, Y., R. Amundson, P. Gong, and Q. Yu. 2006. Quantity and Spatial Variability of Soil Carbon in the Conterminous United States. Soil Sci. Soc. Am. J. 70(2): 590–600. doi: 10.2136/sssaj2005.0162.

H. Jenny, A.E. Salem, J.R.W. 1968. Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil Fertility. Pontif. Acad. https://scholar.google.com/scholar_lookup?title=Interplay of soil organic matter and soil fertility with state factors and soil properties. Study Week on Organic Matter and Soil Fertility. Pontif. Acad&publication_year=1968&author=H. Jenny&author=A.E. Sal (accessed 12 June 2021).

Hall, R.M., N. Penke, M. Kriechbaum, S. Kratschmer, V. Jung, et al. 2020. Vegetation management intensity and landscape diversity alter plant species richness, functional traits and community composition across European vineyards. Agric. Syst. 177: 102706. doi: 10.1016/j.agsy.2019.102706.

Hamzehpour, N., H. Shafizadeh-Moghadam, and R. Valavi. 2019. Exploring the driving forces and digital mapping of soil organic carbon using remote sensing and soil texture. Catena. doi: 10.1016/j.catena.2019.104141.

Han, F.X., M.J. Plodinec, Y. Su, D.L. Monts, and Z. Li. 2007. Terrestrial carbon pools in southeast and south-central United States. Clim. Change. doi: 10.1007/s10584-007-9244-5.

Han, L., Z. Wan, Y. Guo, C. Song, S. Jin, et al. 2020. Estimation of soil organic carbon storage in Palustrine Wetlands, China. Int. J. Environ. Res. Public Health 17(13). doi: 10.3390/ijerph17134646.

Heuvelink, G.B.M., M.E. Angelini, L. Poggio, Z. Bai, N.H. Batjes, et al. 2020. Machine learning in space and time for modelling soil organic carbon change. Eur. J. Soil Sci. doi: 10.1111/ejss.12998.

Homer, C., J. Dewitz, S. Jin, G. Xian, C. Costello, et al. 2020. Conterminous United States land cover change patterns 2001–2016 from the 2016 National Land Cover Database. ISPRS J. Photogramm. Remote Sens. 162: 184–199. doi: 10.1016/j.isprsjprs.2020.02.019.

Homer, C., and J. Fry. 2012. The National Land Cover Database. US Geol. Surv. Fact Sheet.

Hoosbeek, M.R., and R.B. Bryant. 1992. Towards the quantitative modeling of pedogenesis-a review.

Hudson, B.D. 1992. The Soil Survey as Paradigm-based Science.

Lutz J.F. 1935. The Relation Of Soil Erosion To Certain Inherent Soil Proper... : Soil Science. https://journals.lww.com/soilsci/Citation/1935/12000/the_Relation_of_Soil_Erosion_To_Certain_Inherent.2.aspx (accessed 19 April 2021).

Jenny, H. 1941. Factors of Soil Formation: A System of Quantitative Pedology. Science (80-.). 349(6250). http://scholar.google.com/scholar_lookup?title=Global+cancer+statistics&author=A.+Jemal&author=F.+Bray&author=M.+M.+Center&author=J.+Ferlay&author=E.+Ward&author=D.+Forman&publication_year=2011%0Ahttps://anthrosource.onlinelibrary.wiley.com/servlet/linkou.

Jobba´gy, Esteban G; Jackson, R.B. 2000. The Vertical Distribution Of Soil Organic Carbon And Its Relation To Climate And Vegetation - Jobbágy - 2000 - Ecological Applications - Wiley Online Library. https://esajournals.onlinelibrary.wiley.com/doi/full/10.1890/1051-0761%282000%29010%5B0423%3ATVDOSO%5D2.0.CO%3B2 (accessed 28 June 2021).

Johanson, J., and J. Brown. 2012. Ecological site development: Accelerating the effort. Rangelands 34(2): 29–31. doi: 10.2111/RANGELANDS-D-11-00068.1.

Johnston, A.E., P.R. Poulton, and K. Coleman. 2009. Chapter 1 Soil Organic Matter. Its Importance in Sustainable Agriculture and Carbon Dioxide Fluxes. Adv. Agron. 101: 1–57.

doi: 10.1016/S0065-2113(08)00801-8.

Kern, J.S. 1994a. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Kern, J.S. 1994b. Spatial Patterns of Soil Organic Carbon in the Contiguous United States. Soil Sci. Soc. Am. J. 58(2): 439–455. doi: 10.2136/sssaj1994.03615995005800020029x.

Konen, M.E., P.M. Jacobs, C.L. Burras, B.J. Talaga, and J.A. Mason. 2002. Equations for Predicting Soil Organic Carbon Using Loss-on-Ignition for North Central U.S. Soils. Soil Sci. Soc. Am. J. 66(6): 1878–1881. doi: 10.2136/sssaj2002.1878.

Kuhn, M., and K. Johnson. 2013. Applied predictive modeling. Springer New York.

Lal, R. 2008. Carbon sequestration. Philos. Trans. R. Soc. B Biol. Sci. 363(1492): 815–830. doi: 10.1098/rstb.2007.2185.

Lal, R., and J.M. Kimble. 2000. Pedogenic carbonates and the global carbon cycle. Global Climate Change And Pedogenic Carbonates

LaRowe, D.E., and P. Van Cappellen. 2011. Degradation of natural organic matter: A thermodynamic analysis. GeCoA 75(8): 2030–2042. doi: 10.1016/J.GCA.2011.01.020.

Levi, M.R. 2007. Management Dependent Soil Properties of Cultivated Versus Non-Cultivated Southeastern Coastal Plain Ecosystems.

Levi, M.R., J.N. Shaw, C.W. Wood, S.M. Hermann, E.A. Carter, et al. 2010. Land Management Effects on Near-Surface Soil Properties of Southeastern U.S. Coastal Plain Kandiudults. Soil Sci. Soc. Am. J. 74(1): 258–271. doi: 10.2136/sssaj2009.0015.

Liebig, J. 1840. Die organische Chemie in ihrer Anwendung auf Agricultur und Physiologie.

Braunschweig,.

Liu, S., T.R. Loveland, and R.M. Kurtz. 2004. Contemporary carbon dynamics in terrestrial ecosystems in the Southeastern Plains of the United States. Environ. Manage. 33(SUPPL. 1): 442–456. doi: 10.1007/s00267-003-9152-z.

Liu, Z., Z. Yao, H. Huang, S. Wu, and G. Liu. 2014. Land use and climate changes and their impacts on runoff in the Yarlung Zangbo river basin, China. L. Degrad. Dev. doi: 10.1002/ldr.1159.

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. Geoderma 117(1–2): 3–52. doi: 10.1016/S0016-7061(03)00223-4.

McMahon, G., S.M. Gregonis, S.W. Waltman, J.M. Omernik, T.D. Thorson, et al. 2001. Developing a spatial framework of common ecological regions for the conterminous United States. Environ. Manage. 28(3): 293–316. doi: 10.1007/s0026702429.

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013a. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013b. Digital Mapping of Soil Carbon. Advances in Agronomy. Academic Press Inc. p. 1–47

Mishra, U., R. Lal, B. Slater, F. Calhoun, D. Liu, et al. 2009. Predicting Soil Organic Carbon Stock Using Profile Depth Distribution Functions and Ordinary Kriging. Soil Sci. Soc. Am. J. 73(2): 614–621. doi: 10.2136/sssaj2007.0410.

Mount, R., N. Carolina, and S. Carolina. 2020. Ecological site F133AY007NC Atlantic Coastal Plain Wet Longleaf Pine Woodland , Wet - PROVISIONAL.

Natural, Resources, Conservation, and Service. 2009. Part 630 Hydrology National Engineering Handbook.

Nave, L.E., E.D. Vance, C.W. Swanston, and P.S. Curtis. 2009. Harvest impacts on soil carbon storage in temperate forests. doi: 10.1016/j.foreco.2009.12.009.

NRCS. SSM - Ch. 2. Landscapes, Geomorphology, and Site Description | NRCS North Carolina. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/nc/soils/?cid=nrcs142p2_054252 (accessed 24 June 2021).

NRCS NSSC KSSL, U. 2014. Kellog Soil Survey Laboratory Methods Manual; Soil Survey Investigations Report No. 42; Version 5.0 (2014).

O'Neill, R. V., A.R. Johnson, and A.W. King. 1989. A hierarchical framework for the analysis of scale. Landsc. Ecol. 3(3–4): 193–205. doi: 10.1007/BF00131538.

Olson, J.S., J.A. Watts, and L.L.A. 1985. Major World Ecosystem Complexes Ranked by Carbon in Live Vegetation: A Database (NDP-017) (2001 version of original 1985 data) (Dataset) | OSTI.GOV. https://www.osti.gov/biblio/1389497 (accessed 24 June 2021).

Olson, K.R., M. Al-Kaisi, R. Lal, and L. Cihacek. 2016. Impact of soil erosion on soil organic carbon stocks. J. Soil Water Conserv. 71(3): 61A-67A. doi: 10.2489/jswc.71.3.61A.

Ontl, T. A. & Schulte, L.A. 2012. Soil Carbon Storage | Learn Science at Scitable. https://www.nature.com/scitable/knowledge/library/soil-carbon-storage-84223790/ (accessed 11 June 2021).

Pachepsky, Y., and R.L. Hill. 2017. Scale and scaling in soils. Geoderma 287: 4–30. doi: 10.1016/j.geoderma.2016.08.017.

PII: S0167-1987(97)00044-5 | Elsevier Enhanced Reader. https://reader.elsevier.com/reader/sd/pii/S0167198797000445?token=BD3D01F7AD56DB80C79A51C2BC0B9CA7D37A7237E9517245EDD279B413F6D531CADB217F8DBAF1AA104A7BD6ADA87C89&originRegion=eu-west-1&originCreation=20210419154615 (accessed 19 April 2021).

Pribyl, D.W. 2010. A critical review of the conventional SOC to SOM conversion factor. Geoderma 156: 75–83. doi: 10.1016/j.geoderma.2010.02.003.

PRISM Climate Group, Oregon State U. https://prism.oregonstate.edu/normals/ (accessed 7 July 2020).

R Core Team. 2020. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ramcharan, A., T. Hengl, D. Beaudette, and S. Wills. 2017. A Soil Bulk Density Pedotransfer Function Based on Machine Learning: A Case Study with the NCSS Soil Characterization Database. Soil Sci. Soc. Am. J. 81(6): 1279–1287. doi: 10.2136/sssaj2016.12.0421.

Rapid Carbon Assessment (RaCA) | Ag Data Commons. https://data.nal.usda.gov/dataset/rapid-carbon-assessment-raca (accessed 5 July 2020).

Rasmussen, C. 2006. Distribution of Soil Organic and Inorganic Carbon Pools by Biome and Soil Taxa in Arizona. Soil Sci. Soc. Am. J. 70(1): 256–265. doi: 10.2136/sssaj2005.0118.

Rasmussen, C., K. Heckman, W.R. Wieder, M. Keiluweit, C.R. Lawrence, et al. 2018. Beyond clay: towards an improved set of variables for predicting soil organic matter content. Biogeochemistry 137(3): 297–306. doi: 10.1007/S10533-018-0424-3.

Ricker, M.C., and B.G. Lockaby. 2015. Soil Organic Carbon Stocks in a Large Eutrophic Floodplain Forest of the Southeastern Atlantic Coastal Plain, USA. Wetlands 35(2): 291–301. doi: 10.1007/s13157-014-0618-y.

Robertson, G.P., K.M. Klingensmith, M.J. Klug, E.A. Paul, J.R. Crum, et al. 1997. SOIL Resources, Microbial Activity, And Primary Production Across An Agricultural Ecosystem.

Ross, C.W. 2017. A Region-Wide Analysis Of Terrestrial Carbon Cycling Across "The Land Of Pines."

Ross, C.W., S. Grunwald, J.G. Vogel, D. Markewitz, E.J. Jokela, et al. 2020. Accounting for two-billion tons of stabilized soil carbon. Sci. Total Environ. 703: 134615. doi: 10.1016/j.scitotenv.2019.134615.

Salley, S.W., H. Curtis Monger, and J.R. Brown. 2016a. Completing the Land Resource Hierarchy. Rangelands 38(6): 313–317. doi: 10.1016/j.rala.2016.10.003.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016b. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Salley, S.W., C.J. Talbot, and J.R. Brown. 2016c. The Natural Resources Conservation Service Land Resource Hierarchy and Ecological Sites. Soil Sci. Soc. Am. J. 80(1): 1–9. doi: 10.2136/sssaj2015.05.0305.

Scharlemann, J.P., E.V. Tanner, R. Hiederer, and V. Kapos. 2014. Carbon Management Global soil carbon: understanding and managing the largest terrestrial carbon pool. doi: 10.4155/cmt.13.77.

Schillaci, C., M. Acutis, L. Lombardo, A. Lipani, M. Fantappiè, et al. 2017. Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: The role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling. Sci. Total Environ. doi: 10.1016/j.scitotenv.2017.05.239.

Sevastas, S., D. Gasparatos, D. Botsis, I. Siarkos, K.I. Diamantaras, et al. 2018. Predicting bulk density using pedotransfer functions for soils in the Upper Anthemountas basin, Greece. Geoderma Reg. 14: e00169. doi: 10.1016/j.GEODRS.2018.e00169.

Singh, M., B. Sarkar, S. Sarkar, J. Churchman, N. Bolan, et al. 2018. Stabilization of Soil Organic Carbon as Influenced by Clay Mineralogy. Advances in Agronomy. Academic Press Inc. p. 33–84

Soil Drainage Class.

Soil Survey Staff, Natural Resources Conservation Service, U.S.D. of A. Soil Survey Geographic (SSURGO) Database.

Spash, C.L. 2010. The brave new world of carbon trading. New Polit. Econ. 15(2): 169–195. doi: 10.1080/13563460903556049.

SSM - Ch. 9. Assessing Dynamic Soil Properties and Soil Change | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/ref/?cid=nrcseprd1343021 (accessed 19 April 2021).

Stringham, T.K., W.C. Krueger, and P.L. Shaver. 2003. State and transition modeling: An ecological process approach. J. Range Manag. doi: 10.2307/4003893.

Taghizadeh-Mehrjardi, R., K. Nabiollahi, and R. Kerry. 2016. Digital mapping of soil organic carbon at multiple depths using different data mining techniques in Baneh region, Iran. Geoderma. doi: 10.1016/j.geoderma.2015.12.003.

Teferi, E., W. Bewket, and B. Simane. 2016. Effects of land use and land cover on selected soil quality indicators in the headwater area of the Blue Nile basin of Ethiopia. Environ. Monit. Assess. doi: 10.1007/s10661-015-5086-1.

The National Map. https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map (accessed 26 June 2021).

Trail, M., A.P. Tsimpidi, P. Liu, K. Tsigaridis, Y. Hu, et al. 2013. Potential impact of land use change on future regional climate in the Southeastern U.S.: Reforestation and crop land conversion. J. Geophys. Res. Atmos. 118(20): 11,577-11,588. doi: 10.1002/2013JD020356.

Tugel, A.J., S.A. Wills, and J.E.H. 2008. Soil change guide: Procedures for soil survey and resource inventory. Version 1. Natl. Soil Surv. Ctr., Lincoln, NE.

Tugel, A.J., J.E. Herrick, J.R. Brown, M.J. Mausbach, W. Puckett, et al. 2005. Soil Change, Soil Survey, and Natural Resources Decision Making. Soil Sci. Soc. Am. J. 69(3): 738–747. doi: 10.2136/sssaj2004.0163.

US EPA, O. 2001. Ecoregion Download Files by State - Region 4. https://www.epa.gov/eco-research/ecoregion-download-files-state-region-4 (accessed 18 August 2020).

USDA-NRCS. Soil Moisture Regimes of the Contiguous United States | NRCS Soils. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/maps/?cid=nrcs142p2_053997 (accessed 28 June 2021).

USDA:NRCS:Geospatial Data Gateway:Order Data.

https://datagateway.nrcs.usda.gov/GDGOrder.aspx (accessed 31 July 2020).

USDA. 2014. Keys to soil taxonomy. Soil Conserv. Serv. 12: 410. doi: 10.1109/TIP.2005.854494.

USDA, and NRCS. 2006. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and the Pacific Basin.

Vasques, G.M., S. Grunwald, and W.G. Harris. 2010. Spectroscopic Models of Soil Organic Carbon in Florida, USA. J. Environ. Qual. 39(3): 923–934. doi: 10.2134/jeq2009.0314.

Walker, J.D., and J. Geissman. 2009. 2009 GSA Geologic Time Scale Evolution of the Teton fault View project Building Stronger Geoscience Department View project. doi: 10.1130/1052-5173-19.4-5.60.

Wang, B., C. Waters, S. Orgill, J. Gray, A. Cowie, et al. 2018. High resolution mapping of soil organic carbon stocks using remote sensing variables in the semi-arid rangelands of eastern Australia. Sci. Total Environ. doi: 10.1016/j.scitotenv.2018.02.204.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic management for rangelands not at equilibrium.

Wickham, H. 2016. ggplot2. Springer International Publishing, Cham.

Wickham, J.D., S. V. Stehman, L. Gass, J. Dewitz, J.A. Fry, et al. 2013. Accuracy assessment of NLCD 2006 land cover and impervious surface. Remote Sens. Environ. 130: 294–304. doi: 10.1016/j.rse.2012.12.001.

Wills, S., C. Williams, C. Seybold, L. Scheffe, Z. Libohova, et al. 2017. Using Soil Survey to Assess and Predict Soil Condition and Change. : 123–135. doi: 10.1007/978-3-319-43394-

3_11.

Worsham, L., D. Markewitz, and N. Nibbelink. 2010. Incorporating Spatial Dependence into Estimates of Soil Carbon Contents under Different Land Covers. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2008.0412.

Xiong, X., S. Grunwald, D.B. Myers, C.W. Ross, W.G. Harris, et al. 2014. Interaction effects of climate and land use/land cover change on soil organic carbon sequestration. Sci. Total Environ. 493: 974–982. doi: 10.1016/j.scitotenv.2014.06.088.

Xue, D., R. Christenson, R. Genger, A. Gevens, and R.A. Lankau. 2018. Soil Microbial Communities Reflect both Inherent Soil Properties and Management Practices in Wisconsin Potato Fields. Am. J. Potato Res. 95(6): 696–708. doi: 10.1007/s12230-018-9677-6.

Yang, R.M., G.L. Zhang, F. Liu, Y.Y. Lu, F. Yang, et al. 2016. Comparison of boosted regression tree and random forest models for mapping topsoil organic carbon concentration in an alpine ecosystem. Ecol. Indic. doi: 10.1016/j.ecolind.2015.08.036.

Zomer, R.J., D.A. Bossio, R. Sommer, and L. V. Verchot. 2017. Global Sequestration Potential of Increased Organic Carbon in Cropland Soils. Sci. Rep. 7(1): 1–8. doi: 10.1038/s41598-017-15794-8.

3.8 Tables

Table 4.1 Covariables used in the random forest model, their abbreviation, data source and scale. (* represents covariables used in the simpler random forest model)

Covariable	Abbreviation	Dataset	Pixel Resolution (m)
Mean Annual Precipitation*	MAP	PRISM climate data	4000
Mean Annual Temperature*	MAT	PRISM climate data	4000
Current Landcover*	Landcover_Current	MRLC NLCD	30
Landcover History (10 years)*	Landcover_10years_prior	MRLC NLCD	30
Erosion Class*	Erosion_Class	gSSURGO	10
Drainage Class*	Drainage_Class	gSSURGO	10
Hydrologic Soil groups*	Hydrologic_Soil_Group	gSSURGO	10
Soil Order*	Soil_Order	gSSURGO	10
Soil Sub Order	Soil_Sub_Order	gSSURGO	10
Modified Soil Sub Order*	Soil_Sub_Order_mod	gSSURGO	10
Soil Great Groups	Soil_Great_Group	gSSURGO	10
Modified Soil Great Groups*	Soil_Great_Group_mod	gSSURGO	10
Modified Sub Groups*	Soil_Sub_Group_mod	gSSURGO	10
Soil Particle Size*	Particle_Size	gSSURGO	10
Soil pH*	Soil_pH	gSSURGO	10
Elevation*	Elevation	NED USGS	30
Slope*	Slope	NED USGS	30
Linear Aspect (Southwestness)*	Linear_Aspect	NED USGS	30
Minerology*	Minerology	gSSURGO	10

Table 4.2 Clubbing soil Suborder classes into some common classes as modified soil Suborder based on their similarity and available training data (USDA, 2014)

Soil Suborder	Modified Soil Suborder
Umbrepts, Udults, Udolls, Uderts, Udepts, Udalfs, Rendolls, Humods, and Arents	Ud
Saprists, and Hemists	Sap
Psamments	Psa
Orthods, Orthents, and Ochrepts	Och
Fluvents	Flu
Aquults, Aquolls, Aquods, Aquerts, Aquepts, Aquents, and Aqualfs	Aqu

Table 4.3 Clubbing soil Suborder classes into some common classes as modified soil Suborder based on their similarity and available training data (USDA, 2014)

Soil Great Group	Modified Great Group
Umbraquults, Rendolls, Eutrudepts, and Eutrochrepts	Umbra
Udipsamments, Quartzipsamments, and Psammaquents	Psamm
Paleudults, Paleudalfs, and Paleaquults	Pal
Kanhapludults, Kanhapludalfs, and Kandiudults	Kan
Medisaprists, Medihemists, and Humaquepts	Humaq
Udorthents, Udarents, Sulfisaprists, Sulfihemists, Sulfaquents, Ochraquults, Ochraqualfs, Natrudalfs, Natraqualfs, Haprendolls, Haplumbrepts, Hapludults, Hapludolls, Hapluderts, Hapludalfs, Haplosaprists, Haplohumods, Haplaquolls, Haplaquods, Haplaquepts, Haplaquents, Dystrusterts, Dystruderts, Dystrudepts, Dystrochrepts, Dystraquerts, Chromuderts, and Alorthods	Hap
Glossudalfs, Glossaqualfs, and Fraglossudalfs	Gloss
Fragiudults, Fragiudalfs, Fragiaquults, and Fragiaqualfs	Fragi
Udifluvents, and Fluvaquents	Fluva
Hydraquents, Epiaquerts, Epiaquepts, Epiaqualfs, Endoaquults, Endoaquods, Endoaquepts, Endoaquents, and Endoaqualfs	Endoa
Albaquults, and Albaqualfs	Albaq
Alaquods	Alaqu

Table 4.4 Model performance

Soil subgroup and soil great group were not used to develop a simpler model instead only modified subgroup and modified great group were used.

	Training data (80%)		Validation data (20%)	
Model	Ad. R^2	RMSE (Mg ha^{-1})	Ad. R^2	RMSE (Mg ha^{-1})
Complete model	68.37	36.76	55.56	45.71
Simpler model	68.46	36.71	55.6	45.68

Table 4.5 Soil Organic Carbon stock for the 0 – 20 cm soil depth (SOC20) for each year and total SOC20 stock for each year. (Tg= Teragrams; Total number of 250*250 m^2 used for stock calculation= 3,984,042; ~ 24.37 million hectares)

	Carbon Stock (Mg ha^{-1})
Year	Total (Tg)
2001	1335
2006	1331
2011	1311
2016	1311

Table 4.6 Soil Organic Carbon for 20 cm of depth (SOC20) stock statistics for soil orders and total SOC20 stock. (Mha= million hectares; Tg= Teragrams; N= sample size of the training data)

Soil suborder	Year	Minimum	Mean	Median	Maximum	SD	N	Total
		Carbon Stock (Mg ha^{-1})						(Terragram)
Alfisols (1.9 Mha)	2001	24	48	41	348	26.3	72	59
	2006	24	48	41	348	26.2		59
	2011	20	47	40	362	26.5		57
	2016	20	46	40	361	26.4		57
Entisols (4.8 Mha)	2001	21	55	48	284	24.3	165	194
	2006	21	55	48	284	24.4		193
	2011	21	54	47	286	25.0		191
	2016	21	54	47	286	24.9		191
Histosols (0.3 Mha)	2001	42	103	84	289	63.9	15	4
	2006	42	103	84	289	63.9		4
	2011	42	103	86	287	63.9		4
	2016	42	103	86	287	63.9		4
Inceptisols (3.6 Mha)	2001	17	67	50	351	52.0	57	115
	2006	17	67	50	351	52.0		115
	2011	17	65	48	350	52.4		113
	2016	17	65	48	349	52.5		113
Spodosols (0.5 Mha)	2001	210	389	391	456	29.5	5	68
	2006	210	389	391	456	29.5		68
	2011	210	389	391	456	29.6		68

	2016	210	389	391	456	29.6		68
Ultisols (25 Mha)	2001	18	49	42	376	24.1	1022	891
	2006	19	49	42	376	24.0		888
	2011	19	48	41	403	24.2		873
	2016	19	48	41	389	24.2		874
Vertisols (0.4 Mha)	2001	25	45	40	112	14.0	5	4
	2006	25	45	40	112	13.9		4
	2011	24	44	39	114	13.3		4
	2016	25	43	39	114	13.3		4

Table 4.7 Soil Organic Carbon for 20 cm of depth (SOC20) stock for landcover classes over different years in the Southern Coastal Plain (Tg= Teragrams) (Blue color is coded to highlight SOC20 stock and red color is coded to highlight area under landcover type for different years).

Land Cover Class	NLCD class code	2001		2006		2011		2016	
		SOC stock (Tg)	Area (Mha)	SOC stock (Tg)	Area (Mha)	SOC stock (Tg)	Area (Mha)	SOC stock (Tg)	Area (Mha)
Urban- Open Spaces	21	52	1.02	53	1.04	53	1.05	53	1.05
Urban-Residential	23	21	0.41	22	0.43	23	0.45	24	0.47
Barren/Abandoned Land	31	1.5	0.03	1.5	0.03	1.5	0.03	1	0.03
Deciduous Forest	41	102	2.32	97	2.21	96	2.11	94	2.07
Evergreen Forest	42	346	6.38	347	6.5	351	6.66	349	6.58
Mixed Forest	43	111	2.46	110	2.45	104	2.40	104	2.4
Shrub/Scrub	52	75	1.44	74	1.34	78	1.39	79	1.40
Grassland/Herbaceous	71	47.5	0.82	61	1.1	61.5	1.11	64	1.19
Pasture/Hay	81	124	1.86	110	1.65	101	1.58	99.5	1.56
Cultivated Crops	82	170	3.6	170	3.6	162	3.57	164	3.6
Woody Wetlands	90	276	4.43	274	4.38	269	4.38	271	4.41

Herbaceous Wetlands	95	8.7	0.14	11.0	0.18	10.2	0.18	8.8	0.15

3.9 Figures

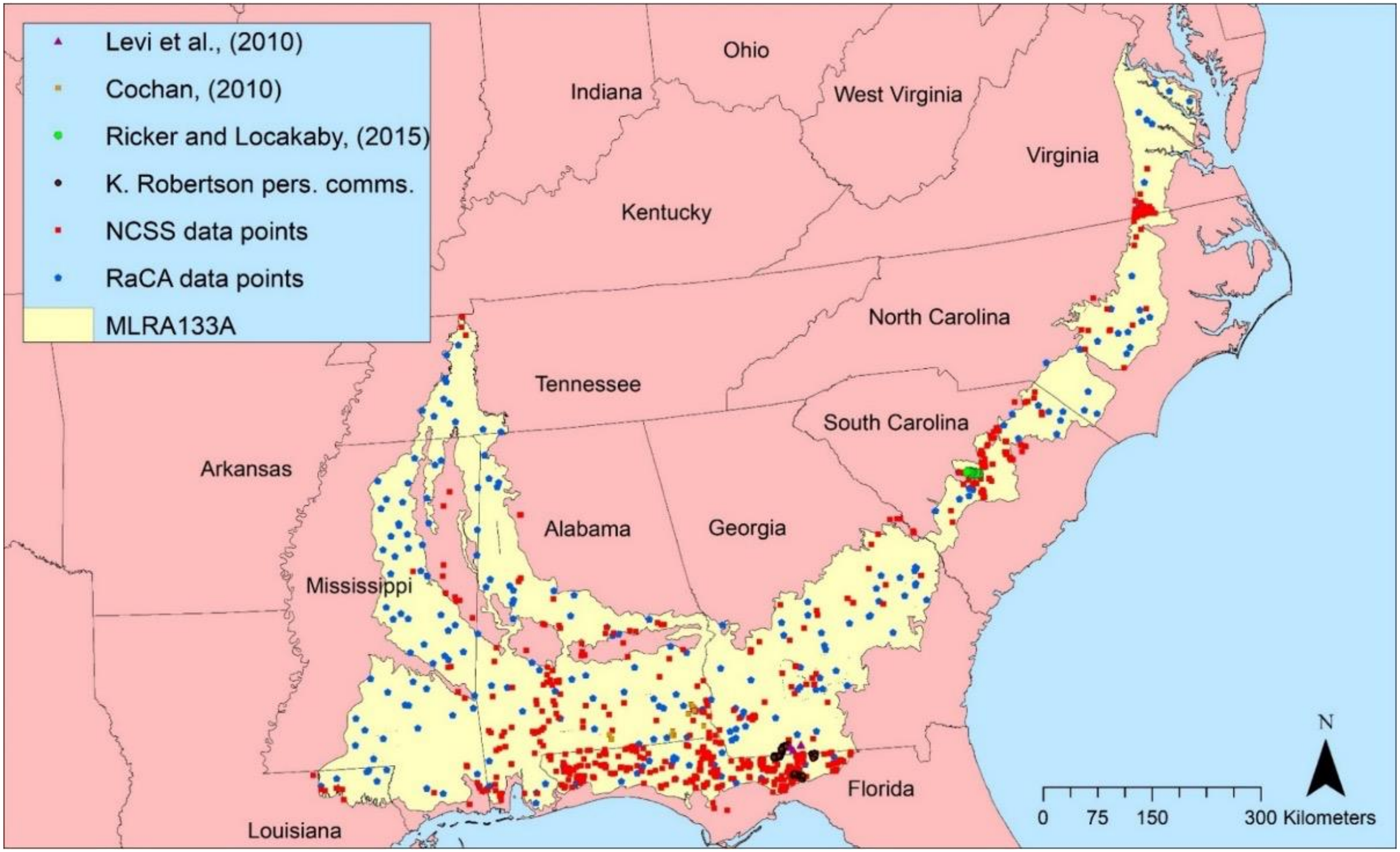

Figure 4.1 Spatial distribution of 1441 point locations in the Southern Coastal Plain (MLRA 133A) with available soil organic carbon measurements from multiple sources.

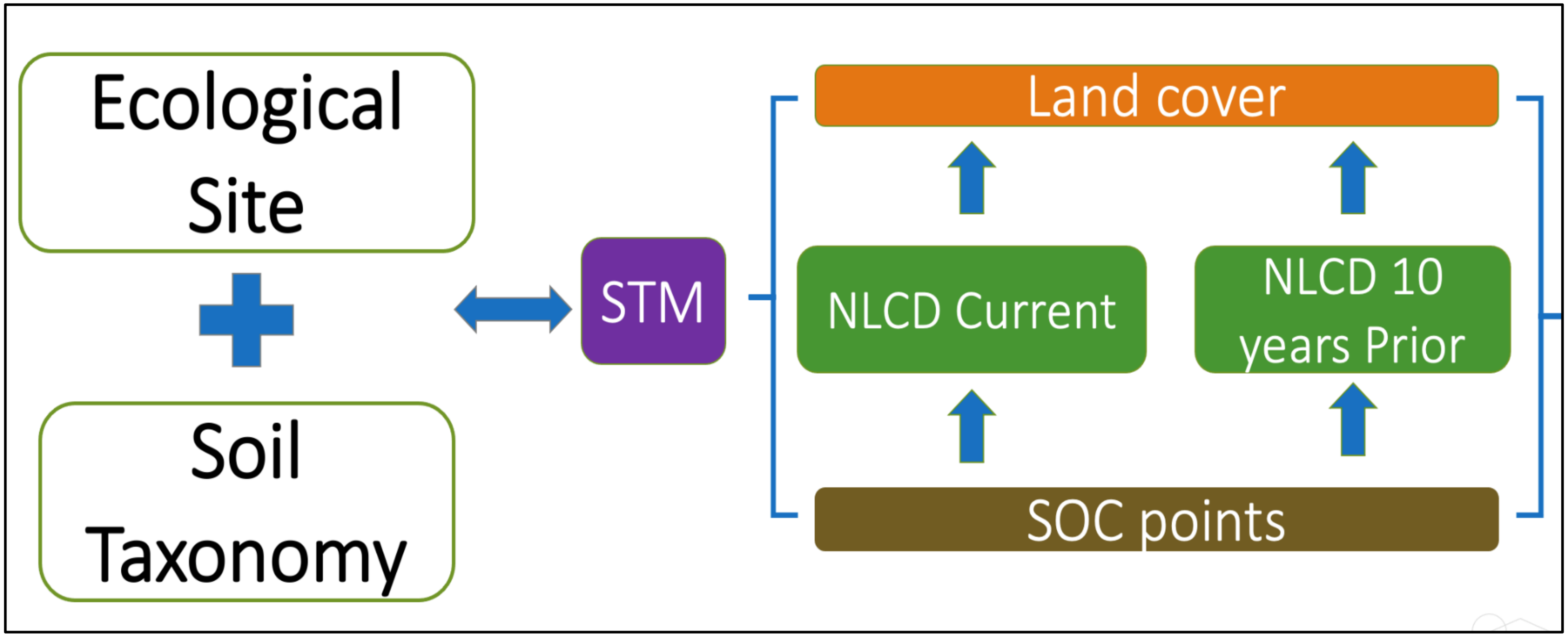

Figure 4.2 Conceptual DSP-Scale approach based on ecological sites and state and transition model.

Spatial variability can be of soil can be explained by a combination of ecological site and soil taxonomy and temporal variability can be explained by landcover changes. A combination of both of these can be utilized to map dynamic soil properties in space and time.

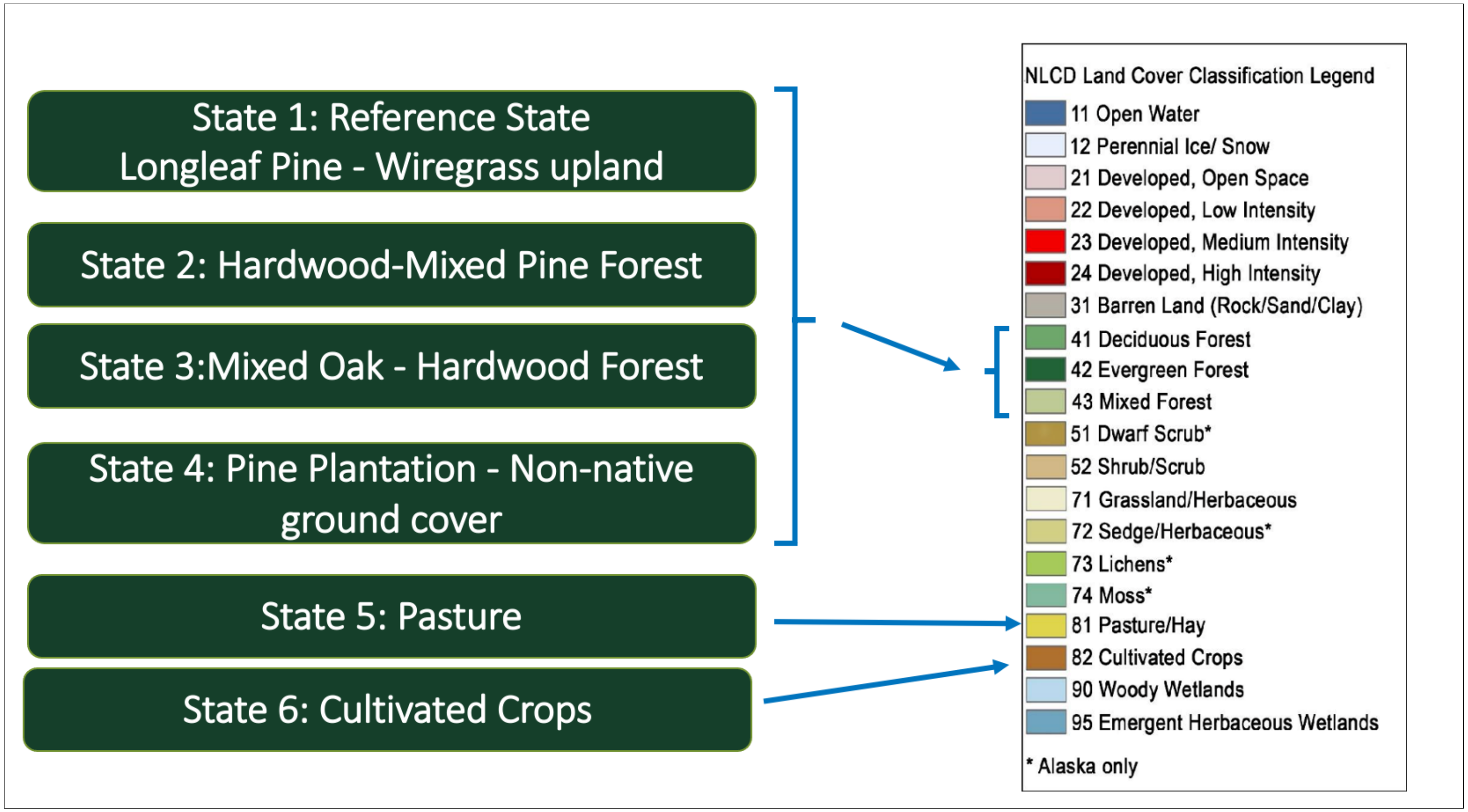

Figure 4.3 Comparison of States in the State and Transition Model for the “Atlantic Coastal Plain Upland Longleaf Pine Woodland Dry” Ecological Site and legend of National land cover database (NLCD) (States are adapted from Mount et al. (2020)).

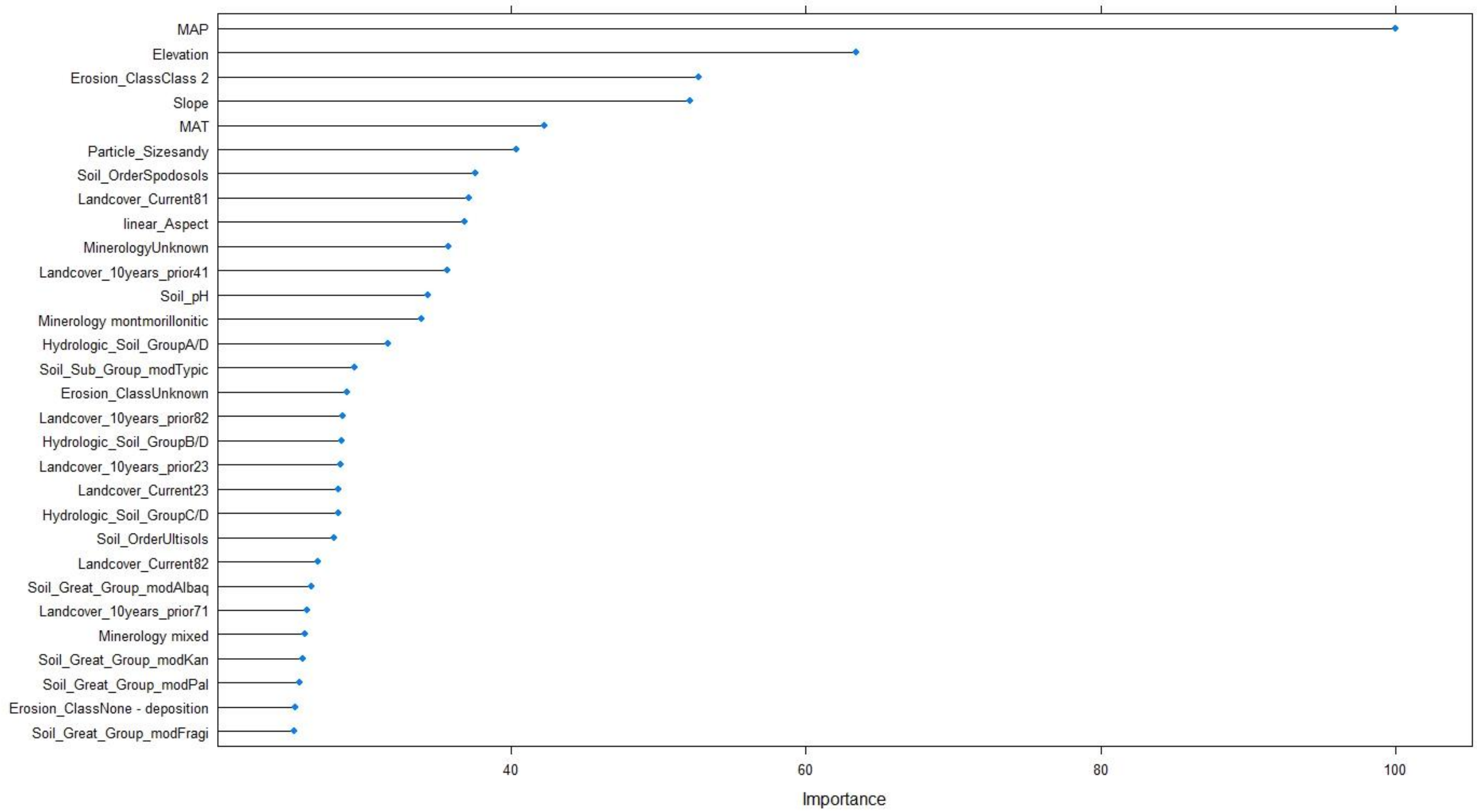

Figure 4.4 Top 30 covariables used in the simpler random forest model ordered by importance. Some factors identify the specific factor level for each variable. Land cover class codes are detailed in Table 3.4.

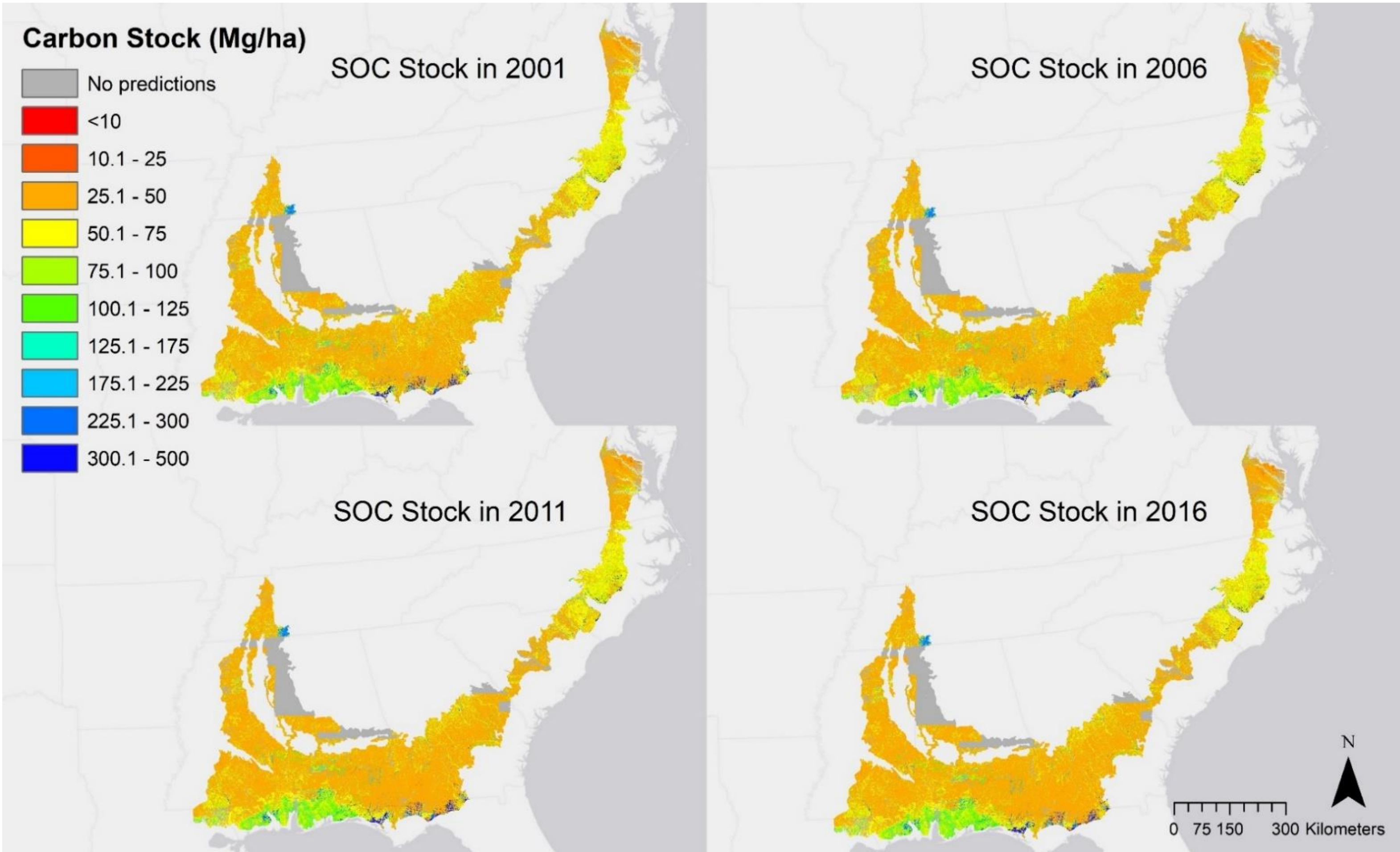

Figure 4.5 Soil carbon stock predictions to 20 cm depth produced using simpler random forest model at 250 x 250 m resolution. Grey areas represent areas with no predictions because of missing data (based on another version of the simpler model with lower R^2 and higher RMSE).

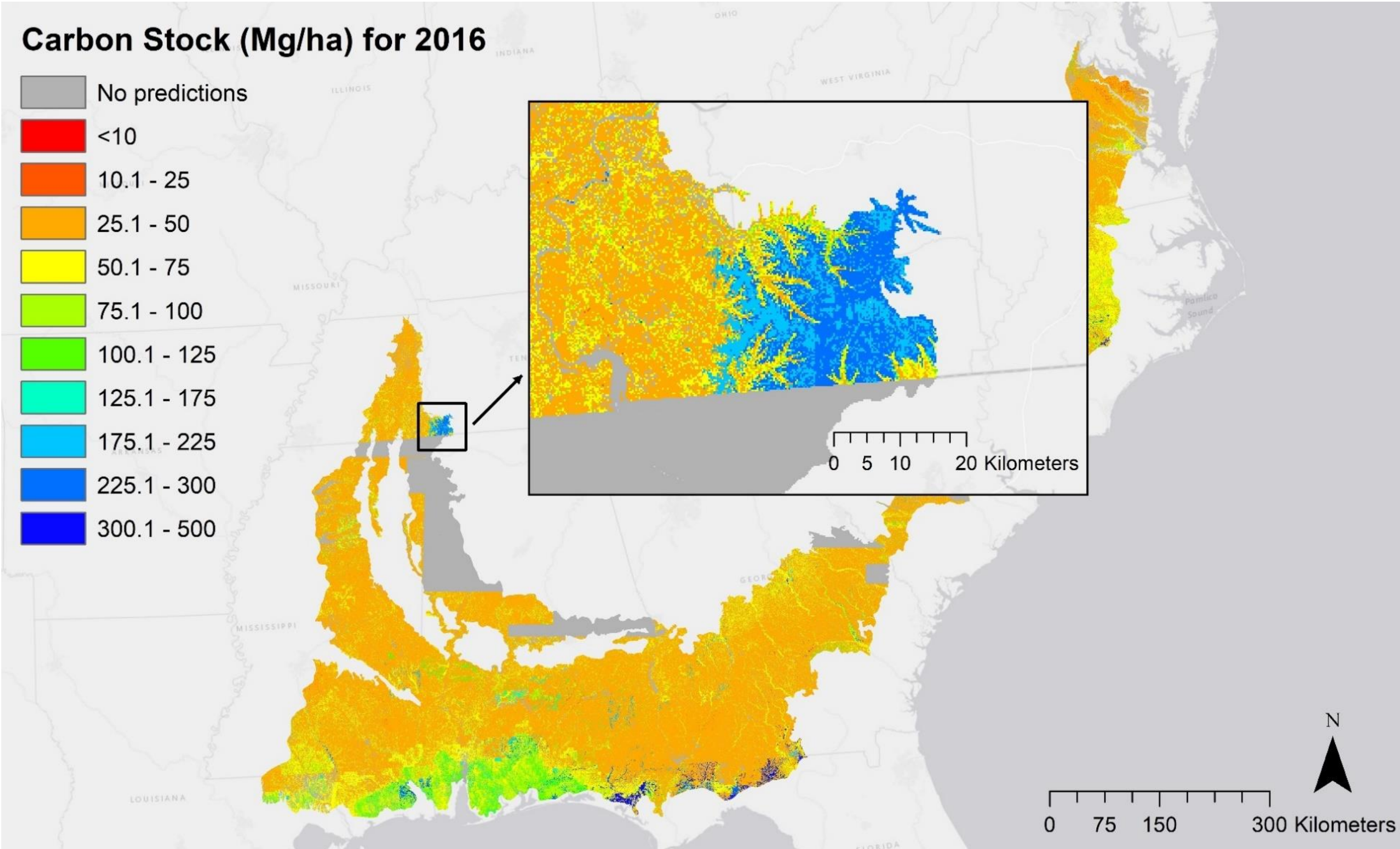

Figure 4.6 Highlighted area of the Southern Coastal Plain with higher SOC20 stock than neighboring areas (based on another version of the simpler model with lower R^2 and higher RMSE).

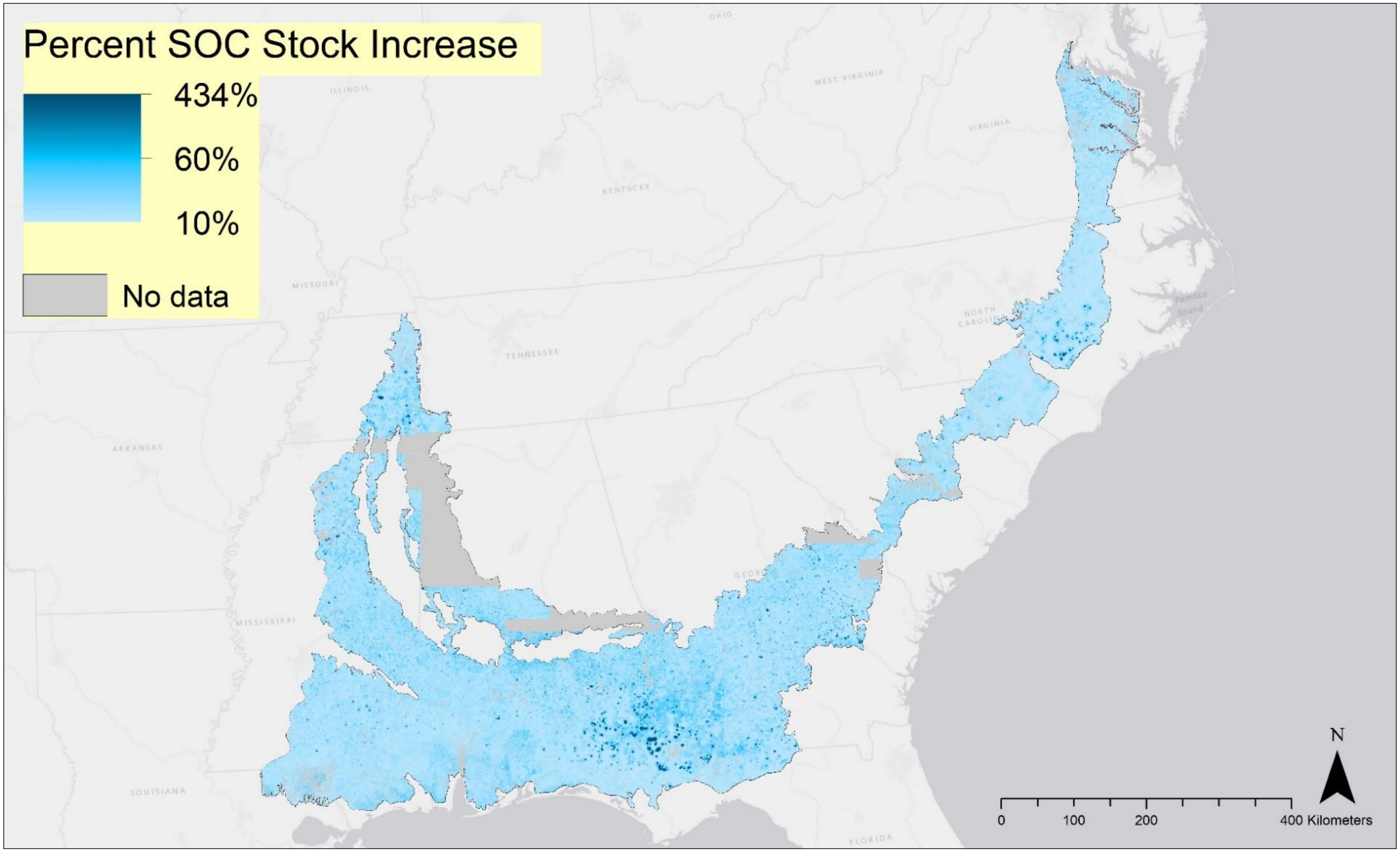

Figure 4.7 Areas highlighted in the Southern Coastal Plain where SOC20 stock increased by more than 10% from 2001 to 2016.

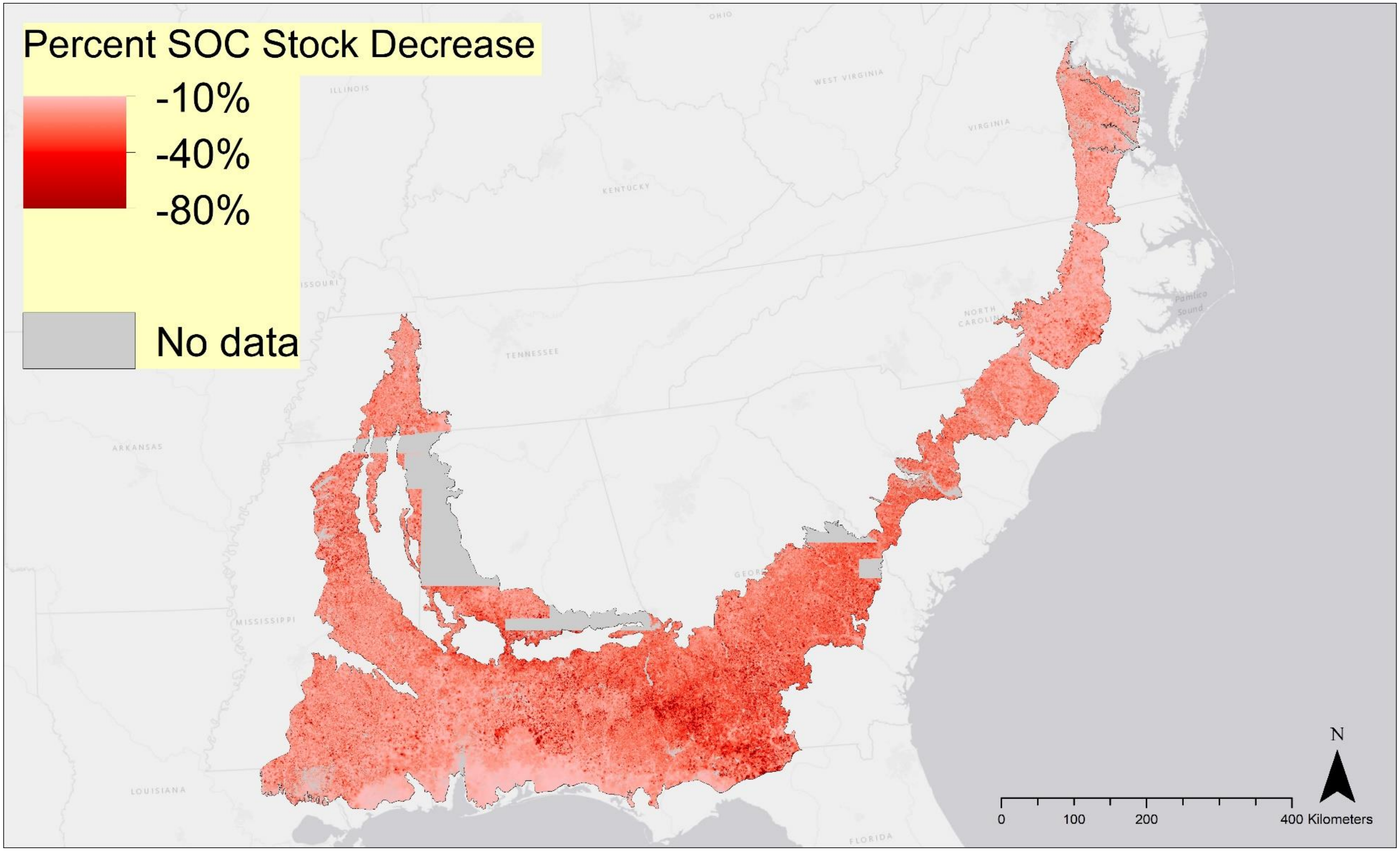

Figure 4.8 Areas highlighted in the Southern Coastal plain where SOC20 stock decreased by more than 10% from 2001 to 2016.

Appendix

Tables from 4.1 to 4.4 tabular shows results from another version of the simpler model with lower R^2 and higher RMSE). Another version of the simpler model was result of changes in the seed value used for developing model. Both models were similar but with different R^2 and RMSE because of difference in the training and testing data.

Table 5.1 Model performance

	Training data (80%)		Validation data (20%)	
Model	Ad. R^2	RMSE (Mg ha^{-1})	Ad. R^2	RMSE (Mg ha^{-1})
Complete model	70.68	34.4	43.96	56.64
Simpler model	70.7	34.35	43.88	56.68

Table 5.2 Soil Organic Carbon for 20 cm of depth (SOC20) stock statistics for each year and total SOC20 stock for each year. (Tg= Teragrams)

Year	Total (Tg)
2001	1327
2006	1322
2011	1304
2016	1305

Table 5.3 Soil Organic Carbon for 20 cm of depth (SOC20) stock statistics for soil orders and total SOC20 stock. (Tg= Teragrams)

Soil suborder	Year	N	Total (Tg)
Alfisols	2001	72	61
	2006		60
	2011		59
	2016		59
Entisols	2001	165	193
	2006		191
	2011		190
	2016		190
Histosols	2001	15	4
	2006		4
	2011		4
	2016		4
Inceptisols	2001	157	117
	2006		116
	2011		115
	2016		115
Spodosols	2001	5	80
	2006		80
	2011		80
	2016		80
Ultisols	2001	1022	869
	2006		866
	2011		852
	2016		854
Vertisols	2001	5	4
	2006		4
	2011		4
	2016		4

Table 5.4 Soil Organic Carbon for 20 cm of depth (SOC20) stock for landcover classes over different years in the Southern Coastal Plain. (Tg= Teragrams)

	Total Carbon Stock (Tg)			
Land Cover Class	2001	2006	2011	2016
Urban- Open Spaces	52	53	53	53
Urban-Residential	21	23	24	25
Barren/Abandoned Land	1.5	1.5	1	1
Deciduous Forest	97	93	91	90
Evergreen Forest	334	335	337	335
Mixed Forest	106	105	99	99
Shrub/Scrub	73	73	78	79
Grassland/Herbaceous	48	60	61	64
Pasture/Hay	133	118	108	107
Cultivated Crops	172	172	167	168

Tables 4.5 and 4.6 show additional data based on the simpler model used in the chapter 3.

Table 5.5 SOC20 stock change due to landcover changes from 2001 to 2016 and area under landcover types in 2016 after landcover change (Land cover classes in 2016 are color separated to assist the visualization of data).

Land Cover in 2001	**Land Cover in 2016**	**SOC stock in 2016 (Tg)**	**Area (Mha)**
Barren/Abandoned Land	Barren/Abandoned Land	1	0.02
Cultivated Crops	Cultivated Crops	158	3.49
Pasture/Hay	Cultivated Crops	3	0.05
Evergreen Forest	Cultivated Crops	1	0.03
Grassland/Herbaceous	Cultivated Crops	1	0.01
Deciduous Forest	Deciduous Forest	89	1.95
Shrub/Scrub	Deciduous Forest	2	0.05
Evergreen Forest	Deciduous Forest	1	0.01
Mixed Forest	Deciduous Forest	1	0.01
Grassland/Herbaceous	Deciduous Forest	1	0.02
Pasture/Hay	Deciduous Forest	1	0.01
Woody Wetlands	Emergent Herbaceous Wetlands	6	0.1
Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	3	0.05
Evergreen Forest	Evergreen Forest	272	5.03
Shrub/Scrub	Evergreen Forest	34	0.7
Grassland/Herbaceous	Evergreen Forest	25	0.46
Pasture/Hay	Evergreen Forest	7	0.15
Mixed Forest	Evergreen Forest	4	0.1
Deciduous Forest	Evergreen Forest	3	0.07
Cultivated Crops	Evergreen Forest	3	0.06
Evergreen Forest	Grassland/Herbaceous	36	0.68
Grassland/Herbaceous	Grassland/Herbaceous	14	0.24
Deciduous Forest	Grassland/Herbaceous	5	0.09
Mixed Forest	Grassland/Herbaceous	5	0.1
Shrub/Scrub	Grassland/Herbaceous	2	0.04
Pasture/Hay	Grassland/Herbaceous	1	0.02
Mixed Forest	Mixed Forest	91	2.11
Shrub/Scrub	Mixed Forest	7	0.17
Deciduous Forest	Mixed Forest	1	0.03
Evergreen Forest	Mixed Forest	1	0.03

Grassland/Herbaceous	Mixed Forest	1	0.03
Pasture/Hay	Mixed Forest	1	0.03
Pasture/Hay	Pasture/Hay	98	1.54
Cultivated Crops	Pasture/Hay	1	0.01
Evergreen Forest	Shrub/Scrub	31	0.57
Shrub/Scrub	Shrub/Scrub	29	0.45
Deciduous Forest	Shrub/Scrub	8	0.15
Mixed Forest	Shrub/Scrub	6	0.14
Grassland/Herbaceous	Shrub/Scrub	3	0.04
Pasture/Hay	Shrub/Scrub	2	0.03
Urban-Open Spaces	Urban-Open Spaces	50	1.01
Evergreen Forest	Urban-Open Spaces	1	0.01
Cultivated Crops	Urban-Open Spaces	1	0.01
Urban-Residential	Urban-Residential	21	0.41
Urban-Open Spaces	Urban-Residential	1	0.01
Evergreen Forest	Urban-Residential	1	0.01
Cultivated Crops	Urban-Residential	1	0.01
Woody Wetlands	Woody Wetlands	265	4.32
Emergent Herbaceous Wetlands	Woody Wetlands	6	0.09

Table 5.6 SOC20 stock change due to landcover changes from 2001 to 2016 separated by soil Order and area under landcover types in 2016 after landcover change separated by soil Order (Land cover classes in 2016 are color separated to assist the visualization of data).

Soil Order	**Land Cover 2001**	**Land Cover 2016**	**SOC stock (Tg)**	**Area (hectares)**
Alfisols	Pasture/Hay	Cultivated Crops	2	4563
	Cultivated Crops	Cultivated Crops	26	69231
	Deciduous Forest	Deciduous Forest	64	153206
	Shrub/Scrub	Deciduous Forest	2	5788
	Grassland/Herbaceous	Deciduous Forest	1	1225
	Pasture/Hay	Deciduous Forest	1	2344
	Woody Wetlands	Emergent Herbaceous Wetlands	2	3450
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	1	3169
	Deciduous Forest	Evergreen Forest	2	5038
	Evergreen Forest	Evergreen Forest	115	233050
	Mixed Forest	Evergreen Forest	2	5481
	Shrub/Scrub	Evergreen Forest	17	36163
	Grassland/Herbaceous	Evergreen Forest	9	19406
	Pasture/Hay	Evergreen Forest	5	12925
	Deciduous Forest	Grassland/Herbaceous	4	6656
	Evergreen Forest	Grassland/Herbaceous	12	23263
	Mixed Forest	Grassland/Herbaceous	3	5750
	Shrub/Scrub	Grassland/Herbaceous	1	1838
	Grassland/Herbaceous	Grassland/Herbaceous	3	5850
	Pasture/Hay	Grassland/Herbaceous	1	1519
	Deciduous Forest	Mixed Forest	1	2194
	Evergreen Forest	Mixed Forest	1	2181
	Mixed Forest	Mixed Forest	64	159013
	Shrub/Scrub	Mixed Forest	6	15050
	Grassland/Herbaceous	Mixed Forest	1	1763
	Pasture/Hay	Mixed Forest	2	3881
	Pasture/Hay	Pasture/Hay	96	159888
	Deciduous Forest	Shrub/Scrub	5	10925
	Evergreen Forest	Shrub/Scrub	12	26025
	Mixed Forest	Shrub/Scrub	4	8325
	Shrub/Scrub	Shrub/Scrub	5	10613
	Grassland/Herbaceous	Shrub/Scrub	1	1056
	Pasture/Hay	Shrub/Scrub	1	2113
	Urban-Open Spaces	Urban-Open Spaces	20	50394

Alfisols	Urban-Residential	Urban-Residential	6	15969
	Woody Wetlands	Woody Wetlands	68	138588
	Emergent Herbaceous Wetlands	Woody Wetlands	2	3463
Entisols	Barren/Abandoned Land	Barren/Abandoned Land	3	4713
	Evergreen Forest	Cultivated Crops	1	1844
	Shrub/Scrub	Cultivated Crops	2	2081
	Grassland/Herbaceous	Cultivated Crops	2	2256
	Pasture/Hay	Cultivated Crops	3	5463
	Cultivated Crops	Cultivated Crops	125	189381
	Deciduous Forest	Deciduous Forest	87	193956
	Evergreen Forest	Deciduous Forest	1	1556
	Mixed Forest	Deciduous Forest	1	2150
	Shrub/Scrub	Deciduous Forest	3	8425
	Grassland/Herbaceous	Deciduous Forest	2	2913
	Pasture/Hay	Deciduous Forest	1	2600
	Woody Wetlands	Emergent Herbaceous Wetlands	10	18363
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	8	12950
	Deciduous Forest	Evergreen Forest	6	13619
	Evergreen Forest	Evergreen Forest	346	626075
	Mixed Forest	Evergreen Forest	7	16756
	Shrub/Scrub	Evergreen Forest	89	219531
	Grassland/Herbaceous	Evergreen Forest	32	59019
	Pasture/Hay	Evergreen Forest	8	18550
	Cultivated Crops	Evergreen Forest	3	3956
	Deciduous Forest	Grassland/Herbaceous	7	14463
	Evergreen Forest	Grassland/Herbaceous	44	78200
	Mixed Forest	Grassland/Herbaceous	7	15881
	Shrub/Scrub	Grassland/Herbaceous	4	6825
	Grassland/Herbaceous	Grassland/Herbaceous	27	38388
	Pasture/Hay	Grassland/Herbaceous	1	2906
	Cultivated Crops	Grassland/Herbaceous	1	725
	Deciduous Forest	Mixed Forest	2	5444
	Evergreen Forest	Mixed Forest	2	4944
	Mixed Forest	Mixed Forest	167	398044
	Shrub/Scrub	Mixed Forest	13	34925
	Grassland/Herbaceous	Mixed Forest	2	4544
	Pasture/Hay	Mixed Forest	2	5350
	Pasture/Hay	Pasture/Hay	119	190013

Entisols	Cultivated Crops	Pasture/Hay	1	844
	Deciduous Forest	Shrub/Scrub	13	26575
	Evergreen Forest	Shrub/Scrub	41	73400
	Mixed Forest	Shrub/Scrub	11	24550
	Shrub/Scrub	Shrub/Scrub	67	87563
	Grassland/Herbaceous	Shrub/Scrub	8	9319
	Pasture/Hay	Shrub/Scrub	2	3944
	Cultivated Crops	Shrub/Scrub	1	925
	Urban-Open Spaces	Urban-Open Spaces	64	111363
	Evergreen Forest	Urban-Open Spaces	1	1006
	Cultivated Crops	Urban-Open Spaces	1	763
	Urban-Open Spaces	Urban-Residential	1	1175
	Urban-Residential	Urban-Residential	23	37025
	Evergreen Forest	Urban-Residential	1	1081
	Cultivated Crops	Urban-Residential	1	913
	Woody Wetlands	Woody Wetlands	525	900613
	Emergent Herbaceous Wetlands	Woody Wetlands	10	17238
Histosols	Cultivated Crops	Cultivated Crops	2	1700
	Woody Wetlands	Emergent Herbaceous Wetlands	1	538
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	2	3556
	Evergreen Forest	Evergreen Forest	2	1813
	Mixed Forest	Mixed Forest	1	819
	Woody Wetlands	Woody Wetlands	29	26731
	Emergent Herbaceous Wetlands	Woody Wetlands	1	650
Inceptisols	Barren/Abandoned Land	Barren/Abandoned Land	1	881
	Pasture/Hay	Cultivated Crops	1	2188
	Cultivated Crops	Cultivated Crops	44	80744
	Deciduous Forest	Deciduous Forest	52	76775
	Shrub/Scrub	Deciduous Forest	2	2956
	Grassland/Herbaceous	Deciduous Forest	1	881
	Pasture/Hay	Deciduous Forest	1	1238
	Woody Wetlands	Emergent Herbaceous Wetlands	12	20144
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	5	7619
	Deciduous Forest	Evergreen Forest	2	3306
	Evergreen Forest	Evergreen Forest	120	156069
	Mixed Forest	Evergreen Forest	2	4169

Inceptisols	Shrub/Scrub	Evergreen Forest	10	16525
	Grassland/Herbaceous	Evergreen Forest	8	10463
	Pasture/Hay	Evergreen Forest	3	7119
	Deciduous Forest	Grassland/Herbaceous	2	4163
	Evergreen Forest	Grassland/Herbaceous	8	12219
	Mixed Forest	Grassland/Herbaceous	2	3794
	Shrub/Scrub	Grassland/Herbaceous	1	825
	Grassland/Herbaceous	Grassland/Herbaceous	3	3925
	Pasture/Hay	Grassland/Herbaceous	1	1069
	Deciduous Forest	Mixed Forest	1	1475
	Evergreen Forest	Mixed Forest	1	1356
	Mixed Forest	Mixed Forest	50	118719
	Shrub/Scrub	Mixed Forest	3	7963
	Pasture/Hay	Mixed Forest	1	2794
	Pasture/Hay	Pasture/Hay	72	99663
	Deciduous Forest	Shrub/Scrub	4	7106
	Evergreen Forest	Shrub/Scrub	9	12881
	Mixed Forest	Shrub/Scrub	3	5669
	Shrub/Scrub	Shrub/Scrub	7	9144
	Grassland/Herbaceous	Shrub/Scrub	1	613
	Pasture/Hay	Shrub/Scrub	1	1175
	Urban-Open Spaces	Urban-Open Spaces	17	29781
	Urban-Residential	Urban-Residential	5	8650
	Woody Wetlands	Woody Wetlands	663	978869
	Emergent Herbaceous Wetlands	Woody Wetlands	11	17231
Spodosols	Evergreen Forest	Cultivated Crops	1	138
	Shrub/Scrub	Cultivated Crops	1	144
	Grassland/Herbaceous	Cultivated Crops	1	156
	Cultivated Crops	Cultivated Crops	25	6875
	Deciduous Forest	Deciduous Forest	2	413
	Woody Wetlands	Emergent Herbaceous Wetlands	7	1831
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	3	781
	Evergreen Forest	Evergreen Forest	162	40981
	Mixed Forest	Evergreen Forest	1	250
	Shrub/Scrub	Evergreen Forest	12	3100
	Grassland/Herbaceous	Evergreen Forest	17	4394
	Cultivated Crops	Evergreen Forest	1	150
	Evergreen Forest	Grassland/Herbaceous	25	6288

Spodosols	Mixed Forest	Grassland/Herbaceous	1	175
	Shrub/Scrub	Grassland/Herbaceous	2	513
	Grassland/Herbaceous	Grassland/Herbaceous	9	2213
	Mixed Forest	Mixed Forest	10	2438
	Pasture/Hay	Pasture/Hay	6	1513
	Evergreen Forest	Shrub/Scrub	17	4200
	Shrub/Scrub	Shrub/Scrub	23	5806
	Grassland/Herbaceous	Shrub/Scrub	5	1150
	Urban-Open Spaces	Urban-Open Spaces	25	6388
	Urban-Residential	Urban-Residential	7	1844
	Evergreen Forest	Urban-Residential	1	156
	Woody Wetlands	Urban-Residential	1	194
	Woody Wetlands	Woody Wetlands	305	78831
	Emergent Herbaceous Wetlands	Woody Wetlands	10	2506
Ultisols	Barren/Abandoned Land	Barren/Abandoned Land	9	16381
	Deciduous Forest	Cultivated Crops	3	5650
	Evergreen Forest	Cultivated Crops	12	25975
	Mixed Forest	Cultivated Crops	1	2800
	Shrub/Scrub	Cultivated Crops	3	6150
	Grassland/Herbaceous	Cultivated Crops	4	9475
	Pasture/Hay	Cultivated Crops	19	42544
	Cultivated Crops	Cultivated Crops	1357	3136900
	Deciduous Forest	Deciduous Forest	679	1521050
	Evergreen Forest	Deciduous Forest	6	11313
	Mixed Forest	Deciduous Forest	4	8944
	Shrub/Scrub	Deciduous Forest	16	33344
	Grassland/Herbaceous	Deciduous Forest	9	18700
	Pasture/Hay	Deciduous Forest	3	6531
	Woody Wetlands	Emergent Herbaceous Wetlands	25	54206
	Emergent Herbaceous Wetlands	Emergent Herbaceous Wetlands	9	20281
	Deciduous Forest	Evergreen Forest	24	51838
	Evergreen Forest	Evergreen Forest	1966	3949969
	Mixed Forest	Evergreen Forest	31	69531
	Shrub/Scrub	Evergreen Forest	213	424200
	Grassland/Herbaceous	Evergreen Forest	187	367038
	Pasture/Hay	Evergreen Forest	53	108069
	Cultivated Crops	Evergreen Forest	25	57338

Ultisols	Emergent Herbaceous Wetlands	Evergreen Forest	1	1206
	Deciduous Forest	Grassland/Herbaceous	40	66313
	Evergreen Forest	Grassland/Herbaceous	266	560819
	Mixed Forest	Grassland/Herbaceous	34	69788
	Shrub/Scrub	Grassland/Herbaceous	16	30950
	Grassland/Herbaceous	Grassland/Herbaceous	102	193375
	Pasture/Hay	Grassland/Herbaceous	9	16250
	Cultivated Crops	Grassland/Herbaceous	2	4719
	Deciduous Forest	Mixed Forest	8	17394
	Evergreen Forest	Mixed Forest	10	21356
	Mixed Forest	Mixed Forest	614	1421825
	Shrub/Scrub	Mixed Forest	50	112700
	Grassland/Herbaceous	Mixed Forest	10	22356
	Pasture/Hay	Mixed Forest	9	18831
	Evergreen Forest	Pasture/Hay	2	3013
	Shrub/Scrub	Pasture/Hay	1	744
	Pasture/Hay	Pasture/Hay	680	1075113
	Cultivated Crops	Pasture/Hay	9	12606
	Deciduous Forest	Shrub/Scrub	53	102363
	Evergreen Forest	Shrub/Scrub	228	453906
	Mixed Forest	Shrub/Scrub	43	96781
	Shrub/Scrub	Shrub/Scrub	184	338569
	Grassland/Herbaceous	Shrub/Scrub	21	31650
	Pasture/Hay	Shrub/Scrub	14	26413
	Cultivated Crops	Shrub/Scrub	3	6531
	Urban-Open Spaces	Urban-Open Spaces	378	809788
	Deciduous Forest	Urban-Open Spaces	2	3425
	Evergreen Forest	Urban-Open Spaces	4	6900
	Mixed Forest	Urban-Open Spaces	1	2106
	Shrub/Scrub	Urban-Open Spaces	1	2100
	Grassland/Herbaceous	Urban-Open Spaces	1	2531
	Pasture/Hay	Urban-Open Spaces	3	5363
	Cultivated Crops	Urban-Open Spaces	5	9788
	Woody Wetlands	Urban-Open Spaces	1	1906
	Urban-Open Spaces	Urban-Residential	4	8950
	Urban-Residential	Urban-Residential	166	343531
	Deciduous Forest	Urban-Residential	2	4863
	Evergreen Forest	Urban-Residential	5	8531
	Mixed Forest	Urban-Residential	1	2219

	Shrub/Scrub	Urban-Residential	1	2325
	Grassland/Herbaceous	Urban-Residential	2	3563
	Pasture/Hay	Urban-Residential	3	5100
	Cultivated Crops	Urban-Residential	6	12656
	Woody Wetlands	Urban-Residential	1	1606
	Woody Wetlands	Woody Wetlands	1055	2180869
	Emergent Herbaceous Wetlands	Woody Wetlands	23	46331
Vertisols	Deciduous Forest	Deciduous Forest	4	8906
	Evergreen Forest	Evergreen Forest	7	19694
	Shrub/Scrub	Evergreen Forest	1	3644
	Grassland/Herbaceous	Evergreen Forest	1	1850
	Evergreen Forest	Grassland/Herbaceous	1	1906
	Mixed Forest	Mixed Forest	5	11800
	Pasture/Hay	Pasture/Hay	7	11438
	Deciduous Forest	Shrub/Scrub	1	1594
	Evergreen Forest	Shrub/Scrub	1	2900
	Urban-Open Spaces	Urban-Open Spaces	1	1569
	Woody Wetlands	Woody Wetlands	8	16856