CHARACTERIZATION OF SALTMARSH SOILS USING REMOTE SENSING AND MACHINE LEARNING ALGORITHM

By

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ABSTRACT

Saltmarshes are capable of providing plants and animals with the biologically desirable environment while sequestering heavy metals. Saltmarshes, which have the highest value of net primary productivity among terrestrial and wetland ecosystems, are adversely impacted and threatened by sea-level rise and anthropogenic activity. Any serious investigation of the prevention or restoration practice of saltmarshes would be strengthened by well-established baselines characterizing vegetation, soil, and water in these coastal areas. In this study, field and laboratory tests were conducted for soil and porewater samples at saltmarsh sites in coastal Georgia (USA). A random forest (RF) model identified correlation among saltmarsh predominant vegetation types, redox potential, and salinity. This model confirmed that moisture content and sand content are two main drivers for the bulk density of saltmarsh soils, which directly affect plant growth and likely root development.

Remote sensing has been widely used as a reliable technique to characterize soils from field to space and has been shown to be an effective approach to model soil properties at a broad scale. This dissertation presents machine learning algorithms such as RF and extreme gradient boosting machines (XGBoost) as well as super vector machines (SVM) and their application to model soil bulk density at saltmarsh sites along Georgia's Atlantic coast, USA. For this study, Landsat-7 Enhanced Thematic Mapper Plus (ETM+) bands (excluding band6) were used as independent variables, and band 1 and band 4 were ranked as the most important attribute for bulk density prediction by XGBoost and RF, respectively. The results reveal that XGBoost algorithm has a higher accuracy (=0.88) than RF and SVM. Further, this study concludes that XGBoost requires less processing time in comparison with SVM in terms of the number of the tuning hyperparameters. SVM is insensitive to enlarging the dataset but XGBoost shows an increase in validation score as the dataset becomes larger.

INDEX WORDS: Saltmarsh, Bulk Density, Hydric Soil, Moisture Content, Halophyte, Remote Sensing, Heavy Metals, Random Forest, XGBoost, SVM

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

Doctor of Philosophy

ATHENS, GEORGIA

2020

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December 2020

DEDICATION

This dissertation is dedicated to my parents, Mandegar and Gholamhossein Salehihikouei, for their love, encouragement, understanding, and support. Thank you for everything.

ACKNOWLEDGEMENTS

There are countless people who have helped me in the course of completing this dissertation, but there are certain people without whom I could not have done this. I would like to thank Sonny Kim for being a great advisor, giving me the opportunity to do the type of research I wanted to do, helping me to become a better researcher than I thought I could be, and for giving me the opportunity to be his grad student for the last three years; Jason Christian for serving on my committee, being an incredible help in the field, and for his great support throughout my PhD program; Lori Sutter for serving on my committee, allowing me to use her laboratory for my research, being a great support and help throughout my graduate career, and for her guidance; Stephan Durham for serving on my committee and always being willing to answer my questions and provide guidance; Bill Tollner for serving on my committee and his assistance with my research; Jidong Yang for his help and time, teaching me machine learning analysis and allowing me to have an office in his laboratory; Mi Geum Chorzepa, for her support and guidance in UGA STRENGTH laboratory, being a great teacher; and Katy House for her help in the field and laboratory. I thank the Georgia Department of Transportation (GDOT) for providing financial support for part of this research. Thank you to all GDOT personnel and staff who helped make the data accessible and possible for this research. Of course, I have to thank my family and friends. My parents, Mandegar and Gholamhossein Salehihikouei fostered and encouraged my interest in science for as long as I can remember, always finding the time and resources when I was young to take me on trips into the natural world. Specifically, I would like to thank my beautiful siblings for all of the support they have given me throughout my life. Further, I would like to thank Margaret Sapp, Sajad Lari Darabi, and Mohammad Najafi. Thank you all, as well as anyone I may have left out, for your help along this journey.

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CHAPTER 1. INTRODUCTION

This chapter presents the background information, objectives, significance, and methodology employed in this study.

1.1. Background

Saltmarsh loss is a nationwide and worldwide concern (Adam, P. 2002). Saltmarshes are highly productive habitats which provide human and aquatic ecosystems with a large number of services including stabilization of coastlines (King, S. E. et al. 1995), provision of refuge habitat translating to enhanced fisheries (Boesch, D. F. et al. 1984), filters for nutrient loads from upland and coastal sources (Deegan, L. A. et al. 2012), and a major carbon sink (Laffoley, D. et al. 2009). Saltmarsh loss results in a drastic change in coastal and estuarine functions (Pethick, J. 1994) and adversely affects global cycles (Silliman, B. R. et al. 2009).

Construction, reconstruction, and maintenance of transportation infrastructure cause disturbances in saltmarshes by altering storm-water runoff patterns (Cintrón-Molero, G. et al. 1992, Callaway, J. C. et al. 2004), increasing soil bulk density (Ballantine, K. et al. 2012), and changing hydrology (Huff, T. P. et al. 2017). Utilizing heavy equipment, staging construction materials, and constructing access/egress roads in these environmentally sensitive areas alter surface elevation (Rogers, K. et al. 2006) and surface soil properties including bulk density (Bradley, P. et al. 1990, Christian, J. et al. 2020), redox potential (DeLaune, R. et al. 1983), alkalinity (Portnoy, J. W. et al. 1997), soil water content (Rogel, J. A. et al. 2000), and hydraulic conductivity (Tempest, J. A. et al. 2015), all of which affect vegetation health and result in altered ecological functionality in the impacted areas (Roman, C. T. et al. 1984, Ballantine, K. et al. 2012). Construction activity and accumulation of vegetation wrack (i.e., large stems and leaves overlaying the area for long enough time to kill the plants) are considered as possible causes of vegetative loss in Georgia saltmarshes (Edwards, J. et al. 1977, Alber, M. et al. 2008). Construction causes changes in soil properties and consequently expedites vegetation loss process in saltmarsh environments (Anastasiou, C. J. et al. 2003, Ogburn, M. B. et al. 2006, Crawford, J. T. et al. 2015).Therefore, the potential connections between soil properties and native vegetation health are necessary to be identified prior to construction disturbances.

A key part of a restoration practice is to re-establish native vegetation in impacted saltmarshes (Warren, R. S. et al. 2002). In order to create the highest likelihood for successful vegetation re-establishment, the structure and the composition of the underlying hydric soil should be returned to the baseline once post construction restoration practice is carried out (Fearnley, S. 2008, Berkowitz, J. F. et al. 2018). Establishing the baseline based on reliable knowledge base prevents significant alteration of the saltmarsh hydrologic and ecological functionality if sites are restored to the pre-existing conditions (or better) after construction activity (Broome, S. W. et al. 1988, Adam, P. 2019).

1.2. Problem statement

With rapid urban development and population increase for more than two decades, extensive tracts of saltmarshes around the world have been drained and disturbed for construction (i.e. port, road and bridge construction, dam building and channel or culvert construction) (Allison, S. K. 1995, Bass, A. S. et al. 1997, Streever, B. 1999). Hydric soil disturbances like drainage, ditches and compaction due to construction activity increase redox potential and salinity (Linthurst, R. A. et al. 1980), accelerate organic matter decomposition rate (Portnoy, J. et al. 1997), increase bulk density (Ballantine, K. et al. 2012), alter carbon and nitrogen distribution pattern (Casselman, M. E. et al. 1981, Bartlett, K. B. et al. 1987), and release heavy metals into aquatic systems (Bai, J. et al. 2019). To improve the efficacy of restoration efforts in impacted saltmarshes, it is necessary to characterize the underlaying soil in terms of chemical and physical properties.

Point-collection methods for determining soil properties at a large saltmarsh site do not yield results that accurately reflect the soil structure and function of the entire area because saltmarshes have a dynamic nature and high spatial variability in soil, vegetation, hydrological pattern (Silvestri, S. et al. 2003, Mulder, V. et al. 2011). Further, traditional soil analyses are based on procedures requiring in-situ sampling and subsequent laboratory processing (Anderson, K. et al. 2009). Field sampling requires a considerable amount of time and effort and may not be cost-effective for a long-term monitoring practice of a large study area (Anderson, K. et al. 2009). To detect biological and ecological disturbances in saltmarshes, it is necessary to take a serious action for carrying out long-term monitoring of the health and the resiliency of such environmentally sensitive areas in terms of soil, water and vegetation.

1.3. Research Objectives

The primary objective of this study is to characterize vegetation, soil, and water of undisturbed saltmarshes located adjacent to construction sites. Construction development is considered as the second-most important threat (after sea-level rise) to coastal marshes (Stedman, S.-M. et al. 2008), and a well-organized knowledge base including the original conditions of these endangered saltmarshes helps restoration scientists have successful post-construction restoration practices. Saltmarsh restoration aims to return an altered marsh or former marsh to its previously existing naturally functioning state and requires intentional preparation, execution, and management to be consistently successful. Utilizing soil mixtures having important properties and conditions prior to disturbances is an integral part of successful restoration and vegetation re-establishment. In this study, we designed and created engineered soil mixtures which mimic saltmarsh soil conditions in terms of particle size distributions, moisture content, and organic matter prior to disturbances. Furthermore, this study is intended to assist restoration scientists in establishing and implementing monitoring protocols to evaluate restoration practices performed in these saltmarshes. The results from this study were used to develop statistical models in order to determine the soil bulk density and pore water redox potential of Georgia's coastal marshes. Machine learning algorithms were used to govern the most important soil parameters influencing bulk density, redox potential, and vegetation zonation, and to determine the most important soil components responsible for retaining heavy metals such as arsenic (As), cadmium (Cd), chromium (Cr), copper (Cu), lead (Pb) and zinc (Zn) in marsh soil substrate.

In addition, remote sensing techniques and machine learning algorithms are utilized to model soil bulk density of saltmarshes located in Georgia's coast. This study evaluates the efficacy of remote sensing as a fast, effortless, and cost-effective approach in characterizing soil properties in saltmarsh environments. Therefore, the current study not only shows the strength and reliability of remote sensing in an investigation of saltmarsh soil parameters at a large scale, but also recommends the most efficient and accurate machine learning algorithm for characterizing soil properties with consideration of the dynamic nature of saltmarsh environments.

1.4. Research Significance and Scope

The primary benefit of this study is to guide engineers to conduct a successful restoration practice in disturbed tidal saltmarshes. Knowing the relationship between halophytes and soil parameters optimizes restoration designs and provides target species with ideal growth conditions. Further, findings from this study are beneficial for monitoring saltmarshes and detecting the changes in soil condition due to both anthropogenic and naturogenic disturbances. In addition, the outputs of this study were utilized in the creation of a draft standard construction specification (appendix A) for consideration by GDOT, detailing the means, methods, and materials for use in re-establishing native saltmarsh soil and vegetation at sites disturbed by construction activity.

This study focuses on application of remote sensing and machine learning algorithms including K-means, super vector machine (SVM), random forest (RF) and extreme gradient boosting (XGBoost) in modeling soil attributes.

1.5. Organization of the Dissertation

This dissertation is divided into seven chapters that describe soil properties importance in saltmarsh health and productivity, which include:

Chapter 1 presents a general background on saltmarsh importance and health. Additionally, research objectives and significance are described.

Chapter 2 describes and summarizes the previous studies on saltmarsh importance and degradation, soil properties, vegetation communities, porewater properties and heavy metals.

Chapter 3 presents data acquisition and includes study sites, experimental design, sampling, sample preparation and test methods.

Chapter 4 outlines a preliminary data analyses conducted to determine soil and porewater properties and vegetation community structure. Furthermore, this chapter includes the analyses governing the relationship between soil properties and vegetation as well as assessing the ecological risk of the heavy metals.

Chapter 5 focuses on machine learning applications in modeling soil bulk density, porewater redox potential and saltmarsh vegetation type. Additionally, this chapter evaluates machine learning algorithms such as RF and XGBoost in determining the most important binding agents responsible for retaining the heavy metals in saltmarsh soil substrate.

Chapter 6 presents remote sensing classification of saltmarsh soil in terms of bulk density through using satellite imagery and machine learning algorithms such as K-means, RF, XGBoost and SVM. Moreover, this chapter compares and evaluates the machine learning algorithms and offers the most accurate algorithm for classifying saltmarsh soil bulk density.

Chapter 7 presents conclusions and recommendations for future studies.

CHAPTER 2. LITERATURE REVIEW

2.1. Overview

In the current study, case histories and research studies regarding saltmarshes both nationwide and worldwide are discussed. Special attention is given to the following:

- Saltmarsh importance and degradation,
- Need for a well-organized knowledge base for successful restoration practice of disturbed saltmarshes,
- Vegetation community,
- Soil properties,
- Interstitial water properties,
- Heavy metals in saltmarshes.

2.2. Saltmarsh Importance and Degradation

Coastal saltmarshes are ecologically sensitive and vital habitats that connect the mainland and the marine environments and provide habitat for a large amount of plants and animals (APPENDIX B, Part 3), embracing many substantial biodiversity resource species (Belluco, E. et al. 2006). Saltmarshes enhance the quality of water, maintain the health of estuaries, and act as a buffer through filtering sediments, nutrients, and other dissolved and particulate constituents in runoff (Deegan, L. A. et al. 2012, Corcoran, J. M. et al. 2013). Saltmarshes, productive ecosystem and powerful carbon sink in the world, are able to sequester millions of tons of carbon in their hydric soils (Macreadie, P. I. et al. 2013). In coastal tidal marshes, carbon is sequestered in the leaves, stems, and roots of the vegetation which is ultimately buried and assimilated into soil (Macreadie,

P. I. et al. 2013). As reported, saltmarshes have a higher rate of carbon sequestration than any other ecosystems in the world, although this rate varies within each saltmarsh (Mcleod, E. et al. 2011). Carbon is released by respiration or soil disturbances like excavation, dredging, or hurricanes (Davidson, E. A. et al. 2006). Saltmarshes are negatively impacted by severe actions of destruction and exploitation (Zhang, M. et al. 1997). These environmentally and ecologically sensitive ecosystems are disturbed through coastal development and sea-level rise (Mishra, D. R. 2014).

Both anthropogenic and naturogenic disturbances cause irreversible alterations in the conditions of saltmarsh communities over time (Bertness, M. D. et al. 2002, Goudkamp, K. et al. 2006). For example, anthropogenic factors like alterations in soil structure (soil compaction) or hydrological patterns (APPENDIX B, Part 3) exert major pressures on saltmarsh ecosystems and habitats (Mayer, A. L. et al. 2011). It is reported that fifty percent of the natural saltmarshes of the United States has been lost due to coastal development and sea-level rise (Kennish, M. J. 2001). Fifty seven percent of saltmarshes along the Gulf Coast of the US has been transformed to open water (Dahl, T. E. et al. 1991). Construction and accumulation of vegetation wrack (APPENDIX B, Part 3) are possible causes of vegetative loss in Georgia's saltmarshes (Edwards, J. et al. 1977, Alber, M. et al. 2008). Coastal development and construction of artificial levees in Georgia U.S. resulted in saltmarsh loss around of 4,047 ha (10,000 ac) (Kundell, J. E. et al. 1988). Although such developments are controlled by related federal and local agencies, they are serious threats to coastal regions. Section 404 of the 1972 Federal Water Pollution Control Act controls dredge and fill activities which impact waters and saltmarshes of the United States (Hough, P. et al. 2009).

In Georgia (U.S.), the Coastal Marshlands and Protection Act (CMPA) of 1970 prohibits any alteration of saltmarsh without a permit (O.C.G.A. 12-5-286)(Mitchler, J. N. 2012). This permit considers the public interests as below (Mitchler, J. N. 2012):

- "whether or not unreasonably harmful obstruction to or alteration of the natural flow of navigational water with the disturbed saltmarsh will arise as a result of the proposal",
- "whether or not unreasonably harmful or increased erosion, shoaling of channels, or stagnant areas will be built",
- "whether or not the accepting of a permit and the completion of the applicant's proposal will unreasonably interfere with the maintaining marine life, wildlife, or other resources, including but not limited to water and oxygen supply (O.C.G.A. 12-5-286)".

But Georgia Department of Transportation (GDOT) has two exemptions to the permit requirements of the CMPA as below (Mitchler, J. N. 2012):

- "Activities of the GDOT for constructing, repairing, and maintaining public road infrastructure in Georgia",
- "Activities of the GDOT and its contractors for the maintenance of the existing drainage infrastructures as long as such activities do not disturb more saltmarshes (O.C.G.A. 12-5-295)".

Georgia Department of Transportation's regulatory requirements related to construction activities in saltmarshes (i.e., Supplemental Specifications, Construction of Transportation Systems, 2016 Edition) are generally found throughout section 107 (Legal Regulations and Responsibility to the Public) and in subsection 107.23.E (Environmental Considerations – Temporary Work in Wetlands Outside of the Construction Limits within the Right-of-Way and Easement Areas). Pursuant to these regulations, guidance for soil stabilization in saltmarshes is provided, including the utilization of construction mats and provisions for matted and compressed soils to be backfilled to the pre-existing elevation with a granular material and covered by excelsior or straw. However, Specification 107.23.E does not explicitly require documentation or restoration of preconstruction soil properties, which inevitably leads to alterations in predominant vegetation and long-term changes in ecosystem functionality. This study presents a draft standard construction specification (appendix A) for consideration by GDOT, detailing the means, methods, and materials for use in re-establishing native saltmarsh soil and vegetation at sites disturbed by construction activity. Furthermore, to detect biological and ecological alterations in saltmarshes, it is necessary to establish a reliable protocol for long-term monitoring of the health and the resiliency of such environmentally sensitive areas (Konisky, R. A. et al. 2006, Dale, P. E. 2008).

2.3. Soil Properties

2.3.1. Soil organic matter

Soil organic matter is a contributing factor for saltmarsh soil bulk density and saltmarsh surface vertical accretion (Nyman, J. A. et al. 1993, Nyman, J. A. et al. 2006). Soil organic matter is a function of vegetation biosynthesis and primary productivity (Loomis, M. J. et al. 2010, Luna, E. et al. 2019). For example, unvegetated patches within saltmarshes contain lower organic matter content and have higher bulk density than nearby vegetated areas because these patches do not support vegetation growth (Berkowitz, J. F. et al. 2018).

Further, because soil organic matter is vital to saltmarsh ecosystem functioning, in saltmarshes where soils are disturbed, restoring soil organic matter is critical to successful restoration. There is an important issue in organic matter deficient saltmarshes due to the slow rate of organic matter accumulation, which occurs naturally over decades. Therefore, considering an adequate soil organic matter content in a restoration program of a disturbed saltmarsh is necessary for maintaining sufficient amounts of moisture content and supporting halophytes growth by providing the necessary nutrients and acceptable bulk density range (Vepraskas, M. J. et al. 2016, Christian, J. et al. 2020).

Soil organic matter is the slowest saltmarsh soil component to develop after restoration (Craft, C. et al. 2003, Noll, A. et al. 2019) and may, in some cases, be impossible to restore due to other limitations on the ecosystem (Langis, R. et al. 1991, Zedler, J. B. et al. 2005). Because restored saltmarsh ecosystems require many years to develop necessary conditions that match those of their native conditions prior to disturbances, ecosystem functioning in restored saltmarshes may be limited (Shaffer, P. W. et al. 1999). Ballantine et al. (2009) reported that even in depressional marshes the surface soil organic matter of restored site achieved only fifty percent of reference original levels after fifty-five years. Therefore, previous studies recommend that providing an acceptable amount of organic matter as a "jump-start" expedites the development of saltmarshes and supports them to attain ecological and biological function more similar to their natural conditions prior to disturbances (Sutton-Grier, A. E. et al. 2009). Because soil organic matter is a critical component of saltmarsh functions including nitrate reduction, the transformation of organic nutrients to inorganic bioavailable forms, soil moisture retention and halophytes growth, adding soil organic matter is invaluable for maintaining or restoring key ecosystem functions (Vepraskas, M. J. et al. 2016). One study conducted on response of the vegetation to the organic amendment at a marsh site concluded that the amendment loading rate of 112 Mg ha^{-1} is optimal in terms of sufficient soil nutrient levels and minimized changes in the soil surface elevation because of the added amendment material (Bailey, D. E. et al. 2007).

Soil in southeastern marshes contains considerable amounts of organic carbon due to high net primary productivity and growth of roots and rhizomes (Frey, R. W. et al. 1969). The proportions vary highly with position on the gradient from creek to high marsh, however, very little with depth.

In Georgia marshes, the soil at the creek bank averages fifty percent clay and nearly twenty percent sand (the influence of the coarser material deposited in the creek bottom and on the levee), while at the high end of the marsh it is nearly sand (Wiegert, R. G. et al. 1990).

2.3.2. Soil bulk density

In saltmarshes, bulk density has been used as an effective means to estimate the collapse of marsh peat (Vepraskas, M. J. et al. 2016). Soil bulk density is correlated with other soil parameters such as nutrients, carbon (C), nitrogen (N), phosphorus (P), and sulfur (S) (Vepraskas, M. J. et al. 2016). At a constant moisture content level, compaction yields an increase in the fraction of soil pores filled with water as average pore size decreases (Logsdon, S. D. et al. 2004). Therefore, an increase in soil bulk density changes soil aeration properties (Stepniewski, W. et al. 1994), an alteration in soil biological processes due to a decrease in soil temperature (Brussaard, L. et al. 1994), an increase in soil denitrification process (Linn, D. M. et al. 1984), loss in mycorrhizal fungi community (Ellis, J. 1998), and restriction in plant root growth (USDA, N. 1996). Bulk density is a commonly measured physical parameter that has been included in some saltmarsh assessment methods (Van Dam, R. et al. 1998, Rokosch, A. E. et al. 2009). Overall, bulk density increases with disturbance, although its response is a function of the type of disturbance (Vepraskas, M. J. et al. 2016). Soil volume decreases (i.e., bulk density increases) as a consequence of organic matter degradation, compaction, and erosion (Twohig, T. M. et al. 2011). This volume increases (i.e., bulk density decreases) with additions of refractory root and rhizome tissue and deposition onto the soil surface of mineral and refractory organic particles, which in turn is affected by aboveground plant biomass (Vepraskas, M. J. et al. 2016).

Bulk density is considered to be an indicator for soil structural stability to support vegetation growth against the destructive impacts of tidal flooding; however, bulk density greater than 1.60 g/cm^3 tends not to be suitable for root and plant growth in saltmarshes (McKenzie, N. et al. 2004). Since highly compacted soils restrict plant growth and root development, the maximum bulk density values based upon soil texture are (Arshad, M. et al. 1997):

- 1.10 g/cm^3 for clay, sandy clay, silty clay, and clay loam.
- 1.40 g/cm^3 for silt loam, silty clay loam, silt, silt loam, sandy clay loam, clay loam, sandy loam, and loam.
- 1.60 g/cm^3 for sand and loamy sand.

Fine-textured soils are capable of holding a higher amount of water and organic matter (lower bulk density) than coarse-textured soils (DeLaune, R. D. et al. 2008). In Georgia's saltmarshes, kaolinite, smectite, and illite tend to be the three major clay components, and quartz, plagioclase, feldspar, and pyrite are predominant constituents of the silt fractions (Kaufmann, R. 1981). Georgia's saltmarshes contain a considerable amount of kaolinite, montmorillonite, vermiculite, illite, chlorite, quartz, feldspar, plagioclase, gibbsite, and meta-halloysite are commonly present in the saltmarsh soils (Letzsch, W. S. 1986).

Easily measured parameters such as soil organic C and bulk density are correlated to important ecosystem characteristics such as vegetation community diversity and nutrient cycling (Hossler, K. et al. 2011). Bulk density is specifically important and valuable as an integrated measure of soil organic matter content, water content, and porosity and is related to a range of biogeochemical processes such as denitrification, plant and microbial biomass production, and soil organic matter, making it a practical measure of performance (Vepraskas, M. J. et al. 2016). As with bulk density, soil C and N have strong relationships with saltmarsh ecosystem processes which are complex and difficult to measure (Vepraskas, M. J. et al. 2016).

Knowing the correlation between soil parameters and the relationship between soil properties and vegetation community is helpful for a successful restoration practice (Broome, S. W. et al. 1988). Although relationships between soil parameters and vegetation community have been investigated in previous research studies (Passioura, J. 1991, Ballantine, K. et al. 2012, Vepraskas, M. J. et al. 2016), using modern machine learning algorithms provides profound insight into these relationships (Achieng, K. O. 2019, Jia, X. et al. 2019, Rivera, J. I. et al. 2020) and helps restoration scientists with more reliable and efficient information (van Beijma, S. et al. 2014, Sullivan, M. J. et al. 2018). Not only is a soil physical property like bulk density an important parameter that should be measured or estimated prior to restoration, but also it is recommended to be considered in the monitoring protocol of the restoration. High soil bulk density can potentially constrict and limit vegetation growth and productivity of common species in a saltmarsh. Unvegetated patches have been found to demonstrate higher bulk density, lower field capacity, and coarser soil textures compared to healthy vegetation patches (Crawford, J. T. et al. 2015). Because measuring soil bulk density is a labor-extensive and time-consuming practice, it is useful to consider an alternative way like developing a simple statistical model to estimate this parameter. Therefore, remote sensing is highly recommended to be used for predicting soil parameters like organic matter and bulk density because this approach is fast, cost-effective, and powerful enough to cope with highly dynamic changes in organic matter and bulk density due to tidal inundation or vegetation production in different seasons.

2.4. Vegetation community

Vegetative species (halophytes) as critical elements of saltmarshes generally establish and develop in the saline environment of the upper intertidal zone (Goudkamp, K. et al. 2006). Halophytes in saltmarshes are found in monotypic stands accompanying with mixed assemblages of many species. Saltmarsh vegetation communities tend to be identified either by the single dominant halophyte or by the dominant members of a mixed assemblage (Pennings, S. C. et al. 2005). The low marsh halophytes grow adjacent to tidal creeks and are able to tolerate twice daily inundations (Mitsch, W. et al. 1993). For example, *Spartina alterniflora* (APPENDIX B, Part 3) as a halophyte is able to survive in highly inundated saltmarshes for longer periods of time than any other halophyte (Mckee, K. L. et al. 1988). On the other hand, high marsh halophytes tend to be more salt tolerant than upland plants, but they are not capable of tolerating extended flooding (Mitsch, W. et al. 1993). On the coast of Georgia, *S. alterniflora* and *Juncus roemerianus* (APPENDIX B, Part 3) are the most common halophytes, and *S. alterniflora* saltmarshes alone constitute nearly seventy nine percent of total tidal areas (Wiegert, R. G. et al. 1990). *S. alterniflora* plays a vital role in shoreline protection and health. With the disappearance of *S. alterniflora*, the buffer capacity of the saltmarsh against erosional forces is considerably reduced (Bruno, J. F. 2000) because *S. alterniflora* buffers chemical and physical coastal stresses, reduces tidal flows and attenuates wave action (Swales, A. et al. 2004). Furthermore, not only is shoreline protection beneficial for coastal communities, but also for the wide variety of animals such as birds, reptiles, fish, and arthropods that may depend on *S. alterniflora* for protection, nutrition, and/or survival (Dunson, W. et al. 1994). *S. alterniflora* saltmarshes are being lost worldwide as a result of a wide range of stressors such as droughts (Silliman, B. R. et al. 2005), sea level rise (Paramor, O. et al. 2007), nutrient loading (Brown, C. et al. 2006), marsh submergence (Phillips, J. D. 1986), and other anthropogenic disturbances such as ditching, canal cutting, spoil dumping, and dredging (Kennish, M. J. 2001).

Previous studies report that *Brocchinia frutescens* (APPENDIX B, Part 3) is a ubiquitous plant in high-elevation marshes, which are not exposed to daily tidal inundations along the Atlantic coastline in the U.S. (Adams, D. A. 1963, Guo, H. et al. 2012, Lonard, R. I. et al. 2014), this species tolerates salinity[*] ranging from 20 to 50 (Antlfinger, A. E. et al. 1979). Further, in Georgia's saltmarshes, *S. alterniflora* and *J. roemerianus* are able to establish and develop as predominant halophytes in higher salinity than *Schoenoplectus tabernaemontani* (APPENDIX B, Part 3) (White, S. N. 2004). The root system and some sophisticated metabolic adaptations, such as ion exclusion in roots and ion secretion in shoots by salt glands, are two important factors helping *S. alterniflora* adapt to a high-salinity (i.e., more than 45) environment (Maricle, B. R. et al. 2002, Waisel, Y. 2012).

Halophytes play a vital role in resiliency and stability of saltmarshes through providing habitat for a vast array of plants and animals and build an important link between terrestrial and marine environments (Adam, P. 1993). Halophytes in coastal saltmarshes protect shoreline through buffering against wave action and trapping suspended soils (D'Alpaos, A. et al. 2007). The soil and vegetation determine saltmarsh productivity and structural stability in the geotechnical foundations of adjacent transportation assets. Soil shear strength and its resistance to erosion is based on the soil's properties, the vegetation structure, and their interaction (Howes, N. C. et al. 2010). Marsh surface erosion increases when vegetation is removed (Sheehan, M. R. et al. 2015), so re-establishing native vegetation is important to slow water velocities and increase

[*] Salinity is measured in PSU, which is a unitless metric and will be reported without units throughout this dissertation.

sedimentation rate (Wiegert, R. G. et al. 1990). Vegetation improves stabilization of the soil surface in saltmarshes and soil shear strength through a deep, strong, and complex root system (APPENDIX B, Part 3) (Broome, S. W. 1989).

Determining the parameters regulating vegetation zonation and structure is a basic, but challenging goal of ecology (Moffett, K. B. et al. 2010). Vegetation zonation pattern and boundary tend to be a function of abiotic conditions of the local environments (Zedler, J. B. et al. 1999). Because of the dynamic nature of a saltmarsh and the complexity of both the biotic and abiotic processes (Pennings, S. C. et al. 2003, Richards, C. L. et al. 2005), developing a model for identification of the most important abiotic parameters responsible for vegetation zonation pattern has proven considerably challenging.

Restoration of saltmarsh functions requires soil development that is tightly related to the vegetative community. Vegetation is essential for the physical stabilization of saltmarsh soils and the development of critical ecosystem processes such as carbon sequestration and denitrification (Vepraskas, M. J. et al. 2016). Vegetation baffles incoming water, reducing water velocity and increasing sedimentation (Mendelssohn, I. A. et al. 2002). Saltmarshes are greatly productive habitat and due to low rates of decomposition; a large portion of organic matter from vegetation is buried in the soil substrates (Reddy, K. R. et al. 2008). This organic matter creates elevation, reduces bulk density, yields higher exchange of materials in the soil profile and provides a source of energy for soil microorganisms (Reddy, K. R. et al. 2008, Vepraskas, M. J. et al. 2016).

2.5. Salinity, Redox Potential, and pH

Halophyte zonation patterns in saltmarshes tend to be a function of many parameters such as salinity, inundation, soil elevation, soil chemistry, and oxygen availability and the adaptations of halophytes to these parameters (Reddy, K. R. et al. 2008, Moffett, K. B. et al. 2010). Vegetation zonation highly depends on redox potential (Eh) which is a function of depth or duration of tidal inundation, and other parameters such as salinity and alkalinity in saltmarsh ecosystems (Gallagher, J. L. et al. 1980, Zedler, J. B. 2000). Eh is a key parameter indicating electron pressure and the available reductants or oxidants in saltmarsh flooded soils. Eh value typically ranges from −300 to 700 mV, with values less than 350 mV suggesting substantial anaerobic microbial respiration in the system (DeLaune, R. D. et al. 2008). Salinity influences vegetation zonation, so salinity should be considered as an important parameter in a restoration practice of a disturbed saltmarsh (Broome, S. W. et al. 1988). Salinity plays a key role in the carbon (C) and nitrogen (N) distribution pattern in tidal marsh soils, and previous studies report that polyhaline (salinity > 18) marshes have less C and N concentration than freshwater (salinity < 0.5) and oligohaline-mesohaline (0.5 < salinity < 18) marshes (Craft, C. 2007, Loomis, M. J. et al. 2010). Craft (2007) reported that there is no significant difference in the C and N accumulation rates of tidal marshes of varying salinity. Changes in salinity adversely impact seed germination, photosynthesis efficiency, and the soil submergence pattern, which affects biogeochemical processing of organic carbon and causes a continual shift in the zonation of the vegetation communities. Saltwater intrusion into freshwater tidal marshes increases salinity and introduces a significant amount of sulfate into these ecologically vulnerable areas (Neubauer, S. C. 2013). Salinity is positively associated with the bulk density of soil ($r=0.47$), and negatively correlated with organic C ($r=-0.61$) and N ($r=-0.74$) (Loomis, M. J. et al. 2010). Freshwater marshes generally have lower bulk density and higher organic C or N than oligohaline-mesohaline and polyhaline marshes (Loomis, M. J. et al. 2010), and high decomposition rates of organic C and N are likely to occur in soils that are high in salinity due to high concentration of sulfate, which is an important input from seawater into a tidal marsh system (Craft, C. 2007). N, C, and bulk density influence the plant diversity and density, and it is hypothesized that flooded soils at oligohaline-mesohaline and polyhaline sites have different bulk densities and contain different total C or total N concentrations.

Soil pH as a rapid chemical indicator of soil characteristics provides information on changes due to human impacts. Soil pH has been utilized as an efficient indicator of hydrological alterations which change saltmarsh soil chemistry. Knowing soil physical and chemical parameters guides restoration practitioners to success. In other words, in order to have a successful re-establishment of a native halophyte in a restored saltmarsh, it is necessary to access reliable data, including the original physical and chemical conditions of the hydric soil prior to disturbances. Therefore, the current study focuses on prioritizing the important abiotic factors of bulk density, organic matter, salinity, Eh, and pH in their role in native halophytes zonation pattern in saltmarshes. Machine leaning algorithms were used to rank these factors in terms of their importance in vegetation community structure. Further, statistical analyses were utilized to determine the typical target ranges of the above parameters with regard to each vegetative species. Also, vegetation type as indicator predictor was used to develop a regression model estimating redox potential, which has a role in shaping vegetation communities in tidal marshes.

2.6. Heavy Metals

Heavy metal concentration in saltmarshes is a function of input sources, soil composition and texture, organic matter content, flooding duration or frequency, riverine circulation, and vegetation community (Williams, T. et al. 1994, Roychoudhury, A. N. 2007). Saltmarshes absorb large amounts of pollution through physical and biological sequestration (Mitsch, W. J. et al. 2009). Soils high in clay and organic matter retain a significant amount of metals due to high cation exchange capacity and particle surface charge (Horowitz, A. J. 1985). Saltmarshes in Georgia (US) have a significant correlation between clay content and heavy metals in flooded soils (He, C. et al. 2012). Therefore, soil texture and composition are important factors responsible for pollutant retention in coastal saltmarshes. Construction activity disrupts the capacity of saltmarshes to serve as heavy metal sinks. Road and agricultural runoff, landfill leachates, industrial sewage, domestic wastewaters, marine dredge spoil or sludge disposal, and atmospheric deposition are major sources of pollutants for estuarine ecosystems (Chenhall, B. et al. 1992).

Recent legislation in favor of environmental protection and public health, both nationwide and worldwide, is based upon information that identifies chemical properties of environmental phenomena, particularly those that affect our food chain and water quality (Wuana, R. A. et al. 2011). Arsenic (As), cadmium (Cd), chromium (Cr), copper (Cu), lead (Pb) and zinc (Zn) are the most critical heavy metals lead to environmental issues in natural resources (Vu, C. T. et al. 2017). An understanding of pollution source, basic chemistry, and environmental and associated health effects (risk assessment) of heavy metals will lead to a more successful and effective remediation practice (Zhao, Q. et al. 2002). Risk assessment is an approach that assists scientists in managing sites with heavy metal contamination in a cost-effective and efficient manner for preserving public and ecosystem health (Zhao, Q. et al. 2002).

When saltmarsh soils suffer from a high level of potentially toxic elements (PTEs), a substantial health risk occurs. This is particularly critical for children's health; children under age of six are more vulnerable to heavy metal toxicity (Singh, U. K. et al. 2017, Rinklebe, J. et al. 2019). Soil pollution with PTEs is considered a worldwide concern because of the ability of PETs to be transferred into the human food chain (Singh, U. K. et al. 2017, Edelstein, M. et al. 2018, Antoniadis, V. et al. 2019). In saltmarsh soils, PTE's transit from the source is regulated through water and surrounding soils (Shaheen, S. M. et al. 2019). Saltmarsh soils are critical sinks for PTEs and play a key role in the remobilization of pollution in aquatic ecosystems under certain circumstances (Ali, M. H. et al. 2005, Shaheen, S. M. et al. 2019). PTEs origin in soils is mostly anthropogenic, and in most cases, high PTE concentrations are associated with human-induced activities (Hooda, P. 2010).

Disturbances like drainage and compaction due to construction activity lead to changes in parameters of hydric soil of tidal marshes, and as a result, redox potential and salinity increase, pH decreases, and organic matter decomposition accelerates (Reddy, K. R. et al. 2008, Brunet, N. N. et al. 2012). Thus, metal cycling in tidal marshes is impacted due to the alteration in soil properties through construction activity (Conesa, H. et al. 2011, Bai, J. et al. 2019). Human activities such as construction and dredging lead to heavy metal contaminations which should be controlled by ensuring full ecological function of saltmarshes especially when restored (Erftemeijer, P. L. et al. 2013). Furthermore, it is neither cost-effective nor easy to remediate saline soils contaminated by heavy metals because of high contaminant mobility in saltwater (Bera, G. et al. 2018, Vane, C. H. et al. 2020). The measurement and evaluation of heavy metal presence and concentration in soils are considered as an important study field in environmental sciences (Tessier, A. et al. 1987, Ustaoğlu, F. et al. 2020).

CHAPTER 3. DATA ACQUISITION AND REDUCTION

3.1. Study Sites

Georgia's coastal marshes encompass approximately 378,000 acres in a four-to-six-mile band behind the barrier islands. These marshes have been identified as one of the most extensive and productive ecosystems in the United States (Edwards, L. et al. 2013). Nearly 286,000 acres of these marshes are covered by a salt-tolerant species of marsh grass, known as *S. alterniflora* or smooth cordgrass (Edwards, L. et al. 2013). The remaining 107,000 acres support other types of salt, brackish, and freshwater marshes. Georgia has the second largest amount of saltmarshes in USA (Edwards, L. et al. 2013). Saltmarshes are the dominant coastal habitat on the Atlantic and Gulf Coasts of the United States and characterized by extremely high annual net primary productivity (typically 800 g m^{-2} y^{-1} (Kirwan, M. L. et al. 2009)). Further, these ecosystems bury and store plant tissue to become substantial carbon sinks (Mcleod, E. et al. 2011).

Eight undisturbed saltmarsh sites were selected along Georgia's Atlantic Coast (Figure 1). Three different representative sampling areas (A, B, and C) were chosen at each location based on vegetative spices. These saltmarshes were selected based on the predominant vegetation and proximity to current or future GDOT infrastructure improvement projects (APPENDIX B, Part 3). The main goal was to correlate the physical and chemical properties to vegetation prior to any disturbance related to roadway construction and maintenance activity. The sampling plan included collecting multiple samples labeled A, B, and C from each site to help quantify variability within and between locations driven by changes in species dominancy.

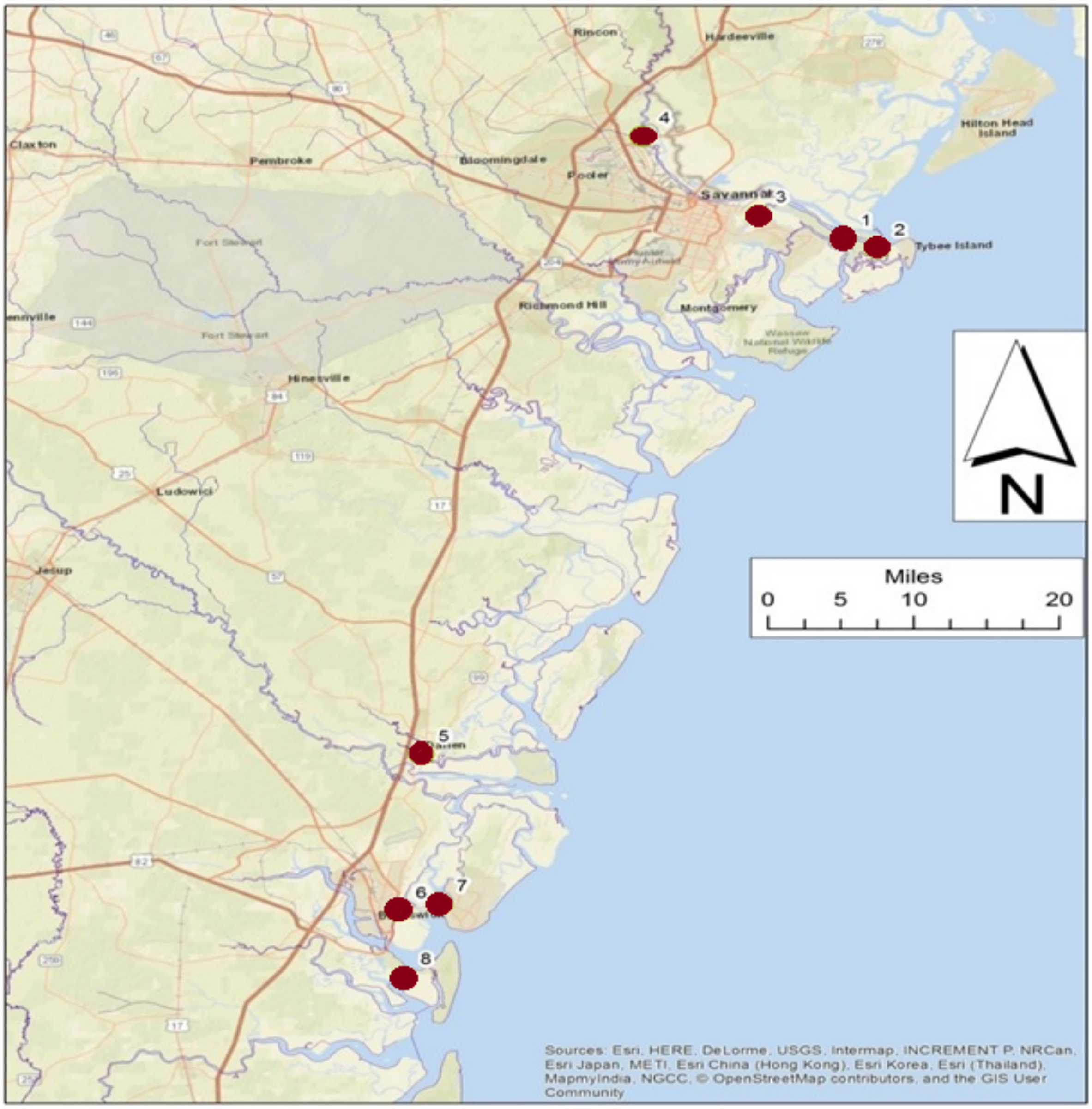

Figure 1 – Sample sites in coastal GA selected as likely candidates for temporary degradation for upcoming infrastructure improvement projects.

3.2. Experimental Design

3.2.1. Sampling and sample preparation

In June 2018, representative soil samples were collected in the first 30 cm (rooting zone) (Vepraskas and Craft 2016) and kept in sealed waterproof containers to avoid oxygen infiltration and moisture loss, for a total of 24 soil samples. All samples were soon transported to a laboratory and stored at 4°C until analysis. Analyses determined particle size distribution, organic matter content, moisture content, metal speciation, clay mineralogy, and carbon and nitrogen content. Porewater was withdrawn from the root zone using a PushPoint sampler (APPENDIX B, Part 3) and 60 mL syringes (Cleveland, D. et al. 2017). Salinity, pH, and redox potential were measured in the field using a calibrated HI98194 (Hanna Instruments, located in Woonsocket, Rhode Island, United States) portable meter (APPENDIX B, Part 3). For each distinct vegetation community, species richness and number of individuals were estimated utilizing the cover scale of Braun-Blanquet (Braun-Blanquet, J. 1932). The predominant vegetative species were characterized in accordance with the vegetation survey conducted at all sampling sites. Transects began several meters inside the marsh so that all samples were representative of the marsh itself, not the upland border.

Core bulk samples prepared for x-ray diffraction (XRD) were air-dried and powdered to achieve random particle orientation and mounted as a pressed powder. After air-drying, 10 wt. percent zincite (ZnO) was added as an internal standard. Samples were ground for 10 minutes in a McCrone micronizing mill using corundum pucks to achieve a particle size of <5 µm. XRD patterns were collected using a Bruker D8 Advance diffractometer. Instrument conditions included using CoKa radiation (generated at 35 kV and 40 mA), 217.5 mm goniometer radius, 0.6 mm primary slit, Fe-filter, and a LynxEye position-sensitive solid-state detector. XRD scan parameters were run at 0.3 s/step in 0.01 °2θ step increments. Data were processed using Bruker EVA software, which includes background correction, Ka2 stripping, and peak d-spacing and intensity assignments.

3.2.2. Test Methods

Soil particle size distribution was governed based on the wet sieve method per the American Society for Testing and Materials (ASTM) D1140-17 by sequential sieving at No. 4, No. 10, No. 30, No. 40, No. 50, No. 100, and No. 200, followed by the hydrometer test of ASTM D7928-17 (APPENDIX B, Part 3). Texture of the studied hydric soils was determined based on the U.S. Department of Agriculture (USDA) soil classification system, and the soils were categorized as sand (0.5–2 mm), silt (0.002–0.05 mm), clay (<0.002 mm), or a combination of these particle sizes. Moisture and organic matter contents were measured based on ASTM D2216-10 and ASTM D2974-87, respectively. A soil corer (Blake, G. 1965) was utilized to collect an undisturbed soil sample from the root zone to determine the bulk density (ASTM D7263-09) (APPENDIX B, Part 3).

Inductively Coupled Plasma (ICP) metal analysis was also performed in accordance with ASTM E1479-99 to measure the elemental constituency of soil samples (APPENDIX B, Part 4). Total C and Total N were determined through dry combustion on a Flash 2000 (CE Elantech, Lakewood, New Jersey (USA)).

CHAPTER 4. ANALYSIS OF TEST RESULTS

4.1. Vegetation community

Salinity exerts a great influence over vegetation community composition in tidal marshes (Silvestri, S. et al. 2005). The site survey found *S. alterniflora* (Table 1) in all sampling sites except site 4 which mainly supports *S. tabernaemontani.* Sophisticated metabolic systems such as ion exclusion in roots and ion secretion in shoots through salt glands facilitate *S. alterniflora* to establish and develop in harsh saline environments (Burke, D. J. et al. 2000). Vegetation in the low salinity marshes generally had a greater average height (Figure 2) and diversity (Table 1) relative to the high salinity marshes, and the vegetation height was inversely related to the interstitial salinity of the underlying soils (Figure 2). This suggests that high salinity may restrict vegetation productivity because internal energy of vegetation is channeled into adaptation to high saline conditions rather than biomass production. Vegetation height is not solely dependent on salt concentration in interstitial salinity. Nitrogen, a necessary nutrient for vegetation growth, was limited in polyhaline marshes in comparison to oligohaline-mesohaline (Figure 3). Changes in the salinity gradient alter carbon and nitrogen distribution patterns in tidal marshes (Casselman, M. E. et al. 1981); polyhaline saltmarshes have lower carbon and nitrogen concentrations than freshwater, oligohaline-mesohaline marshes (Craft, C. 2007, Loomis, M. J. et al. 2010, Sutter, L. A. 2014). Nitrogen was in low supply in polyhaline marshes because lack of oxygen and abundant C lead to high denitrification rate. This is particularly true with soils having a considerable amount of sand which leads to low organic matter content and cation exchange capacity (Broome, S. W. et al. 1988, Zedler, J. B. et al. 2000). A minimum of 100 g N m^{-2} is necessary to establish and support a productive vegetation community in saltmarshes of the US southeastern coast (Craft, C. et al. 2003); that takes five to fifteen years to develop post-construction, depending upon the soil nitrogen accumulation rate.

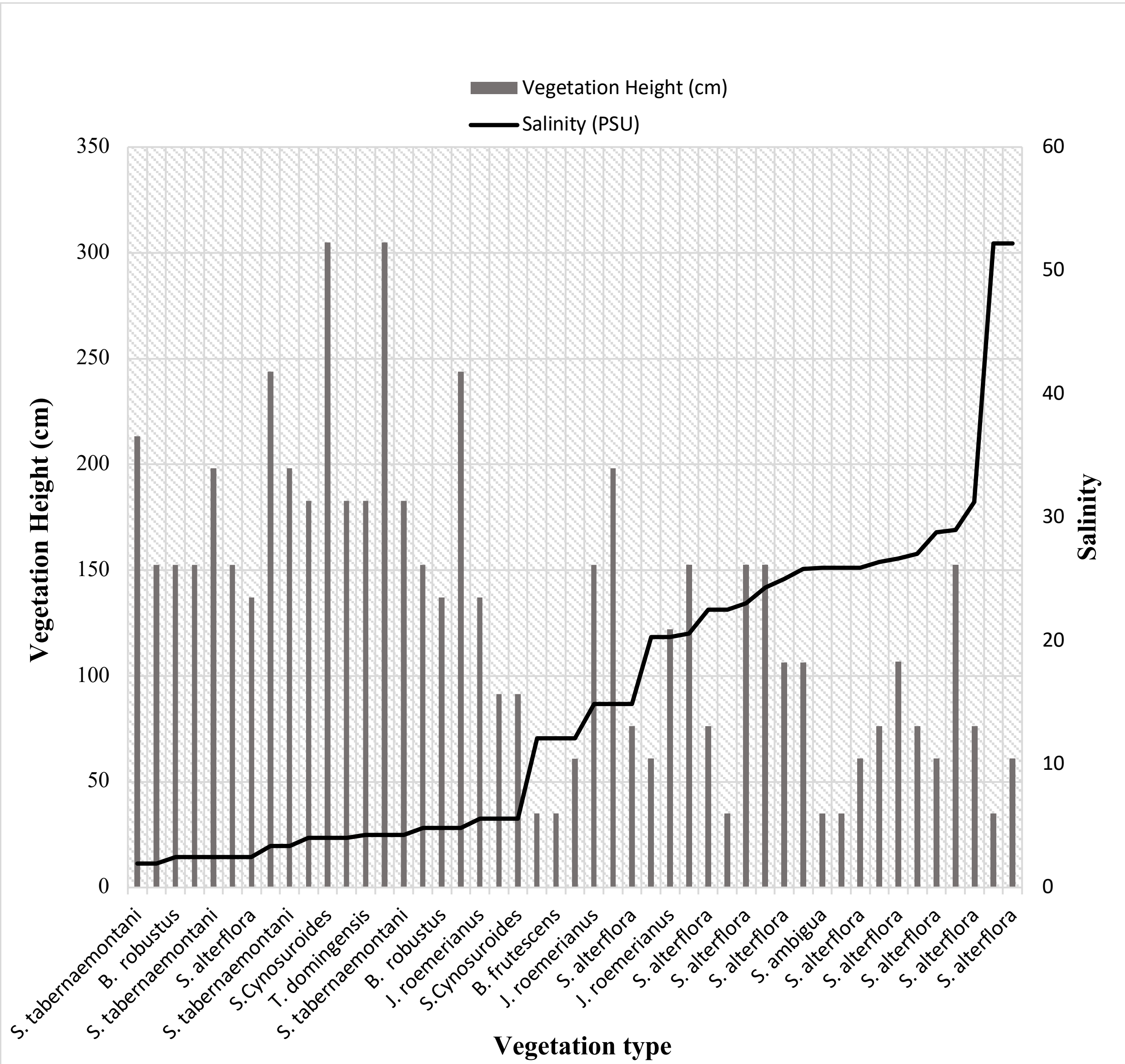

Figure 2 – Vegetation community and height at the study sites with regard to salinity gradient.

Table 1 – Plant cover percent at the sampling sites.

Location			Plant coverage %							
Site ID	Latitude	Longitude	*S. alterniflora*	B. frutescens	*J. roemerianus*	*S. cynosuroides*	*S. tabernaemontani*	T. *domingensis*	B. *robustus*	*S. ambigua*
1.A	32.02745	-80.92530	100							
1.B	32.02725	-80.92532	100							
1.C	32.02717	-80.92535	100							
2.A	32.01383	-80.88522	75	25						
2.B	32.01387	-80.88505	100							
2.C	32.01405	-80.88518	100							
3.A	32.05983	-81.02370	10		90					
3.B	32.05982	-81.02402	65		10	25				
3.C	32.06010	-81.02438	10		75	15				
4.A	32.16555	-81.15735				35	50	15		
4.B	32.16565	-81.15735				25	60	15		
4.C	32.16587	-81.15748				25		15	60	
5.A	31.36427	-81.43903					80	20		
5.B	31.36443	-81.43905	20			15	65			
5.C	31.36448	-81.43922	20			10	50	10	10	
6.A	31.16308	-81.45445	100							
6.B	31.16230	-81.45472	100							
6.C	31.16222	-81.45463	100							
7.A	31.17008	-81.42262	40							60
7.B	31.17010	-81.42260	30	50						20
7.C	31.16993	-81.42270	30	50						20
8.A	31.07410	-81.46598	100							
8.B	31.07413	-81.46598	100							
8.C	31.07418	-81.46595	100							

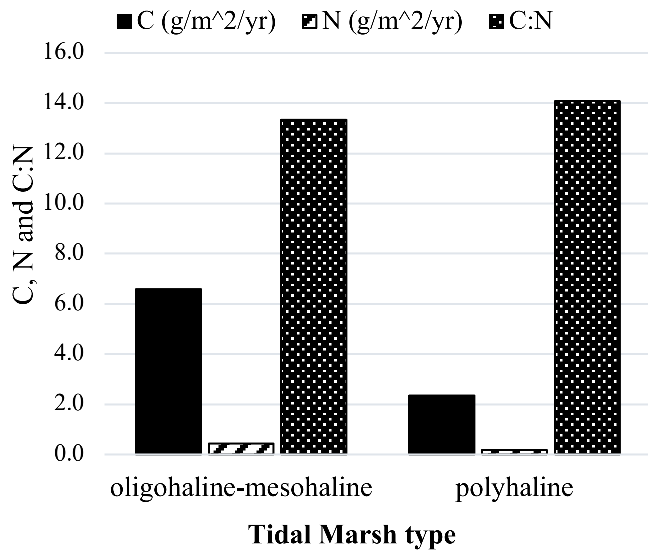

Figure 3 – Average values of N, C and C:N in the study oligohaline-mesohaline and polyhaline marshes.

The interstitial salinity of the soils was a function of the salinity of the estuarine water since the soils are not bare long enough to allow considerable evaporation. As distance from the nearest source of estuarine water increases, enough evaporation occurs to allow salts diffusion into the soils because that distant area is higher in elevation than the creek (Odum, W. E. 1988). Therefore, higher interstitial salinity often indicates less frequent tidal flooding. Construction interferes with marsh hydrology and changes tidal flooding frequency and interstitial salinity; as such, construction indirectly alters the structure of vegetation community.

4.2. Soil and interstitial water parameters

Organic matter content ranged from a minimum of less than 2 % of the soil at site 7.A to a maximum of 28.8% at site 4C (Table 2). Soil at site 4C had the highest organic matter content as well as the finest texture (clay and silt) among the study sites (Table 2). This site supported *S. tabernaemontani* which grows far from creek banks. *S. tabernaemontani* is sensitive to water draining and reflooding due to its soft stem (Svengsouk, L. J. et al. 2001). This plant was not as tolerant as *S. alterniflora* to high salinity conditions (Table 2). On the other hand, site 7 had the highest content of sand and the highest value of bulk density. This site supported *B. frutescens* which is able to establish and develop in sandy soils and high salinity conditions. High sand content expedites water drainage and particulate organic matter loss due to daily inundations. Sandy soil structure is not capable of holding water and necessary nutrients for vegetation growth (Reddy, K. R. et al. 2008). Further, sandy soils generally had high salinity (Table 2) due to high evaporation rate which introduces salt to soil substrate.

Table 2 – Soil properties at sampling site.

Site	OM[1]	MC[1]	BD[1]	Clay	Silt	Sand	Salinity
	%	%	g/cm^3	%	%	%	
1.A	2.44	35.97	1.44	16.17	34.75	49.08	27.03
1.B	7.22	201.72	0.40	35.25	27.28	37.47	26.39
1.C	10.57	225.00	0.40	14.96	25.13	59.91	25.00
2.A	1.46	48.14	1.18	12.10	7.19	80.72	22.50
2.B	3.59	77.95	0.87	23.06	22.32	54.62	31.22
2.C	5.99	181.32	0.44	47.09	45.56	7.35	26.65
3.A	3.73	90.65	0.76	44.57	29.28	26.15	20.29
3.B	0.24	25.11	1.50	17.02	11.18	71.80	5.56
3.C	0.54	38.20	1.31	17.22	11.32	71.46	14.88
4.A	23.85	428.17	0.18	22.68	70.65	6.67	4.04
4.B	19.54	278.87	0.27	56.46	37.10	6.44	4.26
4.C	28.88	309.00	0.29	28.27	54.52	17.21	4.84
5.A	8.02	227.01	0.39	38.90	33.15	27.95	3.38
5.B	7.76	215.31	0.37	59.35	34.08	6.57	1.94
5.C	8.54	254.17	0.35	55.15	39.99	4.86	2.46
6.A	0.89	63.82	1.07	16.52	22.01	61.47	25.79
6.B	7.80	338.30	0.31	22.68	72.52	4.80	28.76
6.C	5.66	261.39	0.37	19.61	73.11	7.28	28.95
7.A	1.47	24.60	1.56	7.52	13.12	79.36	52.19
7.B	1.59	23.08	1.67	8.55	11.02	80.43	12.09
7.C	1.09	34.87	1.45	9.70	10.19	80.11	25.93
8.A	3.81	185.54	0.46	30.48	35.71	33.81	20.57
8.B	1.05	35.64	1.36	17.87	22.31	59.82	23.02
8.C	5.98	213.95	0.40	39.11	55.59	5.30	24.28

Note: [1] OM: Organic Matter, MC: Moisture Content, and BD: Bulk Density

Anaerobic conditions and circumneutral pH were observed at all sampling sites (Table 3). pH above 4 increases saltmarsh capability to support halophytes (Craft, C. et al. 1991) because acidic soils tend to be low in necessary nutrients like nitrogen and phosphorous for vegetation growth (Craft, C. et al. 1988). Sulfidic components are responsible for creating the acidic environments in saltmarshes (Craft, C. et al. 1991).

Tukey's honest significance test (HSD) (Table 4) shows a significant difference (P-value < 0.05) in mean pH values of study saltmarshes supporting *S. alterniflora, S. tabernaemontani, J. roemerianus,* and *B. frutescens.* A significant difference in mean pH was found between *B. frutescens* and *J. roemerianus, B. frutescens* and *S. tabernaemontani, S. alterniflora* and *J. roemerianus, S. alterniflora* and *S. tabernaemontani* (Table 4). *B. frutescens* was found at sites having higher pH (closer to the neutral) than other species, and *J. roemerianus* grew at sites less alkaline than other vegetation types.

Table 3 – 95%-confidence interval for salinity, pH and redox with regard to vegetation.

Vegetation	Salinity	pH	Redox
B. frutescens	(5.44,32.57)	(6.75,6.93)	(-209.95, -123.14)
J. roemerianus	(12.28,22.88)	(6.33,6.56)	(-18.75, -9.94)
S. alterniflora	(23.6,32.14)	(6.70,6.81)	(-380.56, -171.86)
S. tabernaemontani	(2.83,4.73)	(6.40,6.55)	(-134.70, -46.72)

Table 4 –Mean pH in each vegetation community (Tukey's HSD).

Vegetation	Difference in mean pH	P-value
B. frutescens vs. *J. roemerianus*	0.3951	0.0012*
B. frutescens vs. *S. tabernaemontani*	0.3652	0.0002*
S. alterniflora vs. *J. roemerianus*	0.3162	0.0007*
S. alterniflora vs. *S. tabernaemontani*	0.2863	<.0001*

4.3. Soil properties at sampling sites

4.3.1. Soil Texture

Particle size distribution is a fundamental physical property of soil and used for classifying soil type (Tyler, S. W. et al. 1992). Soil particle size fraction (Figure 4) showed considerable variability within a relatively small area at a saltmarsh site. Soil texture had a high spatial variability at study saltmarsh sites. For example, site 3.A was near site 3.B but they were classified as clay and sandy loam, respectively. 3.A had 44.57% of clay and 26.15% of sand, while 3.B contained 17.07% of clay and 71.80% of sand. The spatial variability in soil texture should be taken into account within a restoration practice because soil texture influences soil bulk density, organic matter content and moisture content. Site 7 (classified as loamy sand) had the highest average bulk density (1.56 g/cm^3) and lowest average organic matter content (1.38%), with 80% sand on average (Table 2). On the other hand, site 4 had the lowest average bulk density (0.24 g/cm^3) as well as the highest organic matter and moisture content (Table 2). Fine-textured soil and high organic matter content resulted in low bulk density of soils at site 4 (Table 2).

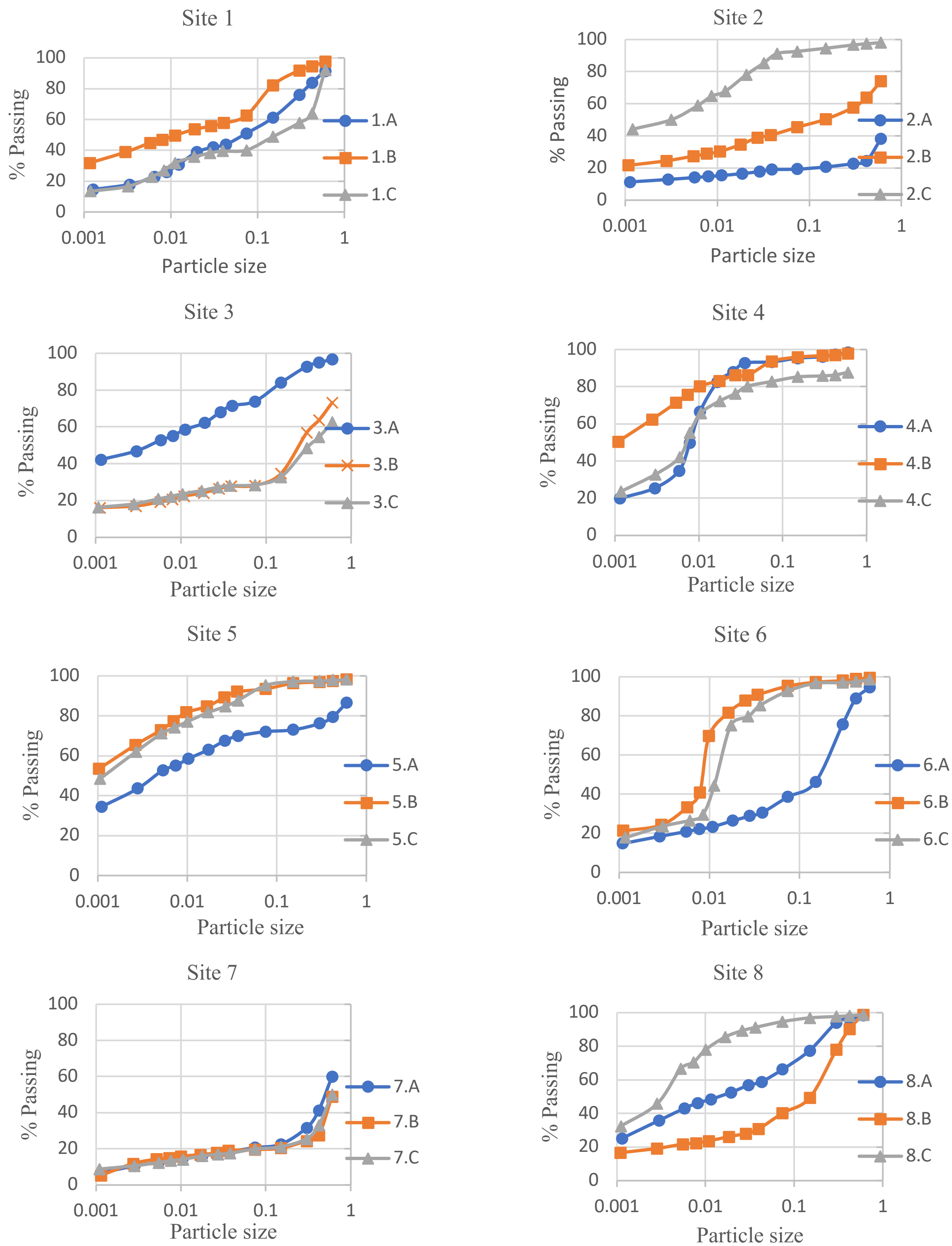

Figure 4 – Grain-size analysis of soils by sieve and hydrometer tests.

The average clay content in the oligohaline-mesohaline marshes was 9.95% greater than this average in the polyhaline marshes (Table 5 and Figure 5), and statistical analysis found negative but moderately strong association (correlation coefficient (r) =-0.49) between clay content and salinity. Clay particles are transported to a greater distance from the coast than sand particles because a smaller grain size causes higher surface area, more friction and slower settling rate (Harter, S. K. et al. 2003, Bartholdy, J. et al. 2010).

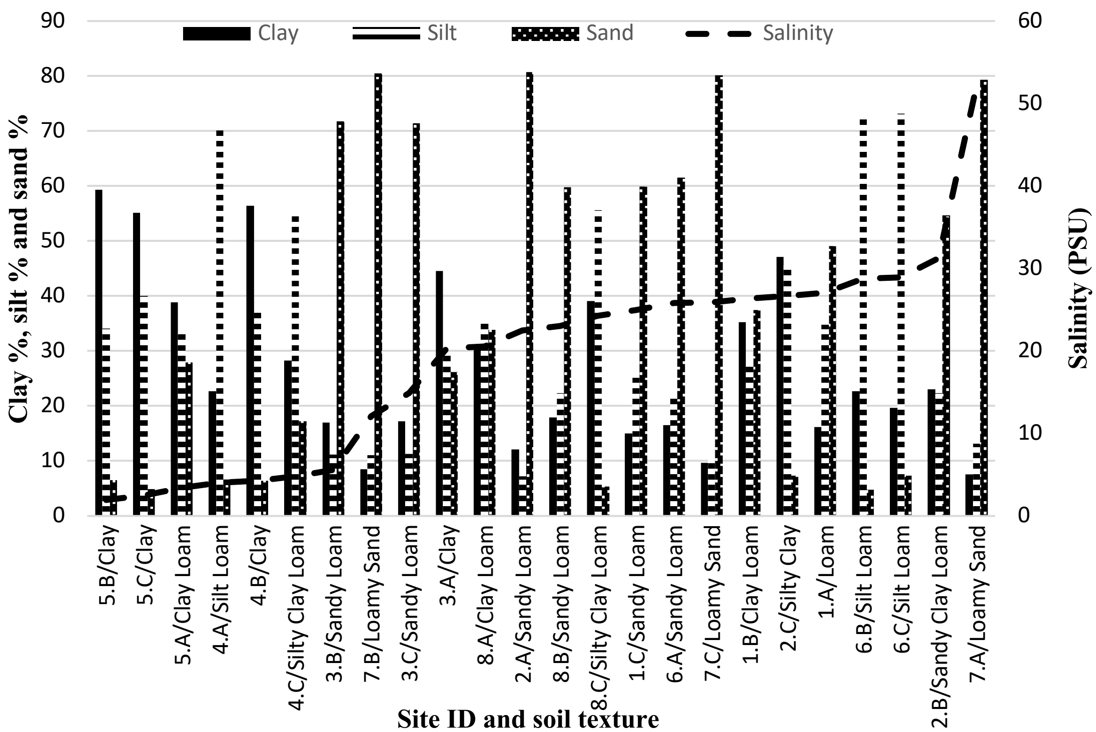

Figure 5 – Soil texture within the salinity gradient.

Table 5 – Difference in means of soil properties and metal concentration (in mg/kg) in bulk saltmarsh soil samples from oligohaline-mesohaline and polyhaline marshes.

	Mean in the oligohaline-mesohaline marshes	Mean in the polyhaline marshes	t-test	P-value
Bulk density(g/cm^3)	0.70±0.60	0.83±0.46	0.58	0.56
Clay (%)	33.73±19.35	23.77±12.61	2.30	0.03
Fe (mg/kg)	18352±12093.11	14791±8889.21	0.83	0.41
Mn (mg/kg)	134±122.32	122.9±71.92	0.28	0.78
Organic matter (%)	10.99±10.58	4.18±2.93	2.37	0.02*
Plant height (cm)	161.19	86.96	2.73	0.01*
C:N	13.32±4.48	14.07±3.09	0.48	0.63
P (mg/kg)	508±378.68	423±235.15	0.67	0.50
As (mg/kg)	4.42±2.96	5.40±4.00	0.63	0.53
Cd (mg/kg)	0.94±0.42	0.65±.21	2.30	0.03*
Cr (mg/kg)	29.39±23.03	16.11±10.06	1.96	0.06
Cu (mg/kg)	11.30±8.33	5.06±2.51	2.73	0.01*
Pb (mg/kg)	18.87±16.17	9.40±6.87	2.00	0.05*
Zn (mg/kg)	36.75±27.07	19.91±11.52	2.13	0.04*

Note: * significant at the 0.05 level.

4.3.2. Soil mineralogy

According to XRD tests results (Figure 6 – Figure 13 below and Figure 32 and Figure 47 found in APPENDIX B), all sampling sites with the exception of site 6 (A, B and C) contain kaolinite and chlorite, and gibbsite is present in all sampling soils except site 7 (A, B and C) and site 8 (A, B and C).

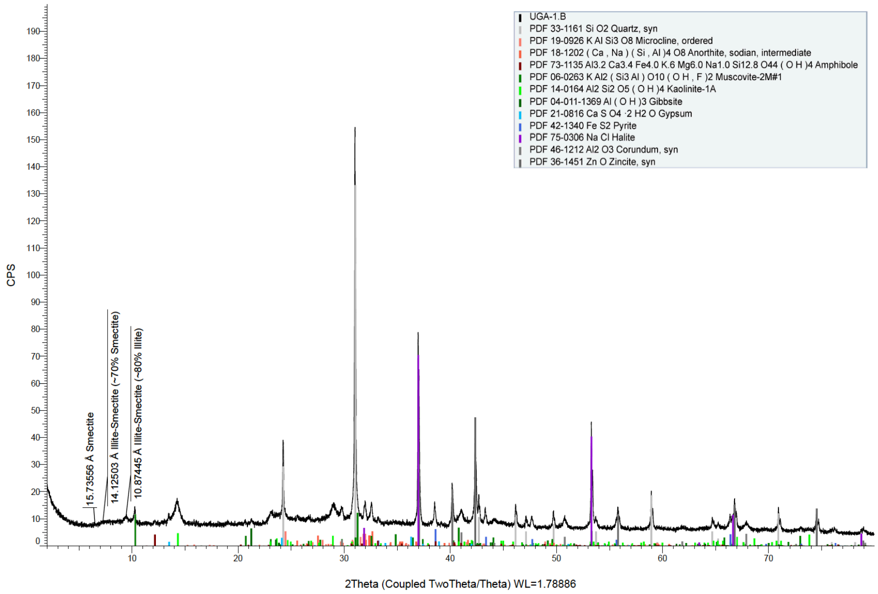

Figure 6 – XRD test result on soil sample of site 1.B.

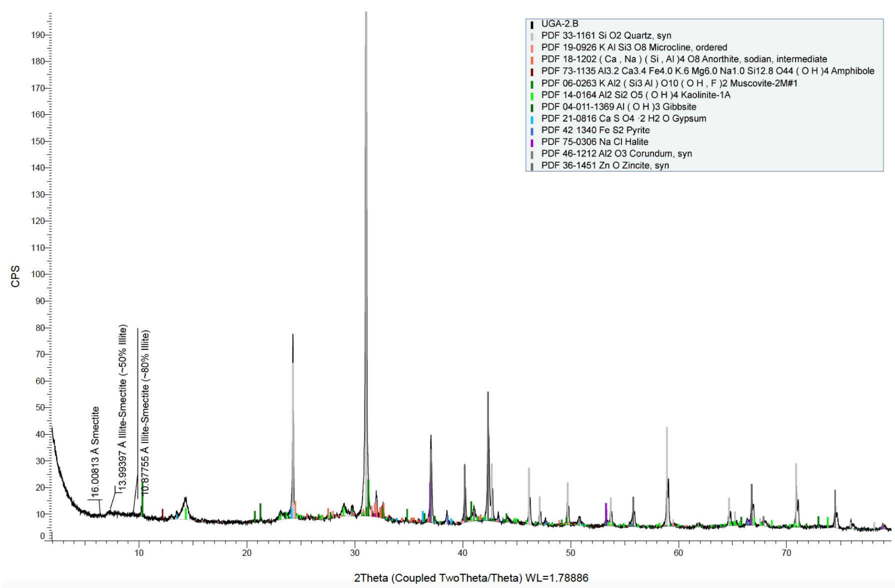

Figure 7 – XRD test result on soil sample of site 2.B.

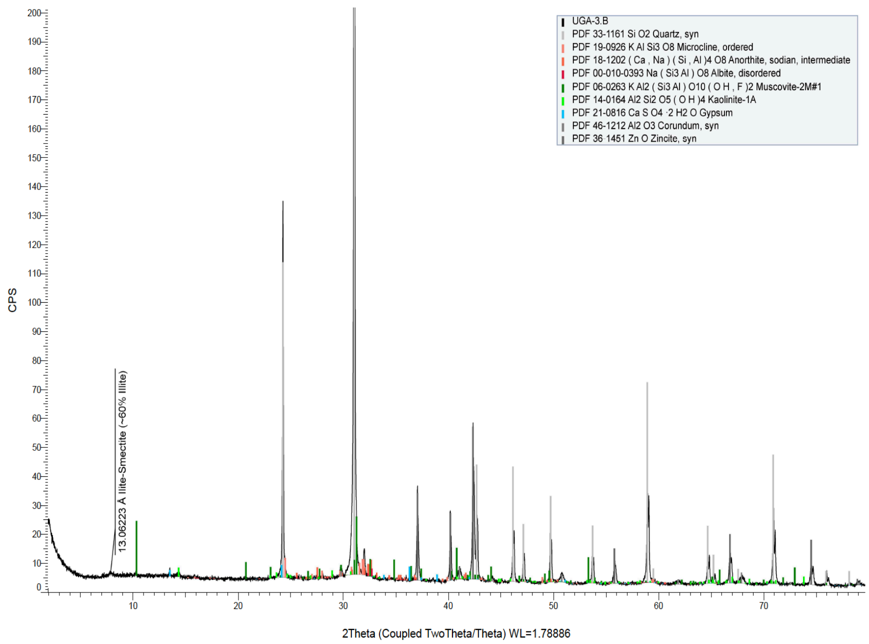

Figure 8 – XRD test result on soil sample of site 3.B.

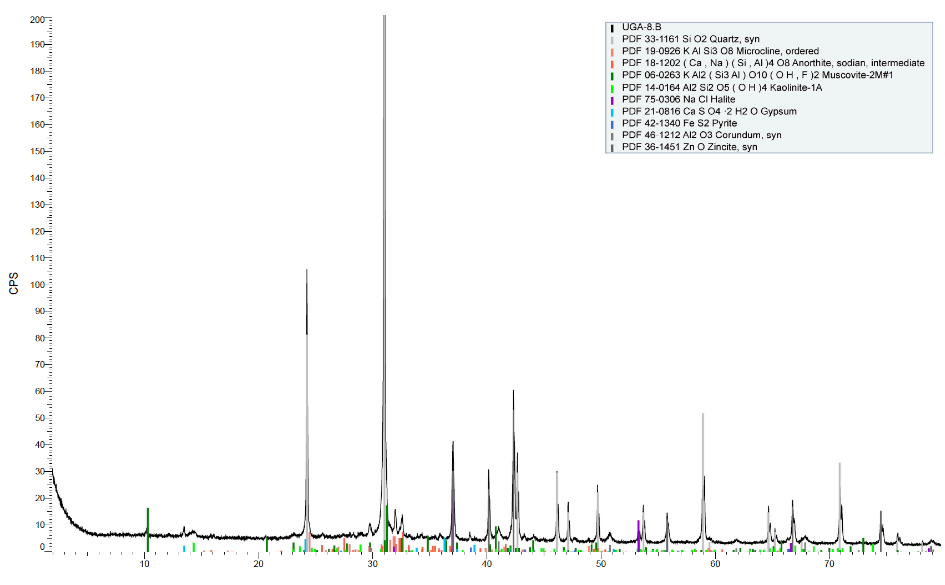

Figure 9 – XRD test result on soil sample of site 4.B.

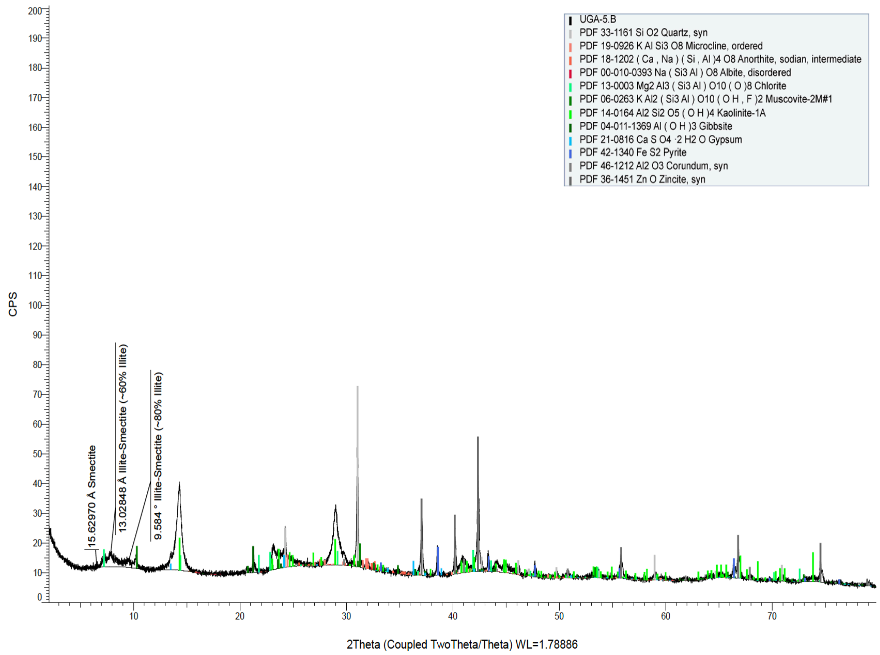

Figure 10 – XRD test result on soil sample of site 5.B.

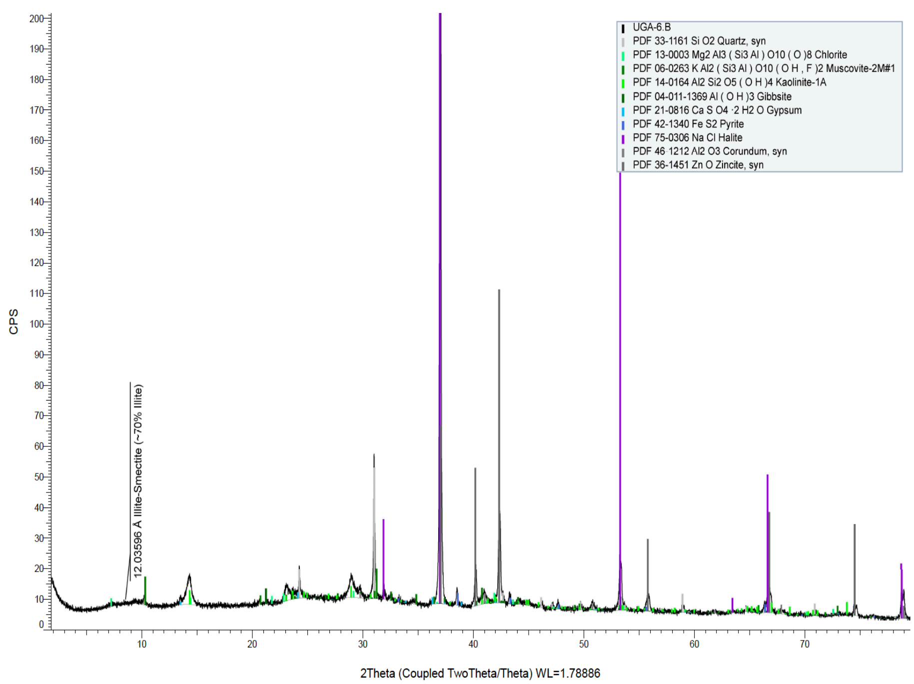

Figure 11 – XRD test result of on soil sample site 6.B.

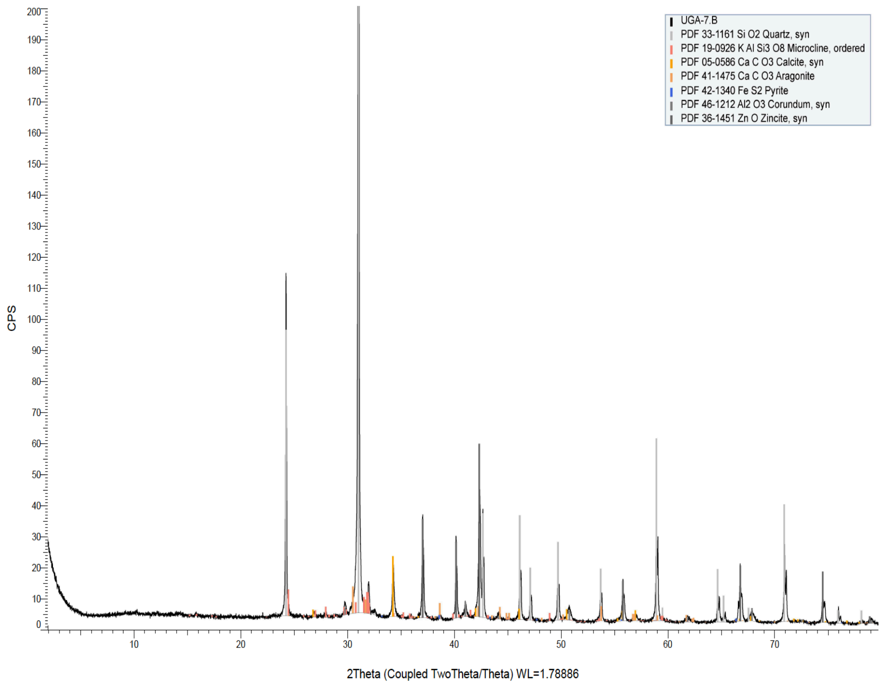

Figure 12 – XRD test result on soil sample of site 7.B.

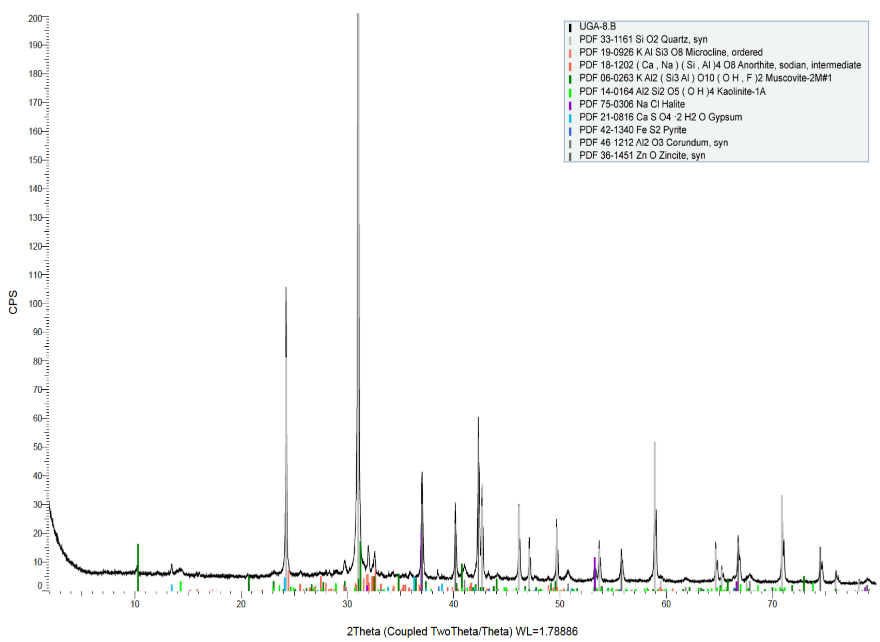

Figure 13 – XRD test result on soil sample of site 8.B.

Quartz was identified in all samples, and mica minerals were also found as muscovite in all samples other than 6.A, 6.B, 6.C and 8.C. All sites except 6.B and 6.C consisted of feldspar minerals such as microcline and anorthite. Amphibole group minerals were detected in such samples as 1.B, 1.C, 2.B, 2.C and 6.A. Calcite and aragonite were present in sampling soils of site 6 (A, B and C). According to XRD test results, pyrite was identified in all sampling soils except 7.C. Pyrite burial in marine environments was considered as a long-term preservation and plays an important role in sustaining the alkalinity of the soil-water system (Peiffer, S. et al. 1999). Construction in tidal marshes disturbs the delicate balance of the system in regulating the effects of sulfide (Kennish, M. J. 2001, Chambers, R. et al. 2003) and inhibits pyrite formation and accumulation in tidal marshes (Fanning, D. et al. 1993). Sample soil from site 7.C (Figure 45 found in APPENDIX B) had no pyrite compound and this site experienced construction disturbance. This disturbance caused exposure of soil to air and release of sulfide into the porewater system, which is a toxic compound for roots (Reddy, K. R. et al. 2008). Site 7.C was less productive than the other sampling sites, and a large salt panne (APPENDIX B, Part 3) was observed adjacent to a bridge infrastructure at this site. On the Georgia coast, salt pannes tend to occur adjacent to the areas impacted by human disturbances; where free tidal movement, for example, is blocked by road infrastructures across a marsh with only one or two culverts providing drainage (Wiegert, R. G. et al. 1990). The reduced amplitude of high tide landward from the barrier as well as porous nature of soils having a considerable amount of sand yield an increase in salinity to the point where no halophytes can survive and salt pannes can develop (Wiegert, R. G. et al. 1990, Linhoss, A. C. et al. 2016). Site 7 C was adjacent to bridge infrastructure which affects its hydrology. Site 7C contained a high content of sand which causes drying to a deeper depth and more rapidly due to porous nature of the sandy soil substrate.

4.3.3. Soil organic matter and bulk density along a salinity gradient

Salinity indirectly influences organic matter content in tidal marsh soils (Wang, F. et al. 2019). In the present study, oligohaline-mesohaline marshes had higher mean organic matter content than polyhaline marshes, probably because polyhaline marshes receive a considerable amount of sulfate from seawater. Reducing sulfate to sulfide is the main pathway for organic matter breakdown in saltmarshes, which leads to a higher rate of organic matter decomposition than the common (methanogenesis) pathway in low salinity marshes (Reddy, K. R. et al. 2008). Further, vegetation in tidal marshes is the main source for organic matter (Reddy, K. R. et al. 2008) and high saline environments inhibit the vegetation production (4.1. Vegetation community). The results showed that vegetative species in oligohaline-mesohaline marshes were taller (Table 5) than the ones observed in polyhaline marshes, and the areas low in salinity had higher organic matter content, total C and total N (Table 5 and Figure 3) in comparison to the mashes high in salinity. The average carbon to nitrogen ratio (C:N) was nearly 0.74 higher in the polyhaline than the oligohaline-mesohaline marshes, and there was a positive association (r=0.22) between C:N and salinity. The difference between organic matter content (%) in oligohaline-mesohaline and polyhaline marshes was statistically significant (P-value>0.05) (Table 5).

4.4. Linear regression models for bulk density and redox potential prediction

Bulk density was a function of percent mineral and organic matter in the soil substrate. In this study, Equation 1, R^2=0.809 and P-value<0.001, was developed for predicting bulk density based on organic matter, clay, and silt content. Organic matter content had a negative, strong and linear association (r = -0.735) with bulk density.

$$\widehat{Bulk\ Density} = 1.674 - 0.017 * \widehat{OM} - 0.013 * \widehat{Clay} - 0.011 * \widehat{Silt} \qquad R^2 = 0.809 \quad (1)$$

Where bulk density is given in g/cm^3 and organic matter (OM), clay and silt are given in percent (by mass). Bulk density has a negative association with organic matter content, clay content and silt content (Equation 1). According to Equation 1, 1% increase in organic matter content leads to 0.017 (g/cm^3) decrease in soil bulk density, if the clay content and silt content are kept unchanged.

The following statistical model, Equation 2 with R^2=0.783 and P-value<0.001, was developed to predict redox potential based on predominant vegetative species observed in the sampling tidal saltmarshes.

$$\widehat{\mathrm{Eh}} = -91.46 - 77.11 * \widehat{J.roemerianus} - 222.20 * \widehat{S.\ alterniflora} - 75.08 * \widehat{B.frutescens} \qquad (2)$$

Where Eh is given in mV, and vegetation are considered as a binary indicator variable, which is either 0 (not predominate) or 1 (is predominant). According to the Equation 2, *S. alterniflora* is able to grow in a higher reduced condition than *J. roemerianus, S. tabernaemontani* and *B. frutescens*.

4.5. Heavy metals

4.5.1. Threshold Effects Levels (TELs) and Probable Effects Levels (PELs) analysis of heavy metals

The most common heavy metals in the environment in order of abundance are Pb, Cr, As, Zn, Cd, and Cu (Wuana, R. A. et al. 2011). These heavy metals are potentially capable of reducing biomass production through bioaccumulation and biomagnification processes (Wuana, R. A. et al. 2011). Further, they are capable of polluting waterways (USEPA 1996). The fate and transport of a heavy metal in a hydric soil depends substantially upon the chemical form and speciation of the heavy metal (Vane, C. H. et al. 2020). In soil, heavy metals are adsorbed through initial rapid reactions (occurring over hours) which are followed by gentle adsorption reactions (occurring over days). Then, they are redistributed into varying chemical forms with different bioavailability, mobility, and toxicity (Shiowatana, J. et al. 2001). Threshold Effects Levels (TELs) and Probable Effects Levels (PELs) (APPENDIX B, Part 4) were used to assess the ecological risks of heavy metals of the study samples (Ustaoğlu, F. et al. 2020).

We found that there is a significant difference in mean concentration of organic matter, Cd, Cu, Pb and Zn in oligohaline-mesohaline versus polyhaline marsh soils (Table 5). Arsenic concentration in these marshes was lower than TEL and PEL values (APPENDIX B, Part 4), and there was no significant difference in mean arsenic concentration in oligohaline-mesohaline and polyhaline marshes (Table 5). The mean concentrations of other metals in study marshes did not pass the thresholds (both TELs and TPLs), except Cd which had a concentration of 0.94 (mg/kg) and 0.65 (mg/kg) in oligohaline-mesohaline and polyhaline marshes, respectively. The mean concentration of Cd in oligohaline-mesohaline marshes passed TELs for Cd (0.94 mg/kg > 0.68 mg/kg) which could be a threat and ecological risk for the aquatic system. The present study found a negative and linear association (r=-0.529) between Cd and salinity, and as salinity increases, Cd concentration in soil decreases. Mobilization and concentration of Cd varied along the salinity gradient in flooded marshes probably because Cd had a great tendency for chloride which is abundant in seawater, and a high concentration of chloride in salt caused Cd mobilization from soil to interstitial water (Du Laing, G. et al. 2009).

4.5.2. Organic matter as a binding agent for heavy metals based on a linear statistical analysis

The organic matter from plants or detritus of marine species form metal-organic complexes, and as such, organic matter is capable of retaining a high amount of heavy metals (He, Y. et al. 2019). There was a strong, positive and linear association between the concentration of the metals like Cr, Cu, and Pb and the organic matter content in flooded soils (Table 6); In other words, the presence of Cr, Cu and Pb in soil highly depended upon organic matter content, and organic matter was responsible for retaining Cr, Cu, Pb, and Zn in soil substrate increases. Therefore, organic matter in soil played a key role in heavy metal cycling in hydric soils. In tidal marshes, disturbances due to construction increase soil exposure to air and accelerate organic matter decomposition (Ballantine, K. et al. 2012) and lead to heavy metals release into adjacent aquatic systems or groundwater (Bai, J. et al. 2019).

Organic matter had significant effects on mobility of copper (Cu) in soil and water system. The present study found a positive, strong and linear relationship (r=0.85) between organic matter and Cu (Table 6). Because Cu has a high tendency to bind to soil organic matter, hydric soils containing organic matter retain Cu through forming metal-organic complexes (Inaba, S. et al. 2005). This suggests that organic matter plays a key role in Cu accumulation in soil system. Although Cu is considered as an important nutrient for flora and fauna (Soetan, K. et al. 2010), it is toxic at concentrations (Casado-Martinez, M. C. et al. 2010). The concentration of 0.025 to 0.140 mg/kg is the typical range for copper in soil solution (Williams, T. et al. 1994), and Cu concentrations in the sampling sites were considerably high (APPENDIX B, Part 4) .

Table 6 – Pearson Correlation coefficients between metals or nutrients and binding agents.

	Correlation Coefficient			
	OM %	**Fe**	**Mn**	**Clay %**
As	0.22	0.77	0.33	0.56
Cd	0.78	0.88	0.67	0.61
Cr	0.9	0.86	0.79	0.57
Cu	0.85	0.82	0.74	0.56
Pb	0.91	0.84	0.83	0.45
Zn	0.87	0.9	0.83	0.59

4.6. Engineered soils

Creating and utilizing soils having important properties and conditions prior to disturbances is an integral part of successful restoration and vegetation re-establishment. In this study, we designed and created engineered soil mixtures which mimic soil conditions found in the sampling saltmarshes in terms of particle size distributions, moisture content, and organic matter prior to disturbances. In engineered mixtures, dredged material (Figure 14), sand (Figure 15) and straw were utilized as fine mineral substrate, coarse material substrate and organic matter, respectively, which varied by site (Table 7).

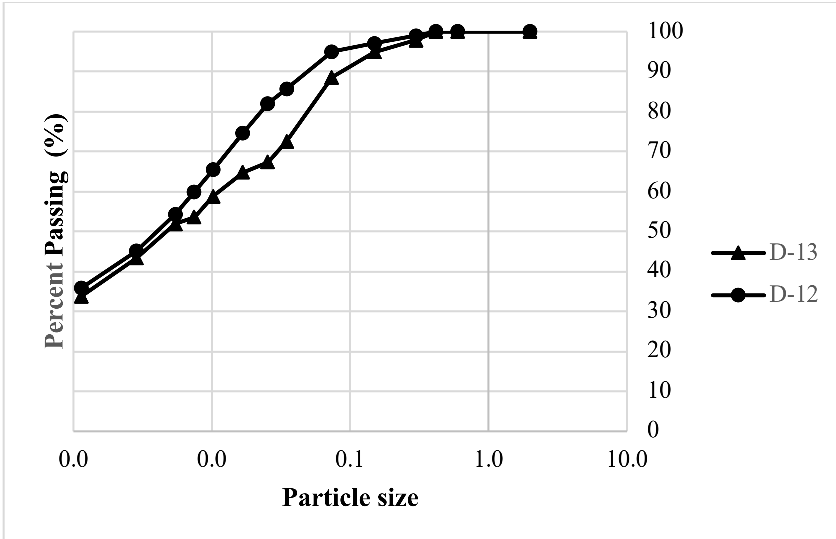

Figure 14 – Particle size distribution for dredged material.

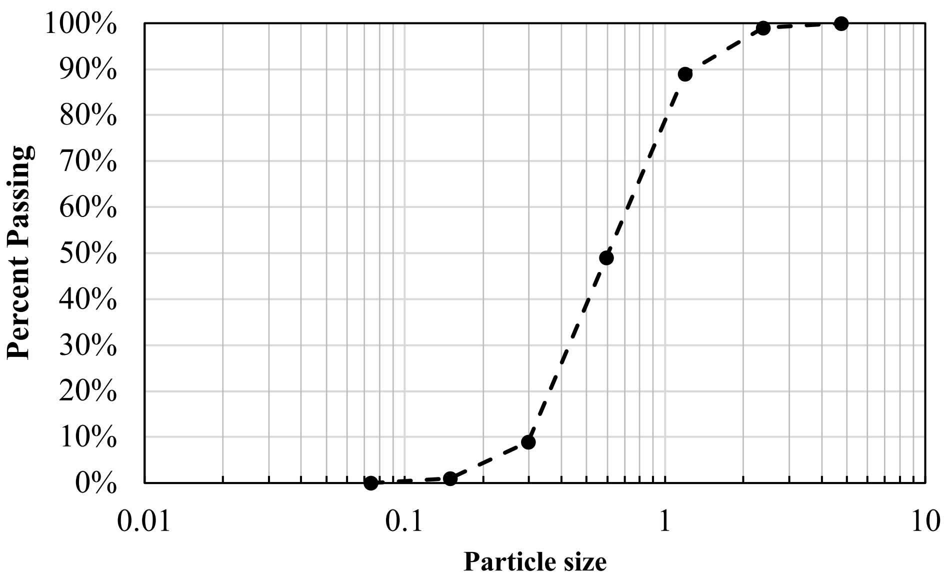

Figure 15 – Particle size distribution for sand.

Table 7 – Design mixtures of engineered soils.

Site ID	Mixture 1					Mixture 2				
	Total Sand (%)	Total Clay (%)	Total Silt (%)	Total Organic Matter	Soil Texture	Total Sand (%)	Total Clay (%)	Total Silt (%)	Total Organic Matter	Soil Texture
1	23.37	33.37	43.26	18.57	Clay Loam	28.77	29.33	41.90	14.59	Clay Loam
2	50.39	21.60	28.01	14.14	Sandy Clay Loam	52.52	19.56	27.93	12.66	Loam
3	62.79	16.20	21.00	13.39	Sandy Loam	71.51	11.73	16.76	10.95	Sandy Loam
4	29.13	30.86	40.01	28.04	Clay Loam	24.02	31.29	44.69	28.11	Clay Loam
5	11.41	38.58	50.01	18.11	Silty Clay Loam	5.03	39.11	55.86	17.48	Silty Clay Loam
6	11.41	38.58	50.01	17.88	Silty Clay Loam	5.03	39.11	55.86	17.06	Silty Clay Loam
7	84.05	6.94	9.00	10.96	Loamy Sand	90.50	3.91	5.59	9.84	Sand
8	64.56	15.43	20.00	13.82	Sandy Loam	62.01	15.64	22.34	12.49	Sandy Loam

Two different dredged material sources, D-12 and D-13, were collected from the Savannah Dredge Material Containment Area in Savannah, Georgia (Figure 14). Two sources of dredged material were collected to ensure a more representative sample and an appropriate amount of material. The first design mixture was created using the dredged material from D-13 and the second design mixture was created using the dredged material of D-12 from the Savannah Dredge Material Containment Area. Both engineered soil mixtures were within around 10% of one another to ensure that they did not vary significantly.

The primary goal for designing engineered soil was to provide saltmarsh vegetation with the ideal growth conditions and make a saltmarsh more resilient to disturbances. Engineered soils had both inherent and dynamic properties, or qualities of saltmarsh site prior to disturbances. Inherent soil quality helps natural ability of soils to function. For example, sandy soil drains faster than clayey soil because soil capability for holding water is regulated by soil texture. The texture of engineered soils was designed based on soil conditions prior to disturbances. Soil particle distribution analysis on engineered soils confirmed that engineered soils have similar texture properties to saltmarshes prior to disturbances (Figure 16). The particle size distribution curves for the two design mixtures and the particle size distribution curves of the engineered design mixture plotted next to the original soil are also found in APPENDIX B, Part 2. These curves demonstrate that the engineered soil mixtures mimic the original soils in terms of texture.

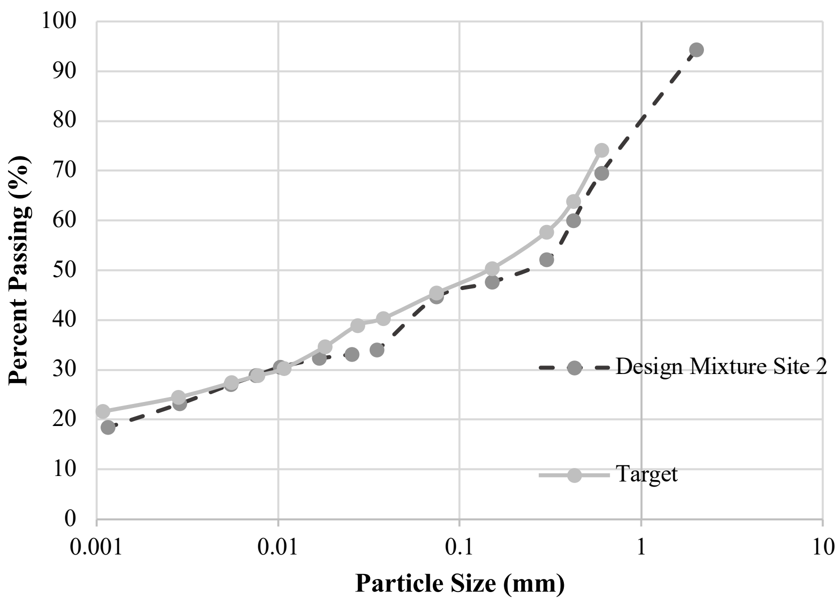

Figure 16 – Particle size distribution for design mixture (engineered soil) vs target for site 2.

Further, dynamic soil quality depends on the parameters like soil organic matter and bulk density. Because bulk density of engineered soils must be similar to saltmarsh conditions prior to disturbances, organic matter content of ten percent was used as a target value of sampling saltmarshes with less than ten percent. Our study showed that organic matter content regulates bulk density in soil substrates and these two parameters were highly correlated (Figure 17). Therefore, when designing the engineered soil mixtures, the organic matter content of 10% was a target value of sites with less than 10% to help limit the bulk density.

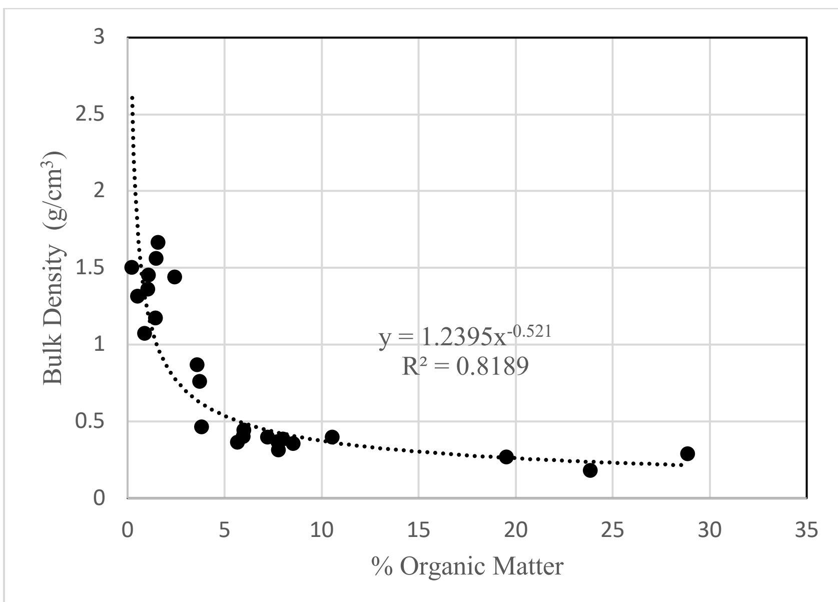

Figure 17– Bulk density vs percent organic matter.

4.7. Summary

Understanding the relationship among halophytes, soil, and interstitial water parameters optimizes restoration designs and provides the target species with ideal growth conditions. Saltmarshes adjacent to a construction site or exposed to the future disturbances should be characterized in terms of soil, interstitial water, and vegetative species prior to disturbance. When targeted soil and interstitial water properties such as Eh, bulk density, and salinity are returned, the time required for re-establishing vegetative cover after construction activity will be reduced and the density and vigor of natural vegetation in disturbed areas will likely improve, leading restoration practitioners toward a stronger chance of favorable outcomes.

The results from this chapter guide scientists toward successful restoration in disturbed tidal saltmarshes. These results were used to design and create engineered soils and draft of specification (APPENDIX A) for post-construction restoration. Utilizing engineered soils helps impacted saltmarshes be more resilient to disturbances and leads to successful restoration because engineered soils have all necessary conditions of saltmarsh soils prior to disturbances. In other words, engineered soils mimic original saltmarsh soil properties prior to disturbances, in terms of texture, organic matter, moisture content and bulk density.

CHAPTER 5. MACHINE LEARNING APPLICATION

5.1. Background

In this study, random forest (RF) and extreme gradient boosting (XGBoost) models were used to determine the most important binding agents for heavy metals with assistance of Python language (version 3.7). Both RF and XGBoost are tree-based ensemble methods. RF is considered a "parallel" ensemble because many "trees" are trained from bootstrapped samples in parallel and the results are aggregated (e.g., averaged for regression or majority vote for classification) for final prediction. By amalgamating individual models, the ensemble model generally is less biased with lower variance (Zhou, Z.H. 2009). Besides the bootstrapping technique, RF adopts a random selection of variables at each node split in order to decouple the trees. As such, these generated trees do not have collinearity issues with each other (James, G. et al. 2013). In contrast, XGboost is a sequential ensemble method, which derives individual models in a sequent fashion and each single model learns from the outputs (residual error directly) obtained by the previous model (Chen, T. et al. 2015). Previous studies suggest that boosted tree models exhibit more acceptable performance than other machine learning techniques (Natekin, A. et al. 2013).

5.2. Feature selection

Although feature selection has been used in soil science for characterizing the most important parameters for soil organic matter distribution (Hobley, E. U. et al. 2016, Taghizadeh-Mehrjardi, R. et al. 2017), it has not been applied in the field of remote sensing for predicting soil bulk density.

In this study, XGBoost and RF as ensemble machine learning algorithms were considered to investigate the most important soil and porewater parameters for bulk density prediction.

5.3. Model training

K-fold cross-validation method with k=5 was used for selecting the optimal model parameters by assigning 80% of sample to training dataset. For validation, the fitted model from the training dataset was employed for predicting the testing subset with consideration of calculated error rate. By using five-fold cross-validation technique, the dataset considered for the training part was segmented into five equal subsets in a random manner and the fitting process was repeated five times by using a different subset as a validation subset.

5.4. Model assessment

Model assessment was carried out by using a separate test subset that was not considered for the model training. Mean squared error (MSE) (Equation 3) was considered for assessing the models.

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}[y_{Predicted\ i} - y_{Actual_i}]^2 \qquad (3)$$

Where, $y_{Predicted\ i}$ is the prediction made by a machine learning algorithm and y_{Actual_i} is the actual corresponding observation.

5.5. Machine learning for classifying halophytes and modeling Eh and bulk density

The RF results indicated that Eh and salinity are the two most important parameters for vegetation classification (Figure 18). In other words, Eh and salinity were two contributing factors dictating vegetation type and structure at a saltmarsh site. The RF classification model had accuracy (the number of correctly classified data instances over the total number of data instances) of 100%.

In saltmarshes, the combination of elevation and tidal inundation characteristics determine the frequency and duration of tidal inundation which has a direct effect on soil Eh (Vepraskas, M. J.

et al. 2016). Some saltmarshes plants (e.g. *S. alterniflora*) take advantage of their physiology to overcome the harsh conditions of submergence and high salinity (Reddy, K. R. et al. 2008). However, some species are not highly salt or water tolerant. Saltmarsh elevation influences both Eh and salinity. Saltmarshes are differentiated into zones based on elevation and the resulting frequency of tidal inundation, and described as low, middle, or high marshes. In high marshes, less flooding leads to an increase in Eh and salinity due to high oxygen availability (i.e., low electron activity) and high evaporation rate, respectively.

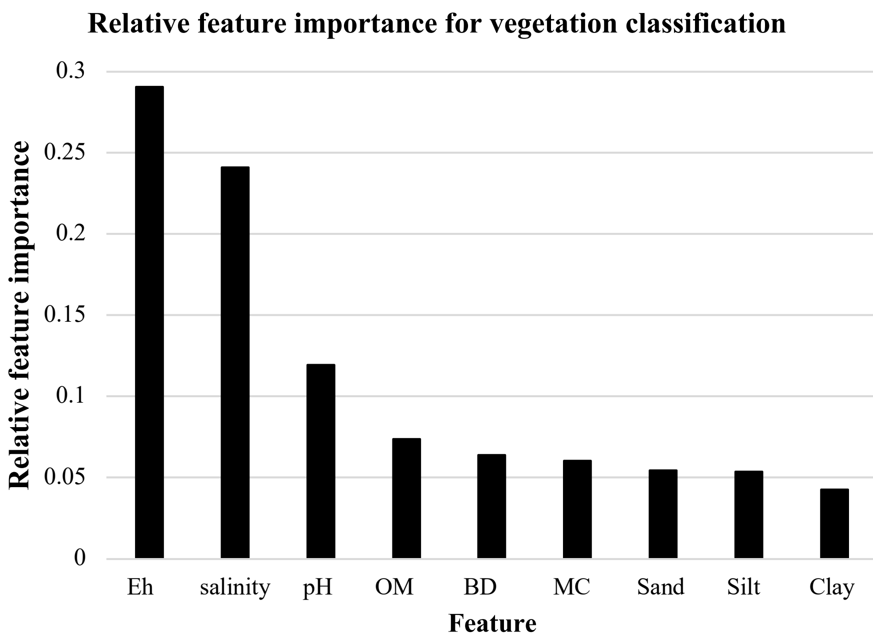

Figure 18 – The parameters importance in plant classification by RF.

According to the RF regression models, moisture content and salinity were the most important parameters for predicting bulk density and Eh, respectively (Figure 19). MSE for bulk density and Eh models was 0.037 and 3339.231, respectively. The relationship between soil bulk density and moisture content was well established. As moisture content increases, the bulk density decreases due to an increase in the volume of the pores in the soil substrate.

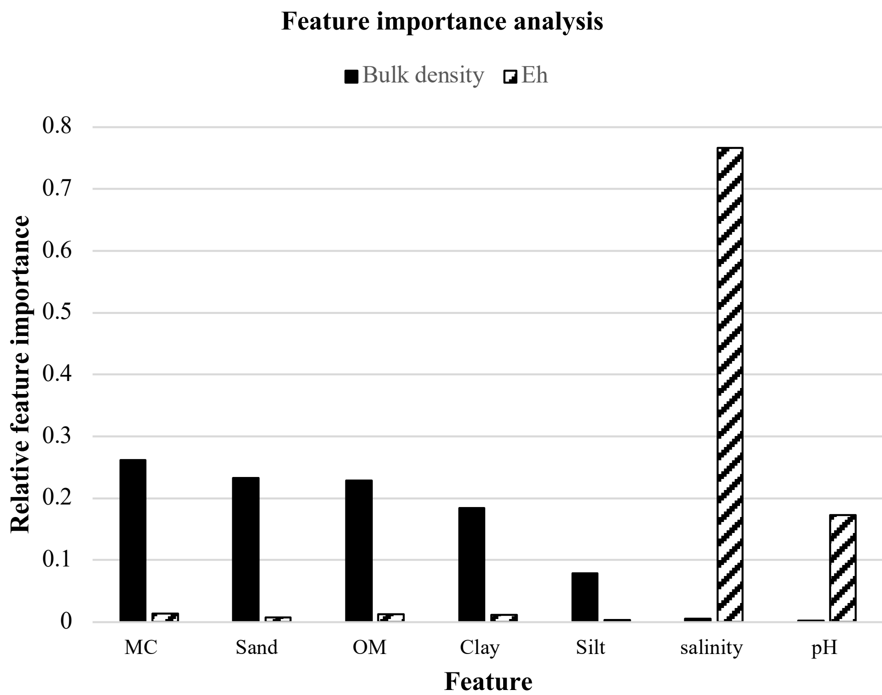

Figure 19 – The parameter importance for predicting bulk density and redox potential (Eh) by RF.

The RF models predicted bulk density ($R^2 = 0.964$) and Eh ($R^2 = 0.872$) well (Figure 20 and Figure 21) with a tendency to underpredict high Eh. The measured soil bulk density varied from 0.314 g/cm^3 to 1.501 g/cm^3 (Figure 21), and the prediction of bulk density did not show a clear tendency of under-prediction or over-prediction. The slopes (Figure 20 and Figure 21) were nearly 1, suggesting that the prediction of the models is about what was observed.

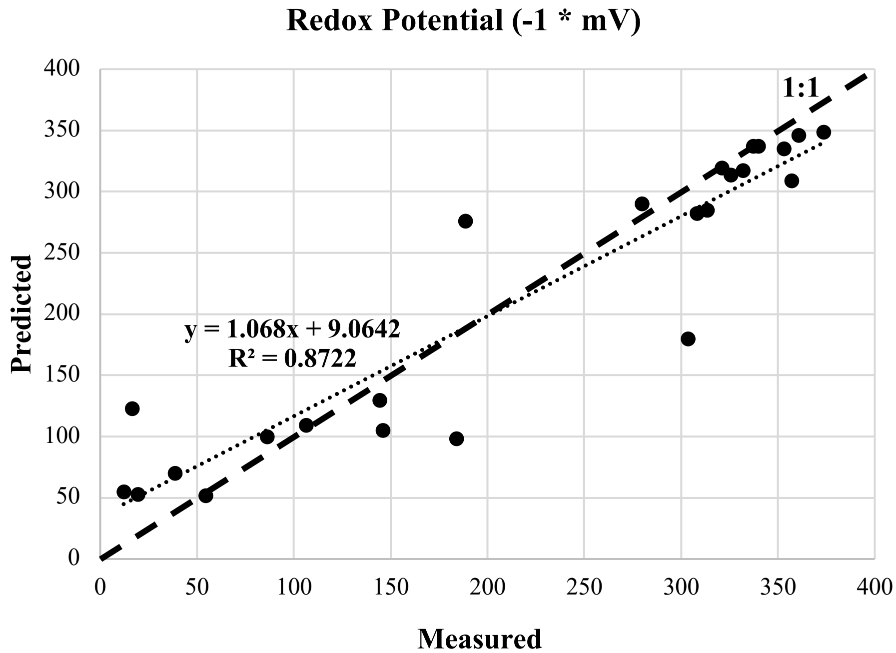

Figure 20 – Predicted vs. measured redox potential by RF model.

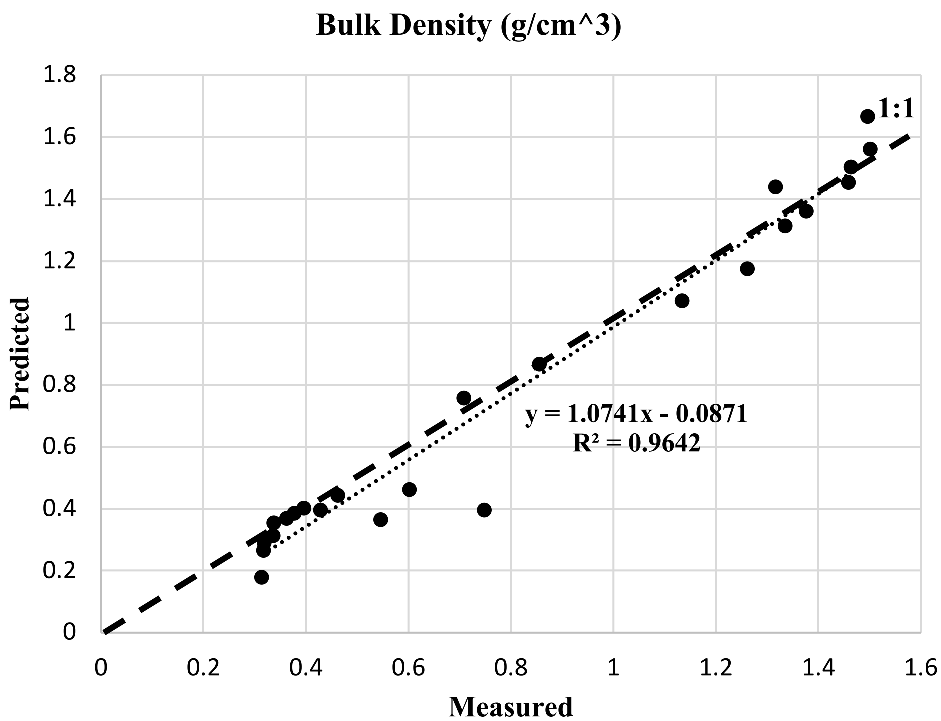

Figure 21 – Predicted vs. measured bulk density By RF model.

5.6. Machine learning algorithms for heavy metals characterization

Machine learning algorithms, such as RF and XGboost, can identify the key drivers of heavy metals in hydric soils. Our RF regression model included 200 trees, which were constructed using the conditional inference forest algorithm (Strobl, C. et al. 2007) by minimizing the mean square error (MSE) prediction. An example decision tree (Figure 22) is provided to visualize where an internal node represents feature (binding agents), the branch represents a decision rule, and each leaf node represents the outcome (heavy metals concentration). The individual trees in the RF model repetitively partitioned a random subset of the data to reduce the error and the results were then combined (e.g., averaged) for the final prediction. Tuning a machine learning model by setting the related hyperparameters was important to control the complexity of the model and combat overfitting. The hyperparameters for our RF model, including the minimum number of samples required for each leaf, the minimum number of samples required to split each node, the maximum number of levels in each decision tree, and the number of trees in the forest, were chosen to be 4, 6, 3, 200, respectively. The XGBoost model was tuned with the hyperparameters of 200 trees in the ensemble, a maximum tree depth of 3 and a learning rate of 0.5. These hyperparameter values for RF and XGBoost were selected based on accuracy and error of the outcome from these two models. They regulated the learning process of the algorithms and found the models with highest accuracy and lowest error.

Iron (Fe) was the most important feature for estimating As concentration (Figure 22). A high concentration of Fe in soil and water can precipitate As and reduce its bioavailability; however, high concentrations of As and Fe can also reduce a plant production. The relationship between soil geochemistry and As concentrations is not yet fully understood. Fe reduces the lability of As, and effectively attenuates As in arsenic-polluted soils (Wang, N. et al. 2017). Fe reduces nearly fifty percent extractable As in soils (Pillai, P. et al. 2020). Goethite (consisting of Fe(III) oxide-hydroxide) is effective to reduce arsenic toxicity in contaminated soil (Sun, X. et al. 1998). Further, water-soluble iron-hydrous oxides regulate the arsenic adsorption–desorption reaction in sludge (Carbonell-Barrachina, A. et al. 2000). Ferrous sulfate ($FeSO_4$) (Artiola, J. F. et al. 1990) and amorphous Fe hydroxide (am-$Fe(OH)_3$) (Shaibur, M. R. et al. 2009) also have a high adsorptive capacity for As. If Fe concentration was more than 12358.51 (mg/kg), organic matter was used as the second most important feature for splitting dataset and predicting As concentration.

The top four binding agents for heavy metals were determined to be clay, organic matter, Mn and Fe. The feature importance analysis by RF (Figure 23) and XGBoost (Figure 24) was determined based on comparable measures (e.g., feature relative importance), which infers the relative contribution of the each feature to the model predictions. As a result, the feature relative importance from the two models showed similar patterns. For instance, Fe was the most important binding agent for Cd according to both models (Figure 23 and Figure 24). The mean concentration of Cd in oligohaline-mesohaline marshes passed TELs, and both XGBoost and RF suggested that the cycle of Fe should be controlled to enhance the health of the aquatic system in such areas. One approach to control Fe cycle is to inhibit saltwater intrusion into low salinity areas because sulfur abundance in seawater plays the key role in pyrite (FeS_2) formation which is a vital part of Fe cycle in marsh soil system (Reddy, K. R. et al. 2008). For example, construction in saltmarshes may change hydrology and saltwater input regime which indirectly influence available free Fe in soil and water system.

Both methods selected Fe as the most important binding agent for heavy metals such As, Cd, Cr and Zn (Figure 23 and Figure 24). Fe compounds considerably influence the behavior of some heavy metals (Bartlett, R. J. et al. 1993). The level to which soil Fe is responsible for heavy metal solubility and availability is greatly determined by some soil factors. On the other hand, heavy metals were also known to affect the bioavailability of Fe (Sipos, P. et al. 2014). Fe has a high sorption capacity, especially for heavy metals (Sipos, P. et al. 2014). The mechanisms of sorption involve the isomorphic substitution of divalent or trivalent cations for Fe ions, the cation exchange reactions, and the oxidation effects at the surface of the oxide precipitates (Sipos, P. et al. 2014).

Organic matter was selected as the most important binding agent for Pb by XGBoost and RF because organic matter forms complexes with Pb and plays a key role in Pb cycling (Chen, B. et al. 2006). Mn was selected as the most important binding agent for Cu concentration modeling by XGBoost and RF because Cu has tendency to form strong ionic bond with Mn (Arulanandan, K. et al. 1973). Overall, the XGBoost regression model performed more accurately (lower MSE) than RF for modeling the concentration of As, Cr, Cu, Cd, Pb and Zn (Figure 25). Based on the MSE values of both methods (Figure 25), XGBoost gave better accuracy than RF to predict Pb concentration in saltmarsh soils because XGBoost repetitively leveraged the patterns in residuals and strengthened the model with predictions made through sequential analysis.

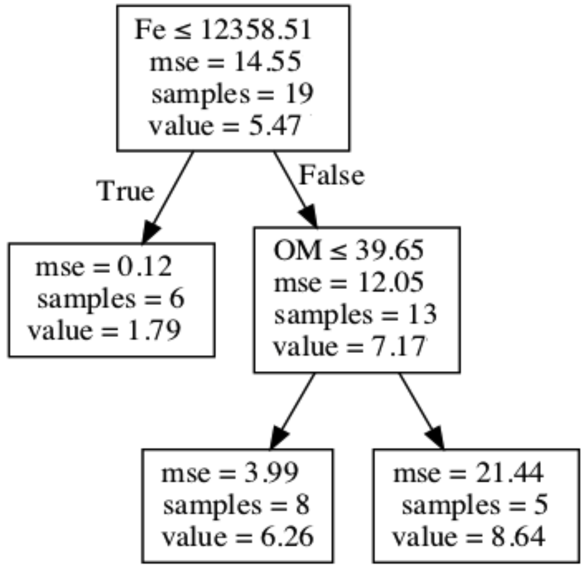

Figure 22– An example of decision tree (a) for arsenic concentration estimation.

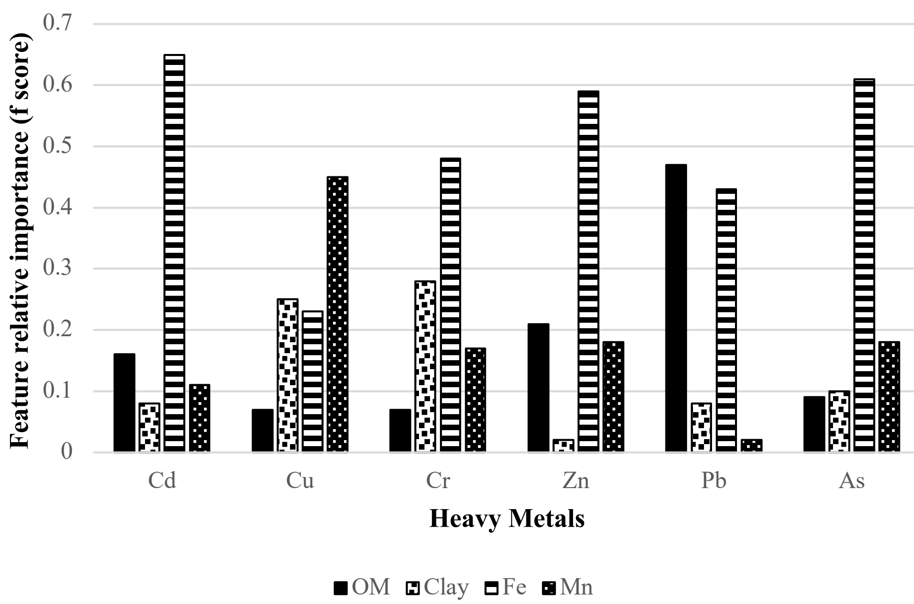

Figure 23 – Heavy metals binding agents prioritized by RF feature selection.

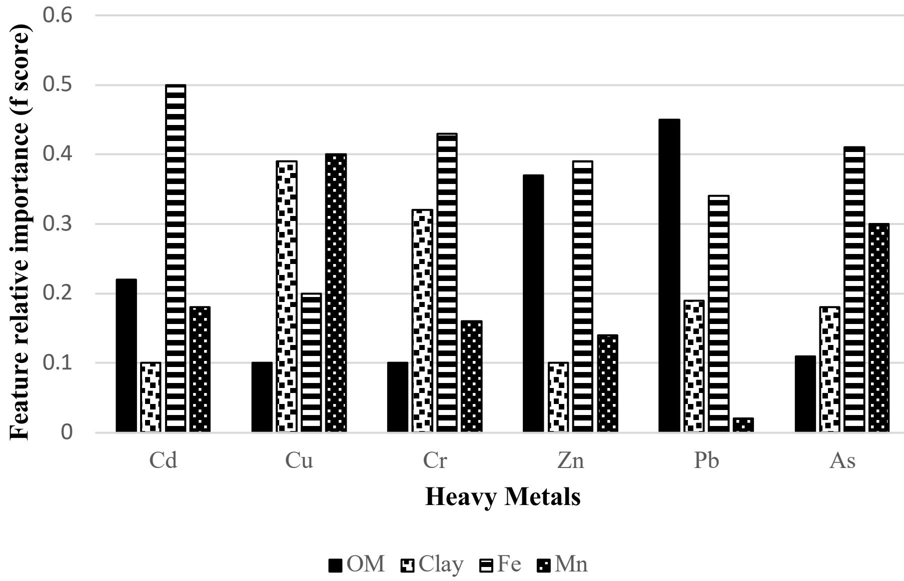

Figure 24 – Heavy metals binding agents prioritized by XGBoost feature selection.

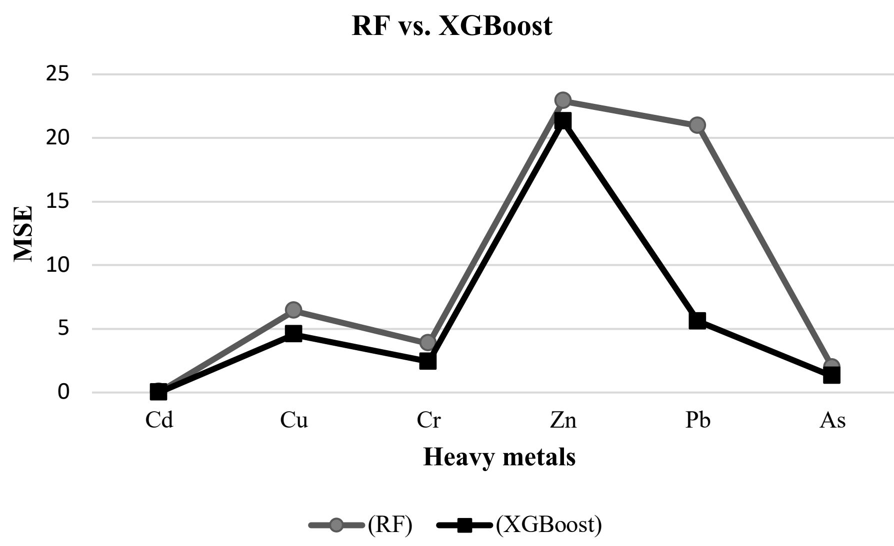

Figure 25 – Comparison of RF and XGBoost models for heavy metals prediction.

5.7. Summary

The RF results indicated that Eh and salinity are the two most important parameters for vegetation classification. In other words, Eh and salinity were two contributing factors dictating vegetation type and structure at a saltmarsh site. The RF classification model had accuracy (the number of correctly classified data instances over the total number of data instances) of 100%. Therefore, RF model is reliable for vegetation classification and predicating vegetation type based on soil and porewater parameters. Furthermore, according to the RF regression models, moisture content and salinity were the most important parameters for predicting bulk density and Eh, respectively. MSE for bulk density and Eh models were 0.037 and 3339.231, respectively.

According to both RF and XGBoost, Fe was the most important binding agent for As, Cd, Cr and Zn. Besides the consistent results from two methods for modeling heavy metals, XGBoost outperformed RF in terms of MSE. Further, Mn and organic matter were determined as the most important binding agent for Cu and Pb, respectively, through the feature selection analysis.

CHAPTER 6. REMOTE SENSING CLASSIFICATION OF SALTMARSH SOIL

6.1. Background

Bulk density is a commonly measured physical parameter which is included in many marsh assessment standards (Rokosch, A. E. et al. 2009). Soil compaction causes an increases in bulk density and a decrease in pore volume (Kooistra, M. J. et al. 1994). Bulk density is a function of many factors such as the parent material, soil texture, vegetation community, and management history (Logsdon, S. D. et al. 2004). For example, silt and silt loam soils, a bulk density of 1.40 g/cm^3 is the minimum threshold for vegetation root development (USDA, N. 1996).

Bulk density is related to soil porosity. An increase in bulk density from 1.1 to 1.4 g/cm^3 yields a 42% reduction in oxygen diffusion rate through waterlogged saltmarsh soil, while the induced changes in soil bulk density from 1.1 to 1.7 g/cm^3 results in a 75% reduction in the rate of oxygen diffusion (Asady, G. et al. 1989). Bulk density reflects soil' structural stability to support vegetation growth against destructive impacts of tidal flooding; however, bulk density greater than 1.6 g/cm^3 is not generally suitable for root and plant growth in saltmarshes (McKenzie, N. et al. 2004).

Soil bulk density has a high spatial variation at landscape scales for a number of ecosystems, including saltmarshes, because of their dynamic nature and constant change in soil texture, age, depth, and plant community structure (Bruland, G. et al. 2005, Wang, H. et al. 2017). In saltmarshes of Georgia and Gulf of Mexico coasts, soil bulk density is regulated by the inorganic portion of soil structure (Hatton, R. et al. 1983, Vepraskas, M. J. et al. 2016) depending upon tidal action, riverine sediment delivery, hurricanes and seasonal storms, and sediment deposition and erosion rate (Nyman, J. et al. 1990, Turner, R. E. et al. 2006, Craft, C. 2007). These physical natural processes vary within a saltmarsh site; which leads to high a spatial variation in soil bulk density (Turner, R. E. et al. 2006, Wang, H. et al. 2017).

Bulk density is typically measured to characterize soil structure and utilized for estimating total porosity (Blake, G. R. et al. 1986). Within a given soil texture, variation in bulk density is directly related to the degree of compactness (Håkansson, I. et al. 2000), aggregation (Aksakal, E. L. et al. 2019), and organic matter content (Morris, J. T. et al. 2016). Bulk density is a fundamental parameter to determine hydraulic conductivity (Aksakal, E. L. et al. 2019) and is used for calculating the total storage of a given nutrient per unit area in a given depth of soil (Reddy, K. R. et al. 2008). Disturbances in saltmarshes negatively impact soil quality, is a critical component for high primary production of saltmarshes (Davidson, E. A. et al. 2006). Soil bulk density change are often used as an efficient indicator of soil quality (Karlen, D. L. et al. 2003). To detect changes in saltmarshes soil structure and carry out the long-term monitoring of soil quality of these environmentally sensitive areas, it is helpful to establish up-to-date documented knowledge base at a broad scale.

Remote sensing has recently recognized as a reliable technique to characterize saltmarsh soils from field to space and an effective approach to model soil properties at a large scale (Anderson, K. et al. 2009, Moffett, K. B. et al. 2010, Zhang, C. et al. 2019). Soil type has been identified based on the vegetation indices and the changes in soil structure were detected by analyzing time series of vegetation indices from remote sensing (Moffett, K. B. et al. 2010, Mulder, V. et al. 2011). Also, soil properties in tidal wetlands have been linked to vegetation density, diversity and health (Odum, W. E. 1988), and it has been shown that soil properties are characterized based on the composite spectral reflectance from saltmarsh surface which includes background moist soil and vegetation canopy (Zhang, C. et al. 2019).

This chapter investigates the use of satellite images to estimate saltmarsh soil bulk density in conjunction with machine learning algorithms. Choosing a high accuracy classification method enhances the value of the application of remote sensing in the field of land surface study (Mcleod, E. et al. 2011). Since satellite images have complex nature and spatial variation, the analysis of these images is restricted to the empirical relationship between the image patterns and the land surface features (Woodcock, C. E. et al. 1988) by assuming that objects existing on the land have a consistent spectral signature in the image. In this study, random forest (RF), super vector machine (SVM), and extreme gradient boosting (XGBoost) are used to predict soil properties like bulk density based on the pixel spectral values on the images sensed remotely.

6.2. Materials and Methods

6.2.1. Data

Saltmarshes along Georgia's Atlantic coast in US were selected for this study. Data sources include multispectral imagery (LandSat-7 Enhanced Thematic Mapper Plus (ETM+)) and soil data collected by field sampling and laboratory analysis. LandSat-7 (ETM+) images with a spatial resolution of 30 meters are available from the U.S. Geological Survey (USGS) Earth Resources Observation and Science Center (http://landsat.usgs.gov/), and approximate scene size of 170 km north-south by 183 km east-west covering the area of interest. LandSat-7 (ETM+) images corresponding to the sampling saltmarshes were obtained and processed over the study period (i.e., from 2000 to 2018 inclusive). Band 6, (10.40 - 12.50 μm), was not used in this study because this thermal band has a different spatial resolution (60 m) from the other study bands. Clouds were nearly absent in the acquired Landsat-7 (ETM+) data and the quality of the multispectral data was good. Furthermore, the obtained images from USGS website were atmospherically corrected (APPENDIX B, Part 3), although the weather was good for the data acquisition time and no smog appeared in the atmosphere. The pixel values of the bands were extracted from the study images by tools provided by SNAP version 7.0 software.

The bulk density datasets were prepared by Coastal Carbon Research Coordination Network (CCRCN) hosted at the Smithsonian Environmental Research Center (SERC). These datasets were downloaded from the Coastal Carbon Atlas, a map interface which accesses the CCRCN's Data Library (https://ccrcn.shinyapps.io/CoastalCarbonAtlas/). Each data source was credited to the original data contributors (Craft, C. 2007, Noe, G. B. et al. 2013, Nahlik, A. M. et al. 2016, Jones, M. C. et al. 2017, Holmquist, J. R. et al. 2018, Krauss, K. W. et al. 2018). The rest of the bulk density data was obtained from Georgia Coastal Ecosystems Long Term Ecological Research Program (https://gce-lter.marsci.uga.edu/) and credited to the original data contributor (Pennings, M. 2001, Pennings, S. 2012).

In addition to the above data sources, sampling occurred in eight tidal marshes along the southeast coast of the US in Georgia in 2018. Three different representative sampling areas were chosen along these transects based on vegetation coverage. Further, the core method was applied for measuring soil bulk density at the root zone (Blake, G. 1965). A soil sampler was utilized to collect an undisturbed soil sample from the root zone to determine the bulk density at the laboratory (ASTM D7263-09).

6.2.2. Machine learning algorithms

K-means algorithm was used to determine clusters number, center and range for bulk density data. K-means clustering method classified bulk density dataset into different clusters including datapoints with similar characteristics. Each bulk density datapoint in the dataset was initially assigned to one of K clusters at random. The centroid location was determined for each cluster and then, each point was re-assigned to a cluster with the nearest centroid. This iteration process stopped when there is no change in cluster membership with additional iterations of the algorithm. After K-means clustering, three machine learning algorithms including support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost) were followed to determine the most accurate classification model for soil bulk density.

6.2.2.1. Support vector machine (SVM)

Overall, SVM as a binary classifier transforms n-class problems into the sequence of binary classification tasks (Belousov, A. et al. 2002). The basic variant of SVM produces a separating hyper-plane in the original space of n coordinates between the points of two distinct classes (Marjanović, M. et al. 2011). In SVM, the hyper-plane was built from the training set and determined a maximum margin of separation between the classes and generated a classification hyper-plane in the middle of the maximum margin.

6.2.2.2. Random Forest (RF)

RF utilized ensemble approaches are based on calculating the average of a large number of separate decision tree models built by finding the best predictor for splitting the results with consideration of the model error (Hastie, T. et al. 2009). Overall, ensemble learning makes predictions based upon a number of different models (Zhou, Z.-H. 2009). By amalgamating individual models (trees), the developed ensemble model generally is not biased and had little variance (Zhou, Z.-H. 2009). The RF trees were developed by a bootstrapped training dataset, and only a small number of variables was chosen at one split. As such, these generated trees did not have collinearity issue with each other.

6.2.2.3. Extreme gradient boosting (XGBoost)

Gradient boosting technique was used for developing boosted decision trees models. In this method, the gradient boosting technique is used to fit the simple base learner functions of decision trees to the pseudo-residuals which are the gradient of the minimized loss function through sequent iterations (Friedman, J. H. 2002). Boosted regression tree model exhibited more acceptable performance than other machine learning techniques. Tree-based models like RF and boosted regression tree classified features based on their relative importance as the following equation:

$$\widehat{J_i}^2 = \sum_{Splits\ on\ x_i} I_t^2 \qquad (4)$$

The approximate relative influence ($\widehat{J_i}^2$) of a predictor variable x_i was calculated by the equation above, where I_t^2 is the empirical improvement by splitting on predictor x_i at that point.

6.2.2.4. Model assessment

Confusion matrix was developed for evaluating machine learning algorithm efficiency and accuracy in classifying saltmarsh soil bulk density. The confusion matrix, a traditional technique for classification assessment, assigned the pixels at reference locations to single classes, and classification accuracy was measures based upon the number of saltmarsh sites (pixels) correctly classified.

6.3. Results and Discussion

6.3.1. K-means algorithm for data labeling based on bulk density and saltmarsh vegetation

K-means clustering algorithm was used to cluster bulk density into two classes; low and high bulk density ranging from 0.032 g/cm^3 to 0.752 g/cm^3 and 0.752 g/cm^3 to 1.893 g/cm^3, respectively. The cluster center for low bulk density class was 0.400 g/cm^3; which tends to be suitable for supporting saltmarsh vegetation having very soft root structure like *S. tabernaemontani.* The center for high bulk density class was 1.108 g/cm^3 which is suitable for halophytes such as *J. roemerianus* and *Borrichia frutescens.* Vegetation survey and bulk density tests were conducted along Georgia's Atlantic coast at 24 saltmarsh sites in June 2018 to determine the importance of bulk density in plant diversity. *S. tabernaemontani* grows in soils with low bulk density, while *B. frutescens* and *J. roemerianus* are able to develop and establish in high bulk density (Figure 26).

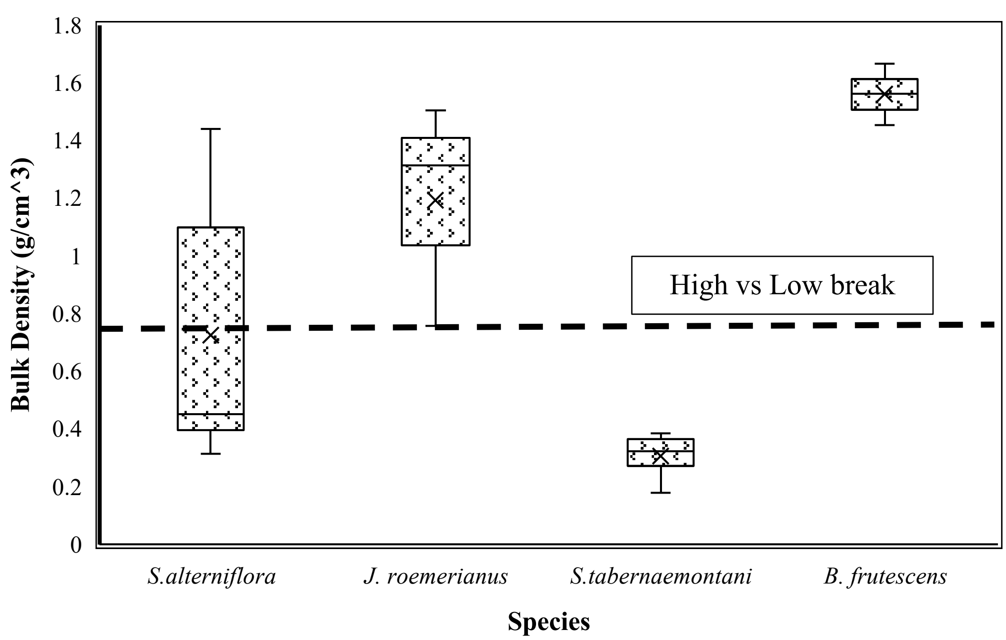

Figure 26 – Bulk density values of four dominant in saltmarshes of the Georgia (USA) coast.

6.3.2. Band selection for modeling soil bulk density by RF and XGBoost algorithms

RF and XGBoost algorithms were used to investigate the most important LandSat-7 (ETM+) spectral bands for modeling saltmarsh soil bulk density. The tuning hyperparameters for the RF model, including the minimum number of samples required for each leaf, the minimum number of samples required to split each node, the maximum number of levels in each decision tree, and the number of trees in the forest, are chosen to be 4, 6, 3, 500, respectively. On the other hand, the XGBoost model was tuned with the hyperparameters of 500 trees in the ensemble, a maximum tree depth of 3 and a learning rate of 0.5. Band1 (blue) and band 4 (near infrared) were selected as the most important attribute for modeling bulk density (Figure 27) by XGBoost and RF, respectively. These hyperparameter values for RF and XGBoost models were selected based on accuracy and error of the outcome from these methods. They regulated the learning process of the algorithms and found the models with highest accuracy and lowest error.

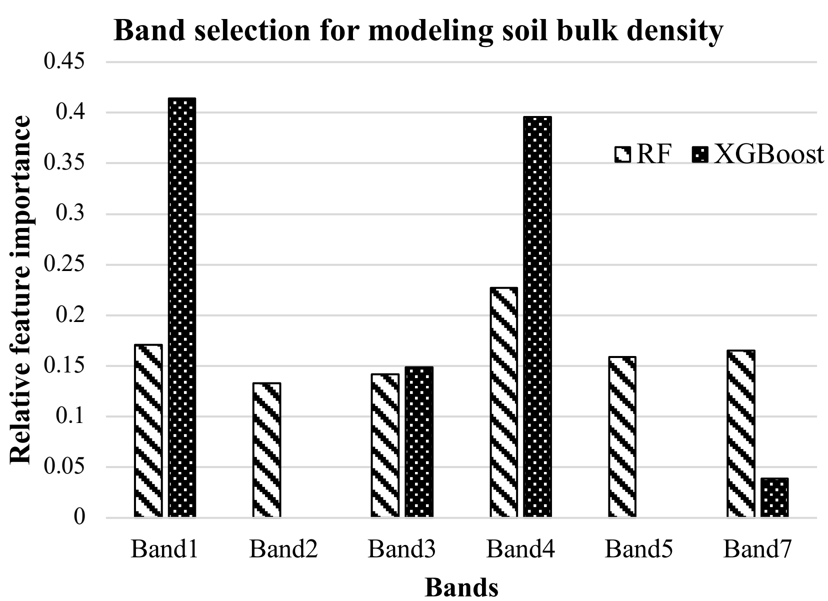

Figure 27 – Relative importance of LandSat-7 bands for modeling soil bulk density of saltmarshes along Georgia coast USA.

Overall, healthy plants tend to absorb electromagnetic energy in the blue region (450-520 nm) due to chlorophyll-a presence. Chlorophyll-a concentration an indicator of biomass abundance in aquatic environments (Ha, N. T. T. et al. 2017). Further, plants with healthy internal leaf structure have a high reflectance in the near infrared region (770-900 nm). As this internal structure varies among different plant species, the near infrared wavelengths (band4) was used to discriminate between different plant species and soil properties because vegetation canopy structure has a substantial influence in soil properties in saltmarsh environments (Odum, W. E. 1988, Zhang, C. et al. 2019).

Feature selection analysis for developing a model for soil bulk density classification through XGboost and RF algorithms resulted in different outputs. This difference in variable selection analysis is potentially attributable to the difference in RF and XGBoost algorithms. The individual trees in RF model repetitively partitioned a random subset of the dataset into ever purer nodes (based upon the best random subset of predictors) and the results were then amalgamated into the ensemble. However, the boosting created an initial (usually quite small) tree, shrunk it, and then repeatedly partitioned the residuals of the previous tree, in essence, similar to incorporating partial regression into a decision tree. Bulk density was modeled through a decision tree algorithm (Figure 28) based on LandSat-7 (ETM+) spectral bands. In this tree structure, an internal node represents a “test” on an attribute (e.g. LandSat-7 (ETM+) spectral bands), a branch represents the output of the test, a leaf node represents a class label (low or high bulk density) and the paths from root to leaf represent classification rules (Figure 28).

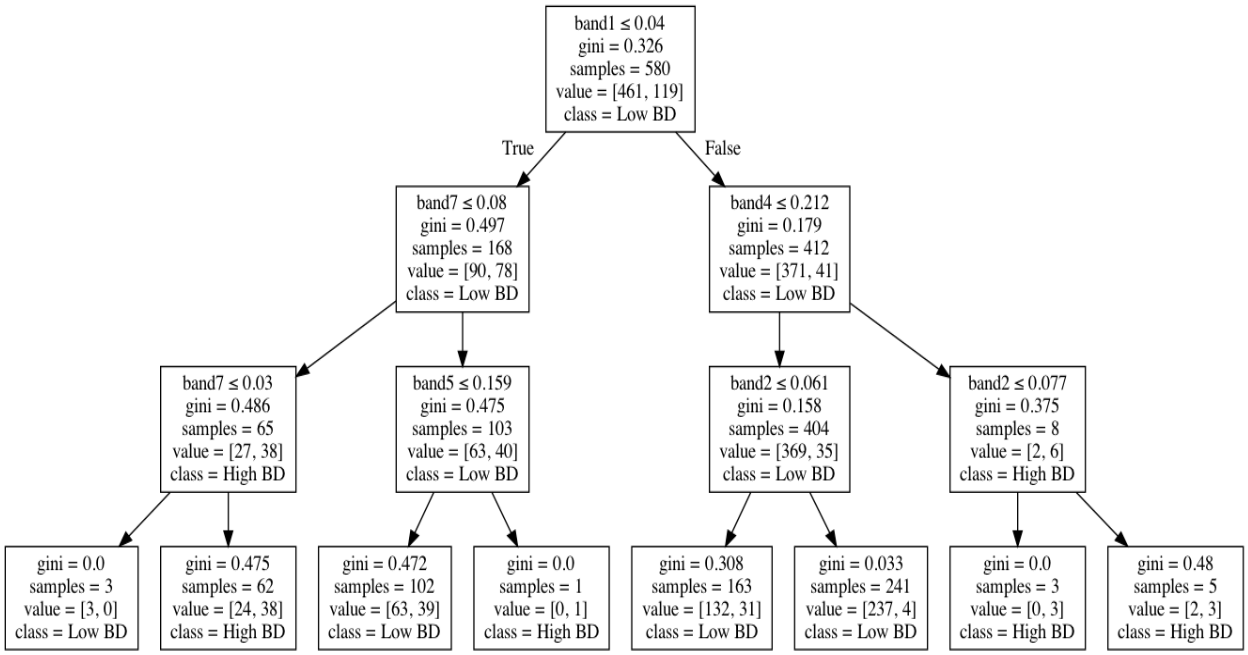

Figure 28 – An example of decision tree for bulk density classification.

6.3.3. Machine learning algorithms for soil bulk density prediction

6.3.3.1. XGBoost and RF algorithms

XGBoost and RF as ensemble tree models were employed to assign the saltmarsh soils into two main classes as low and high soil bulk density. This classification was carried out by only using LandSat-7 (ETM+) spectral band values as independent variables. XGBoost had the highest accuracy of 0.88 among the study algorithms (Table 8). According to RF, low and high bulk density classes had the precision of 0.96 and 0.62, respectively; meaning that once the RF algorithm assigned low bulk density class to a saltmarsh site, it was correct 96% of the time. On the other hand, XGBoost model had the precision of 0.88 and 0.86 corresponding to low and high bulk density, respectively.

The RF model had recall of 0.88 and 0.83 corresponding to low and high bulk density, respectively. In other words, this algorithm correctly identified 88% of all low bulk density and 83% of all high bulk density saltmarshes.

Table 8 – SVM, RF and XGboost models assessment results.

Models	Class	Recall	Precision	Accuracy
SVM	Low BD	0.96	0.87	0.86
	High BD	0.60	0.82	
RF	Low BD	0.88	0.96	0.87
	High BD	0.83	0.62	
XGBoost	Low BD	0.96	0.88	0.88
	High BD	0.61	0.84	

Machine learning algorithms on the test dataset (n=248) had a better performance on identifying the sampling sites with low bulk density than high bulk density (Table 9). For example, XGBoost correctly identified 178 out of 186 of the low bulk density sites, while XGBoost accurately classified 39 out of 63 of the high bulk density marshes.

Table 9 – Confusion matrix corresponding to the machine learning algorithms.

SVM			
		True	
Predicted		Low BD	High BD
	Low BD	178	25
	High BD	8	37
RF			
		True	
Predicted		Low BD	High BD
	Low BD	179	25
	High BD	7	38
XGBoost			
		True	
Predicted		Low BD	High BD
	Low BD	178	24
	High BD	8	39

The XGboost model was overfit (Figure 29) because the classification error in both training and testing dataset reduces as the number of iterations increases and the two curves are converged after 40-time runs once the learning rate is 0.5.

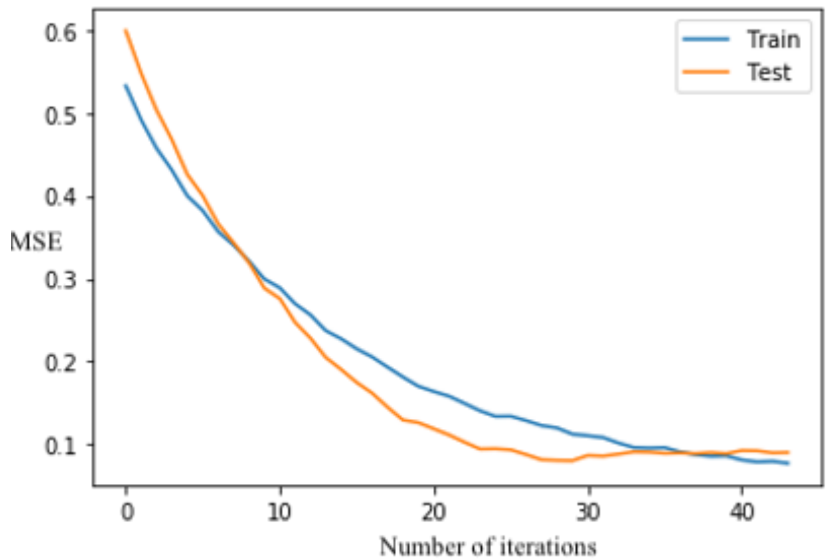

Figure 29 – XGBoost classification error vs number of iterations.

6.3.3.2. SVM algorithm

The SVM algorithm was also employed on the study dataset. The tuned model had the accuracy of 0.86 (Table 8), respectively. A set of user-defined parameters were required to design the SVM model, and the hypermeters (including kernel of poly, kernel coefficient (g) of 40 and regularization parameter (C) of 1) were set to tune the model. The design of SVM model involved selecting an optimal kernel, g and C; which requires a lot of experimentation and processing time.

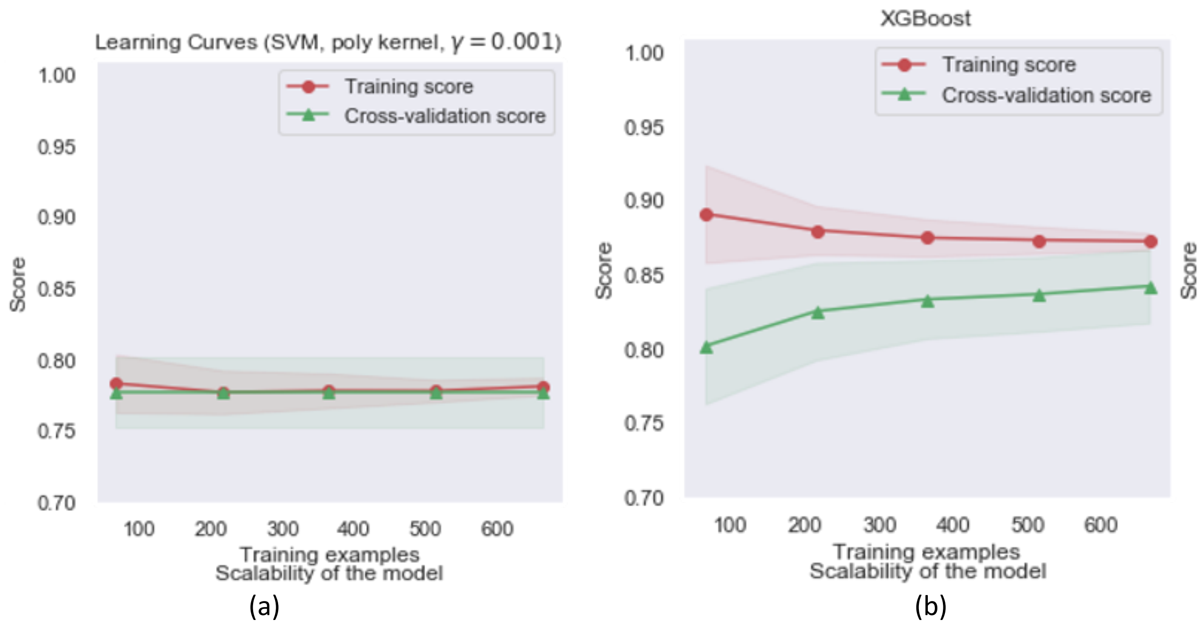

Figure 30 – Learning curves on training and test dataset by (a) SVM and (b) XGBoost algorithms.

A learning curve (Figure 30) exhibited the validation and training scores of XGBoost and SVM algorithms for varying numbers of training samples. For both models, both the validation score and the training score converge to a value that was quite high with increasing size of the training set. The curves corresponding to the SVM model showed that adding more training or testing data is not beneficial although the training and validation scores were relatively high (0.78) at the beginning and the end of the curve and the SVM model did not suffer from a variance error or a bias error. On the other hand, the XGBoost model showed an increase in the validation score as the number of data increases in the test dataset. Therefore, the curve suggested that higher accuracy can be obtained through enlarging the test set (Figure 30).

6.4. Summary

The long-term monitoring and the continuous perseverance of saltmarsh soils help the ecosystem maintain its ecological health and support its native plants and animals. Understanding saltmarsh soil properties such as bulk density guides restoration scientists to an effective restoration practice and a successful re-establishment of native vegetation. Machine learning algorithms and LandSat-7 (ETM+) spectral bands were used in this study to model saltmarsh soil bulk density. RF and XGBoost were utilized to choose and rank the features with the highest efficiency to discriminate between the target classes through predictions obtained from an ensemble tree model. Band1 (blue) and band 4 (near infrared) were selected as the most important attribute for modeling bulk density by XGBoost and RF, respectively. Among the machine learning algorithms such as RF, XGBoost and SVM, XGBoost had the highest accuracy in classifying saltmarsh soils into two main classes; low and high bulk density ranging from 0.032 g/cm^3 to 0.752 g/cm^3 and 0.752 g/cm^3 to 1.893 g/cm^3, respectively. Although these two classes are not specific in determining the critical areas which are not ideal for vegetation growth (bulk density > 1.400 g/cm^3), bulk density estimation based on these two classes helps restoration scientists ensure weather saltmarsh soils are able to support a specific native vegetation post-construction. The cluster center for low bulk density class was 0.400 g/cm^3; which tends to be suitable for supporting saltmarsh vegetation having very soft root structure like *S. tabernaemontani.* The center for high bulk density class was 1.108 g/cm^3 which is suitable for halophytes such as *J. roemerianus* and *Borrichia frutescens.*

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

7.1. Conclusions

Changing saltmarsh soil structure and bulk density due to construction activity potentially result in loss in ecological functionality post-construction. In this study, we developed and created engineered soils which mimic the original conditions of saltmarshes prior to disturbances in order to have successful restoration and expedite vegetation re-establishment. Knowing correlation between soil parameters and vegetation, restoration scientists can optimize designs to govern the ideal growth conditions for target species at disturbed saltmarsh sites.

- Mean bulk densities for sites supporting *S. tabernaemontani* and *B. frutescens* are 0.323 g/cm^3 and 1.560 g/cm^3, respectively. *B. frutescens* is able to establish and develop in soils having relatively high bulk density, up to 1.670 g/cm^3, in comparison to the other vegetation, which is a result of high sand content or low organic matter content. *B. frutescens* is found in the highest average bulk density (around 1.560 g/cm^3) and the lowest average organic matter content (i.e., 1.383 percent). *S. tabernaemontani* grows in the soil with lowest average bulk density (0.478 g/cm^3) and highest average organic matter content (13.83 percent) in comparison to the other vegetative species observed in this study.
- High values of bulk density possibly restrict vegetation growth, productivity and development in the saltmarsh environment. Site 3.B (sandy loam) and 7.B (loamy sand) have bulk densities of 1.504 g/cm^3 and 1.667 g/cm^3 exceeding the USDA threshold values

(1.400 g/cm^3 and 1.600 g/cm^3, respectively). Site 3 and site 7 are dominantly covered by *J. roemerianus* and *B. frutescens*, respectively. These two species grow in higher elevation and higher bulk density than *S. alterniflora.*

- Among the machine learning algorithms such as RF, SVM, and XGBoost, XGBoost had the highest accuracy in classifying saltmarsh soils into two main classes as low and high bulk density through using LandSat-7 (ETM+) data. Although these two classes are not specific in determining the critical areas which are not ideal for vegetation growth (bulk density > 1.400 g/cm^3), bulk density estimation based on these two classes helps restoration scientists ensure weather saltmarsh soils are able to support a specific native vegetation post-construction.
- With the application of remote sensing data as a reliable technique, soil bulk density in saltmarshes can be estimated and a species of halophyte that is appropriate to survive in the estimated density level can be determined to expedite the restoration of saltmarshes that are under anthropogenic and naturogenic disturbances.
- With 95 percent confidence, salinity level of *S. tabernaemontani* is significantly different from *B. frutescens* and *S. alterniflora*. *S. tabernaemontani* has the least and *S. alterniflora* has the highest average salinities, which are 3.783 and 27.873, respectively. High salinity inhibits *S. tabernaemontani* growth in coastal marshes, while the other study species tend to be more salt tolerant. Vegetative species in costal marshes have different tolerance to salinity and as such, this tolerance is recommended to be considered for any restoration practice of disturbed saltmarshes.

- Salinity increase alters the concentration of the metal-binding agents like organic matter in tidal marsh soils. It is observed that oligohaline-mesohaline marsh soils have a greater mean in Cd, Cu, Pb and Zn concentration than polyhaline marshes.
- According to both RF and XGBoost, Fe is the most important binding agent for As, Cd, Cr and Zn. Cycling Fe in hydric soil systems can cause As, Cd, Cr and Zn release into the aquatic environments.
- Besides the consistent results from two different ensemble methods for modeling heavy metals, XGBoost outperforms RF based on relative MSE.
- Further, Mn and organic matter are determined as the most important binding agent for Cu and Pb, respectively, through XGBoost and RF feature selection analysis.

7.2. Recommendations

Future studies are recommended as follows:

- Creating soil bulk density map of the Georgia's saltmarshes using GIS and Remote sensing techniques. In order to have detailed classification of soil bulk density, a high-resolution satellite sensor is recommended and preferred. We used multispectral sensor (LandSat7-ETM+) which is free and available for the public, but it is not specific in determining very low or very high bulk density areas due to low spectral and radiometric resolution.

- Conducting a time series study to monitor saltmarsh soil bulk density. This study is recommended to be carried out by using remotely sensed data in order to detect changes in saltmarsh conditions due to anthropogenic and naturogenic disturbances.

- Developing greenhouse experiment to investigate the effect of sea-level rise or draught stressors on health and growth of saltmarsh plants planted in engineered soils. This experiment underlines the role of engineered soils in helping vegetation survive under harsh environmental conditions. Further, field experiment is recommended to investigate re-establishment success of saltmarsh native vegetation planted in engineered soils at disturbed marsh sites.

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APPENDIX A
PROCEDURE FOR RESTORATION OF IMPACTED SALTMARSH

Part 1: General Description

This work includes site preparation and protection, material preparation, placement of embankment, establishment of vegetation, and post-construction monitoring of impacted saltmarsh.

Definitions

General Provisions 101 through 150.

Related References

General Provisions 101 through 150.

Standard Specification

Section 107—Legal Regulations and Responsibility to the Public

Referenced Documents

1. ASTM D 2487 - Standard Classification of Soils for Engineering Purposes (Unified Soil Classification System)

2. ASTM D 2216 - Standard Test Method for Laboratory Determination of Water (Moisture) Content of Soil, Rock, and Soil Aggregate Mixtures.

3. ASTM D 4318 - Standard Test Method for Liquid Limit, Plastic Limit, and Plasticity Index of Soils.

1. ASTM D 1140 - Standard Test Method for Amount of Material in Soils Finer Than No. 200 Sieve.

2. ASTM D7928 - 17- Standard Test Method for Particle-Size Distribution (Gradation) of Fine-Grained Soils Using the Sedimentation (Hydrometer) Analysis

3. ASTM C 136 - Standard Test Method for Sieve Analysis of Fine and Coarse Aggregates

4. ASTM D 698 - Standard Test Methods for Laboratory Compaction Characteristics of Soils Using Standard Effort (12,400 ft-lbf/ft3 (600 kN-m/m3))

5. ASTM D6938 - 17a- Standard Test Methods for In-Place Density and Water Content of Soil and Soil-Aggregate by Nuclear Methods (Shallow Depth)

Submittals

- Submit location, including addresses and maps, of all borrow areas donating material for incorporation in this work.

- Submit geotechnical characterization of saltmarsh soil composite samples including bulk density (ASTM D4531−15), particle size distribution (ASTM C 136 and ASTM D 1140) and organic content (ASTM D2974-87) for review by Engineer. Submit material samples for independent testing as requested by Engineer.

- Submit geotechnical characterization of fill material to be used including material classification (ASTM D 2487), particle size distribution (ASTM C 136 and ASTM D 1140) and organic content (ASTM D 1140) for approval by the Engineer. Submit material samples for independent testing as requested by Engineer.

- Submit completed Worksheet A of the design soil to be incorporated into the work to the Engineer for approval.
- Provide Engineer with delivery tickets that include source location and quantity (by weight) for each delivery of material obtained from off-site sources.

Part 2: Materials

Materials required to complete the work are shown on the Plans or used as directed by Engineer.

Site Characterization

A. Prior to disturbing areas delineated as saltmarsh, a complete topographic survey shall be provided to document existing surface elevations relative to a project benchmark provided by Engineer.

B. Composite samples with material collected from at least three locations within the saltmarsh shall be analyzed at a rate of one composite sample per acre for purposes of characterizing the geotechnical texture of existing saltmarsh soils. Results of in-situ soil bulk density (ASTM D4531−15), and composite sample organic content (ASTMD2974-87) and particle size distribution (ASTM C 136 and ASTM D 1140) shall be provided to Engineer for approval prior to disturbing saltmarsh areas.

Inorganic Materials

A. Notify Engineer and testing laboratory at least five (5) calendar days in advance of opening soil borrow source to permit obtaining samples for qualification testing. When proposed material does not meet specification requirements, locate another source of borrow.

B. Material to be incorporated in the work cannot originate from existing saltmarsh, freshwater wetlands or other areas under federal or state protection.

C. Classify materials to be used for purpose of quality control in accordance with Unified Soil Classification Symbols as defined in ASTM D 2487.

D. Typically, soils classified as silt (ML), silty clay (CL-ML), elastic silt (MH), organic clay and organic silt (OL, OH), and sand (SC) are acceptable for use under this Specification. Complex soils must be characterized as combinations of clay, silt, and sand, with percentage of each component specified on weight basis according to the following particle sizes present.

   I. Clay: Particle size less than 0.002 mm

   II. Silt: Particle size greater than 0.002 mm and less than0.05 mm, and

   III. Sand: Particle size greater than 0.05 mm and less than 2 mm.

E. No material with more than 2% by weight of soil particles greater than 1 inch (2.5 cm) shall be used in this work. Materials containing rocks larger than 2-inch diameter are not acceptable.

F. Dredge material that is tested and verified to be free of contamination from chemical, biological or heavy metal contamination is a suitable complex material for use in marsh restorations.

Organic Materials

A. Organic matter is required in fill material to achieve the target soil bulk density. Organic material may come as a component already in the borrow soil, or may be added as an amendment prior to final placement of embankment. Clean hay free of seed, fungus and contaminants is an acceptable source for organic material.

B. Vegetation material from existing saltmarsh (i.e., dead floating plant material, called wrack) is NOT an acceptable organic material to incorporate in the work. No pristine saltmarsh may be impacted to facilitate restoration of saltmarsh covered by this Specification.

Delivery, Storage, and Handling

General Provisions 101 through 150.

Part 3: Construction Requirements

Personnel

Supply all personnel necessary for obtaining samples from soil, water and vegetative species, and delivering them to the laboratory.

Equipment

Ensure that all equipment is of an approved design and in satisfactory condition before post-construction activity begins. The equipment required for working at saltmarsh sites will be determined according to the post-construction method used.

Preparation

Site Preparation and Protection

1. Only saltmarsh areas designated on the construction plans may be disturbed.

2. Prior to restoration work under this Specification, remove all construction materials and improvements from disturbed saltmarsh areas that are not to be incorporated into the final work

or that are designated by the design engineer as “temporary” including all pilings, mats, pavement, and coarse aggregate from material layout, work and access/egress areas.

3. Excavate and dispose of unsuitable soil and other materials that have been over-compacted or contaminated during the work.

Material Preparation

1. Grade borrow material used for embankment to be free of lumps greater than 1 inch, rocks larger than 2 inch (5 cm), chemical waste, and other contamination or debris. Only material from an approved source can be incorporated into the work.

2. Provide sufficient volume of clean fill material as determined by results of Worksheet A attached to this Specification. Soils from more than one borrow area, as well as any supplemental organic material required shall be spread in layers of maximum 6-inch lifts and well mixed to full depth by mechanical means (i.e., rototillers or similar equipment) prior to being placed in saltmarsh areas.

Fabrication

General Provisions 101 through 150.

Construction

Placement of Embankment

1. Return all disturbed areas to elevations that existed prior to beginning work. Elevations will be evaluated by comparing tide elevation and surface elevation at a restoration site. The appropriate elevations will be achieved if the measured elevations (i.e., as-built conditions) and the target elevations (i.e., the original elevation prior to disturbances) match or have only minor differences (<5%).

2. Fill material may be placed in maximum 6-inch (152.4-mm) lifts and spread with small, tracked equipment such as a Bobcat T650, or equivalent model not to exceed 5 psi surface loading. Material shall be placed at the final location in a manner that minimizes soil compaction to the greatest extent possible. Areas deemed by Engineer to be over compacted (i.e., more than what exists prior to disturbances) shall be scarified and regraded to target elevation (i.e., the original elevation prior to disturbances). For many sites, a density greater than 1.25 g/cm^3 will not be acceptable.

Establishment of Vegetation

1. Establishment of vegetation shall be accomplished using seedlings of the pre-existing dominant marsh vegetation (to be determined prior to site disturbance). The dominant vegetative species are determined based on the technique of a measure of dominance which governes the most abundant species having more than 50% coverage in the sampling area. Target species will be facultative wetland (FACW+) species or obligate wetland (OBL) species based on current versions of national wetland species lists. Depending on availability during the time of construction, the contractor may choose from a combination of bare root seedling, "plugs," and/or larger container plants.
2. Vegetation shall be from the nurseries provided by the Georgia Native Plant Society (https://gnps.org/georgias-native-plants/sources-native-plants/). Other possible greenhouse sources in nearby states include:

- Legare Farms Inc, South Carolina
- Tennessee Wholesale Nursey, Tennessee
- Pinelands Nursery, Florida
- EarthBalance, Florida

3. Vegetation may be planted manually or mechanically, depending on the size and accessibility of the site. In order to minimize soil compaction, a dibble bar or equivalent tool may be used to plant the transplanted seedlings. If the size of the planting area and/or site conditions dictate otherwise, and with the approval by the Engineer or Project Manager, tractor-pulled planter or other automated equipment may be used. Tractors used must be tracked, have a surface loading of not more than 5 psi (34474 N/m^2), and must not compact placed material to a density greater than 1.25 g/cm^3.
4. Because neighboring plants have been shown to facilitate the growth of all individuals, vegetation shall be planted in a gridded plot pattern with each grid cell being approximately 6 ft by 6 ft (2 m x 2 m) to evenly cover the entire area of the disturbed marsh. At least nine transplanted seedlings (or plants) shall be planted in the center of the specified plot in a clumped conFigureuration, where all transplanted seedlings are touching. All clump conFigureurations shall be at least 6 ft (2 m) from one another. Please refer to the Figure 31 below:

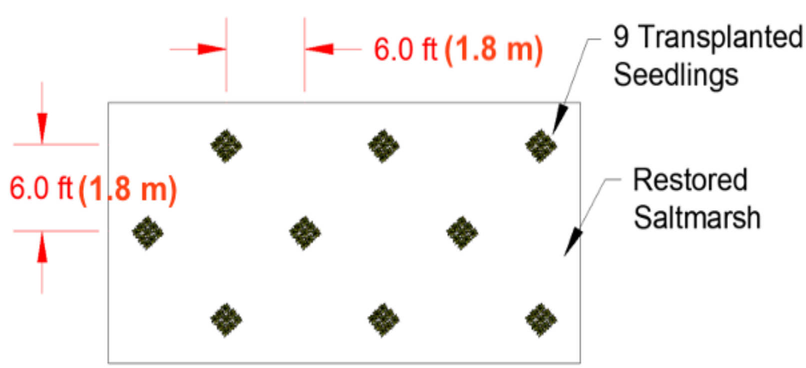


Figure 31 – Clumped conFigureuration of transplanted seedlings.

Quality Acceptance

General Provisions 101 through 150.

Quality Assurance

1. Material testing required in this Specification to be provided by independent geotechnical laboratory approved by the Engineer or Project Manager.

2. Virgin soil material incorporated in this work shall be free from contamination by chemicals or heavy metals. Dredge spoil material is acceptable for use, if it meets all criteria specified in this specification. And, it must also be free from chemical, biological and heavy metal contamination.

Post-construction Monitoring

1. Post-planting inspection of the transplanted seedlings should occur within the same growing season. If less than seven individual plants survive within a cluster, the broken/damaged plants shall be replaced using the previously stated method to achieve the desired density and overall coverage.

2. Post-planting monitoring of the vegetation shall be scheduled annually for three growing seasons (i.e., the part of the year during which local weather conditions such as rainfall and temperature permit normal plant growth), and maintenance operations scheduled as needed to ensure the desired saltmarsh extent, physical integrity, condition, and function are achieved. During this time, any invasive species located at the site must be removed manually or mechanically. See www.invasive.org, for a list of invasive species. The removal can be accomplished using a weed wrench, root talon, or root jack. Foliar application of herbicide treatment is not acceptable in these aquatic environments. Once removed, the invasive species

shall be disposed off-site in an acceptable landfill. Reproductive parts of the plants should be isolated during transport to prevent spread.

Contractor Warranty and maintenance

General Provisions 101 through 150.

Measurement

Restoration of a saltmarsh is measured by the unit as indicated on the Plans and in the Proposal. Payment is full compensation for all necessary labor, equipment, tools, materials and incidentals required to complete the work to the satisfaction of the Engineer.

Limits

General Provisions 101 through 150.

Payment

Payment for work performed under this specification shall be a unit (acre) cost based on saltmarsh area delineated and restored. Restoration of a saltmarsh is paid for at the Contract Unit Price bid per each for the specified operation as defined in this specification. Payment is full compensation for furnishing all labor, equipment, materials, tools and incidentals, and performing the work.

Adjustments

General Provisions 101 through 150.

APPENDIX B

Part 1: X-ray Diffraction Test Results

The following sections align with the sections in 3.2.2. Test Methods. Figure 32 – Figure 47 show the results from the X-ray diffraction tests.

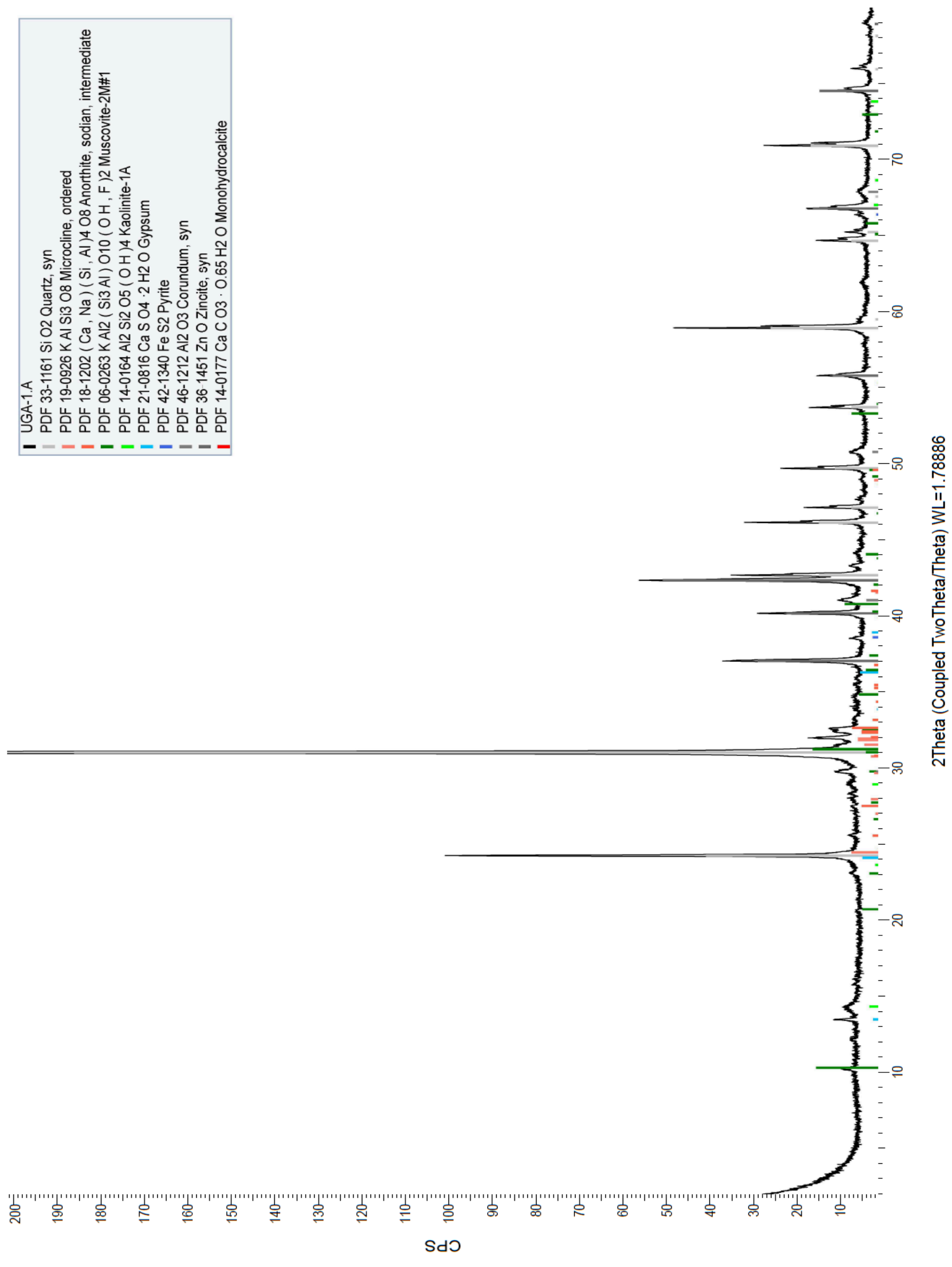


Figure 32 – XRD test result on soil sample of site 1.A.

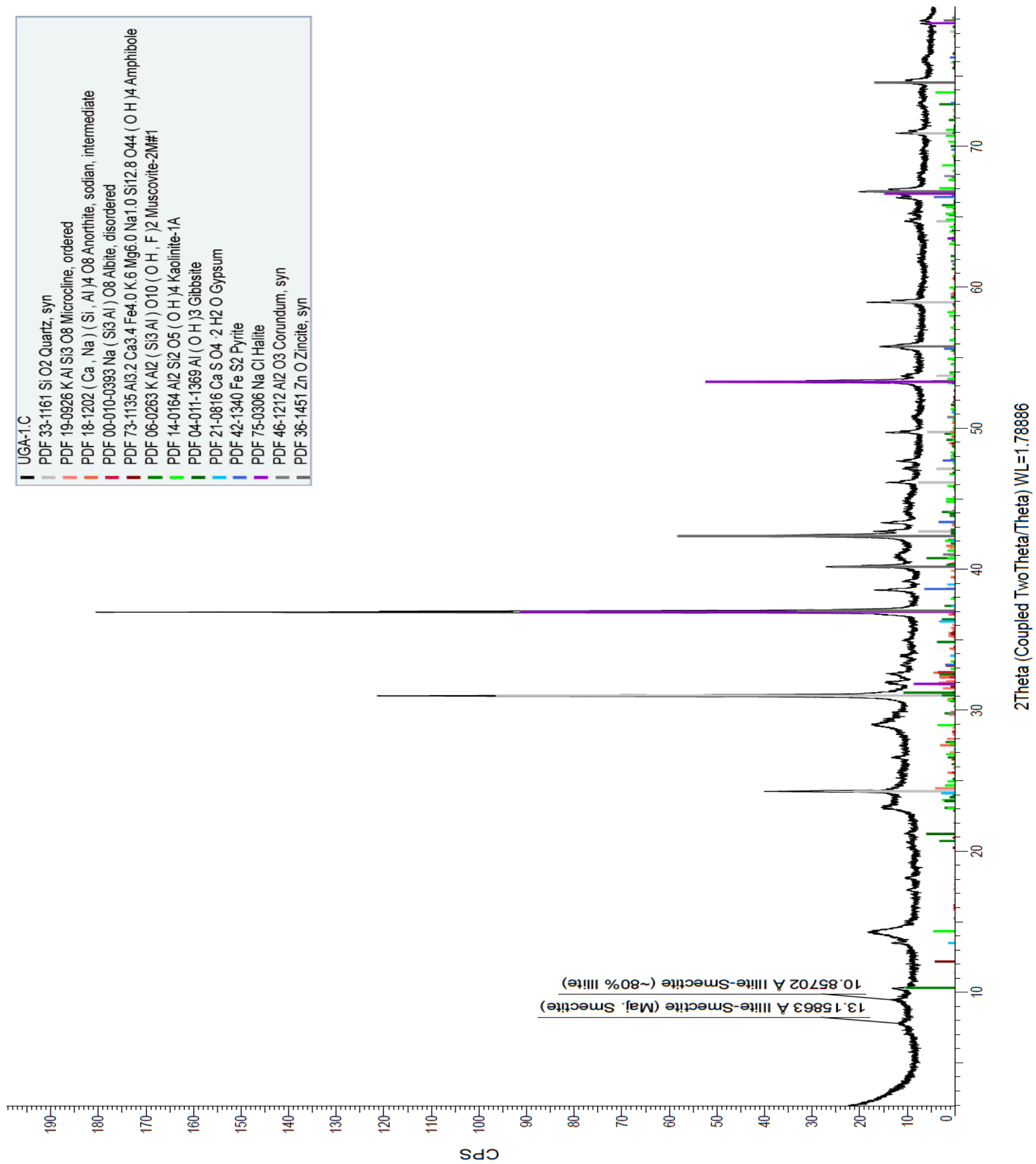


Figure 33 – XRD test result on soil sample of site 1.C.

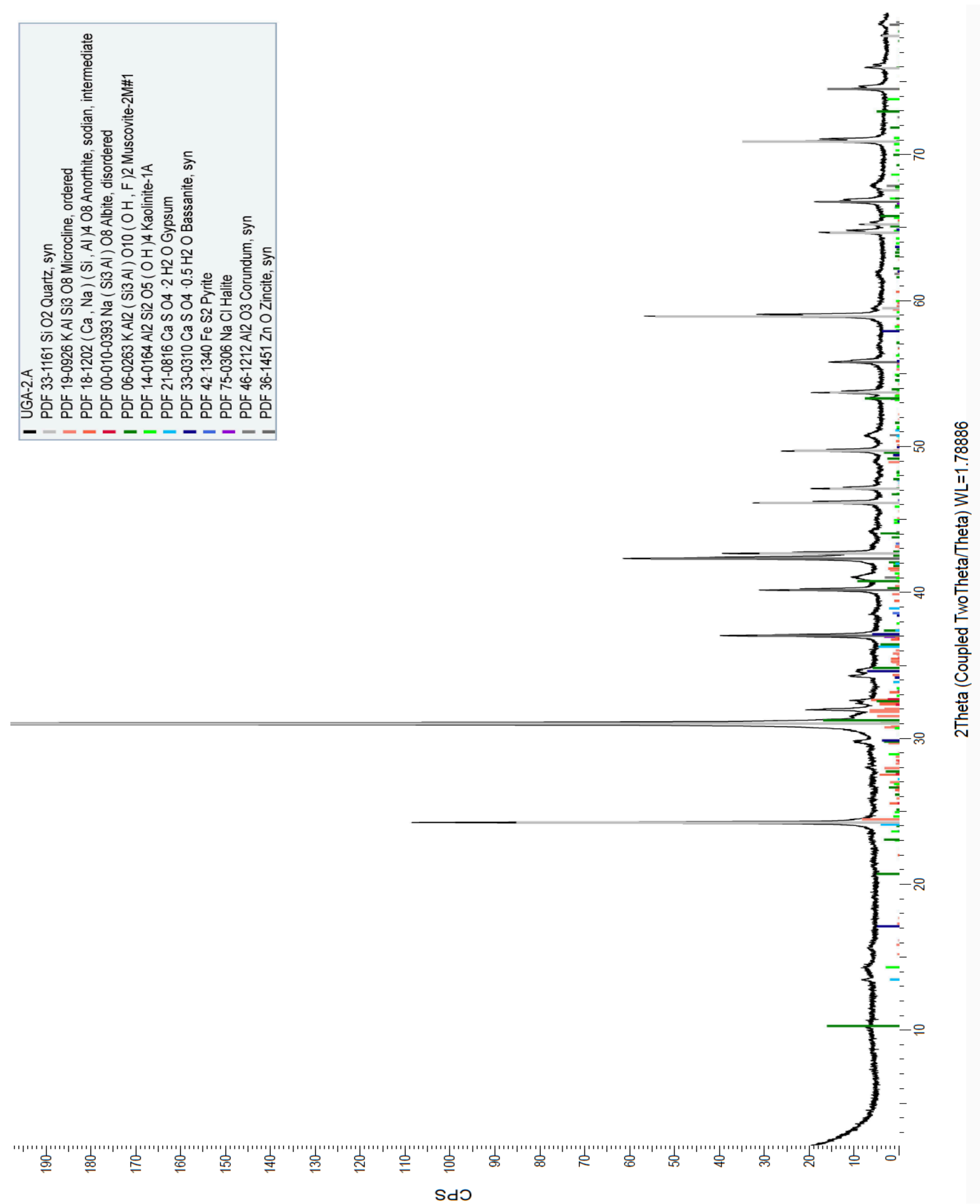


Figure 34 – XRD test result on soil sample of site 2.A.

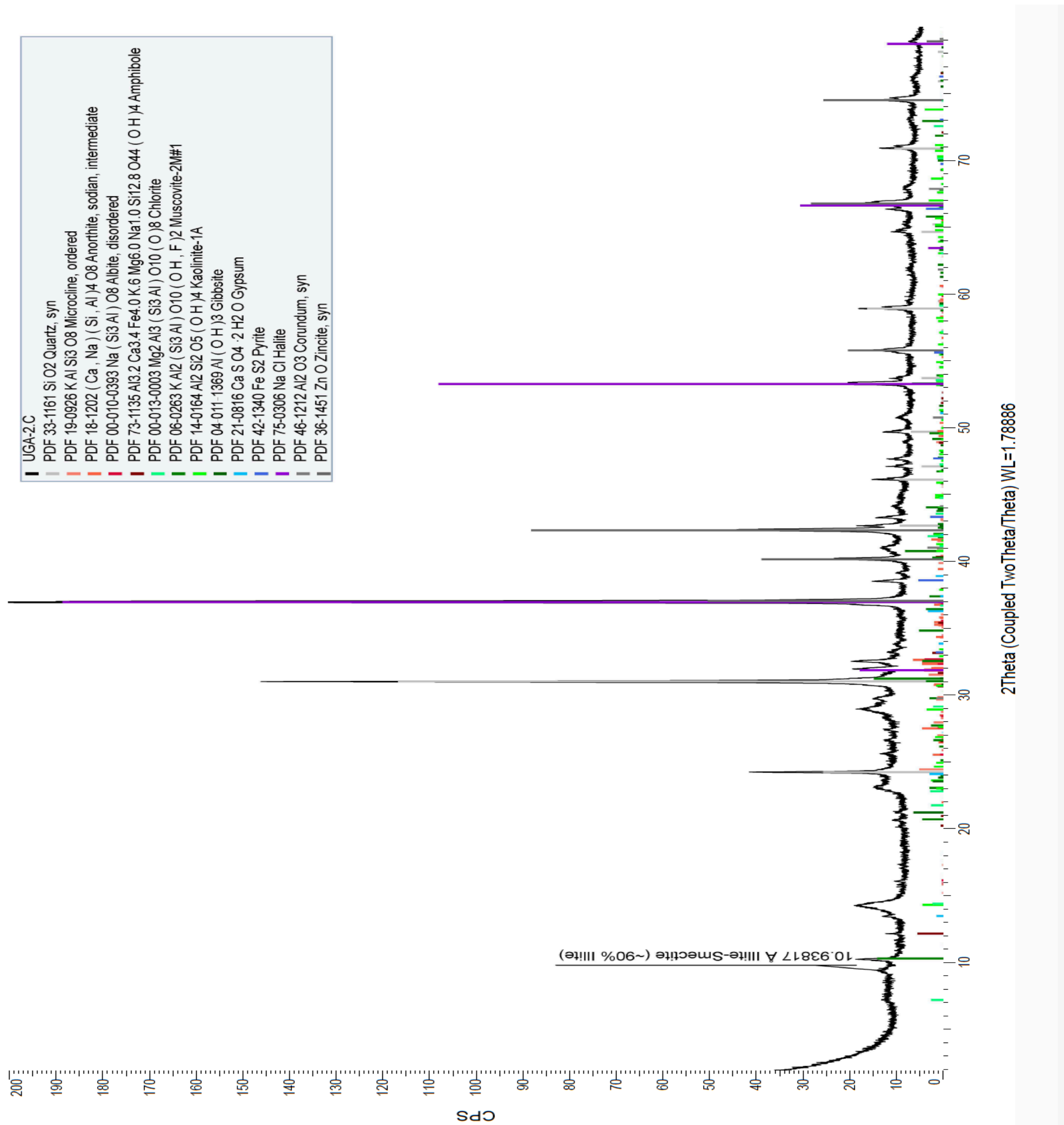


Figure 35 – XRD test result on soil sample of site 2.C.

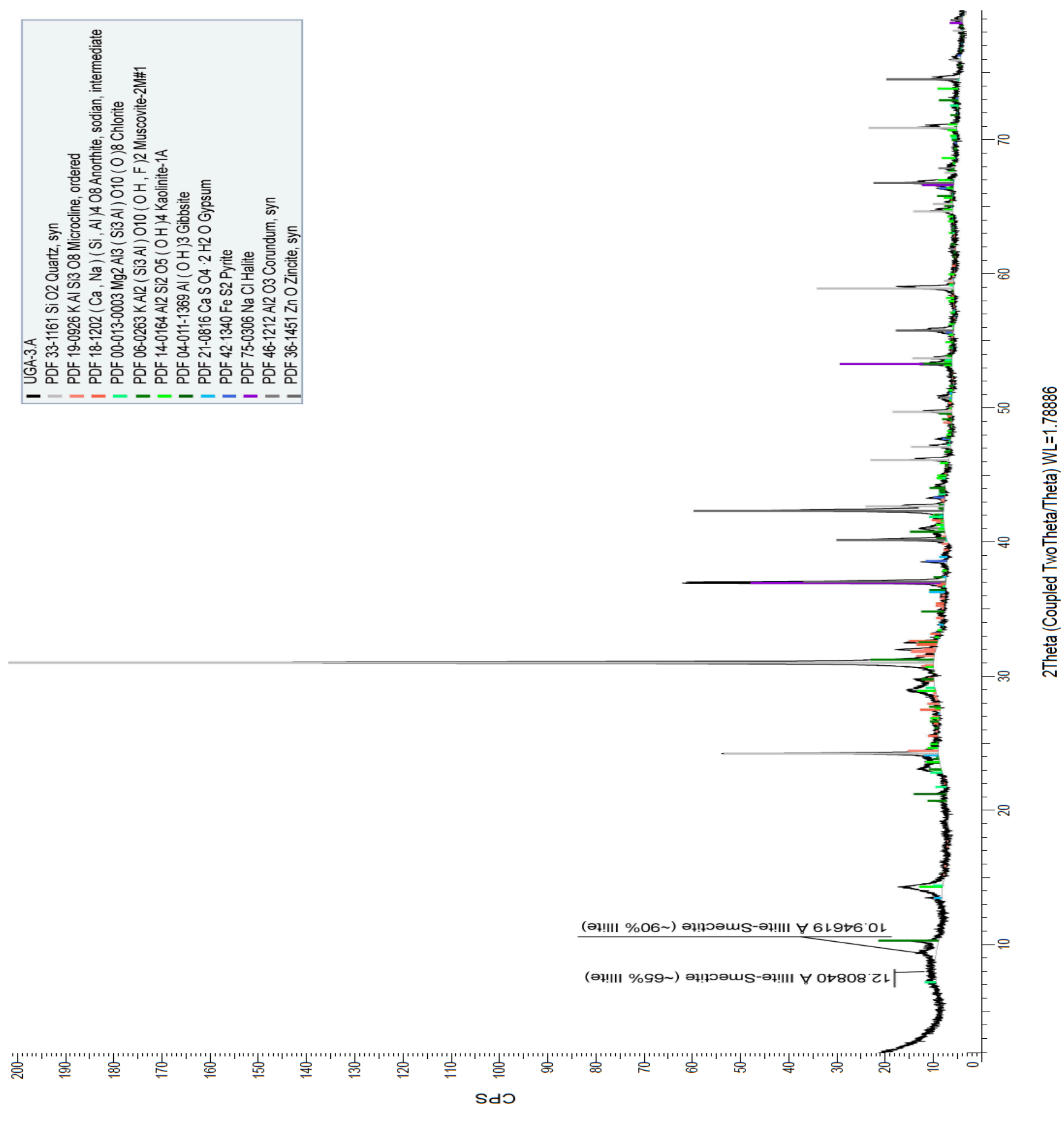


Figure 36 – XRD test result on soil sample of site 3.A.

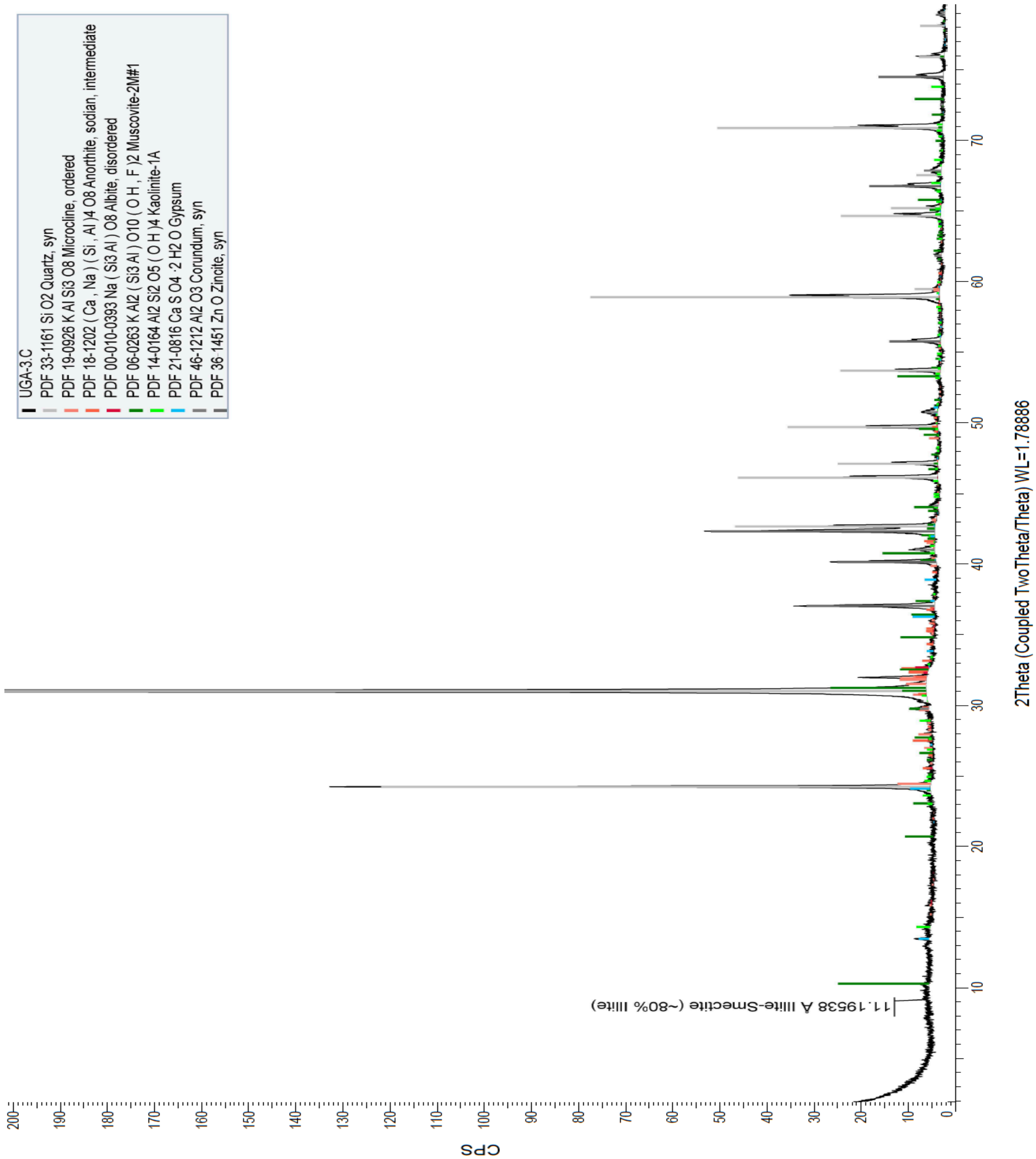


Figure 37 – XRD test result on soil sample of site 3.C.

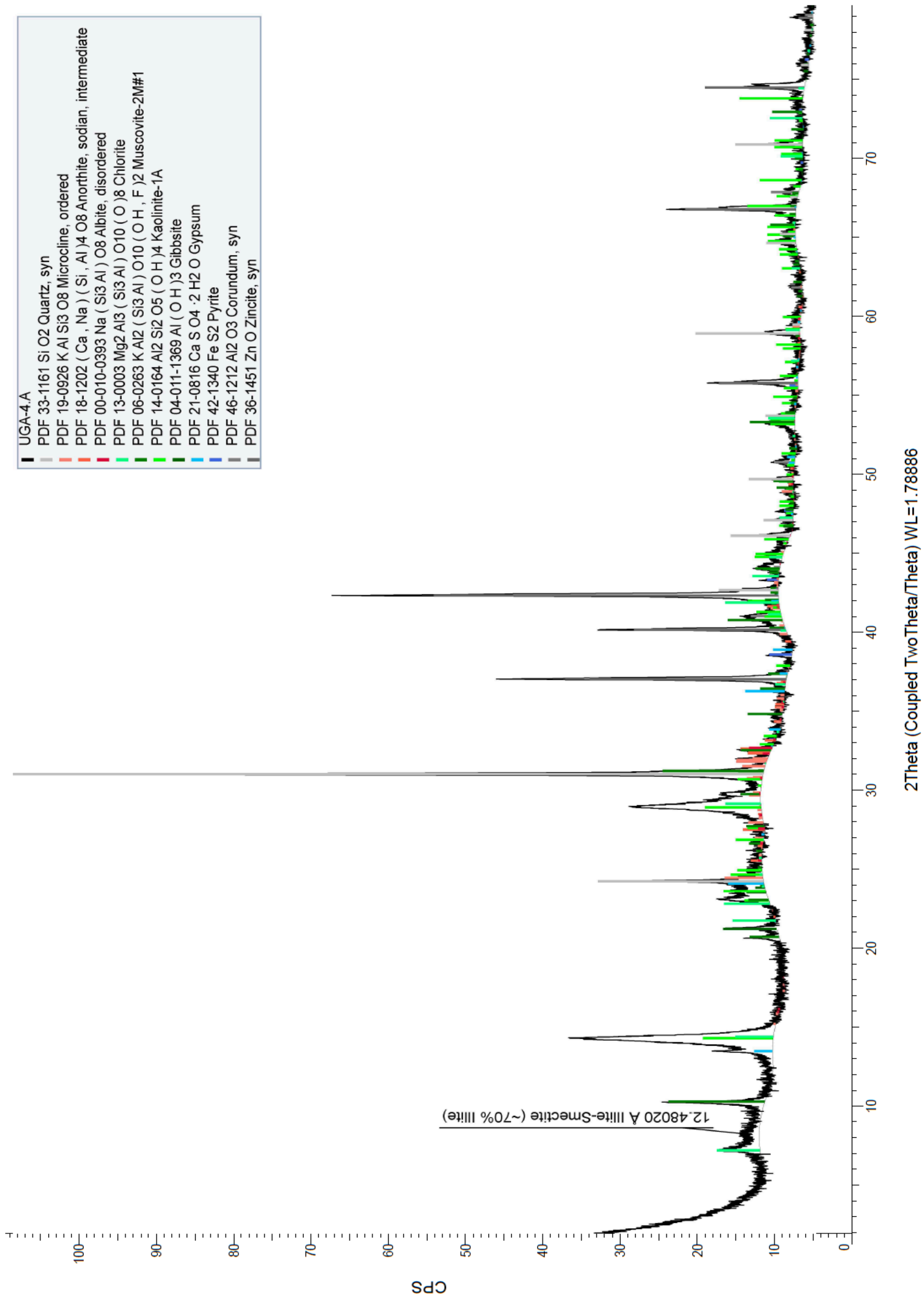


Figure 38 – XRD test result on soil sample of site 4.A.

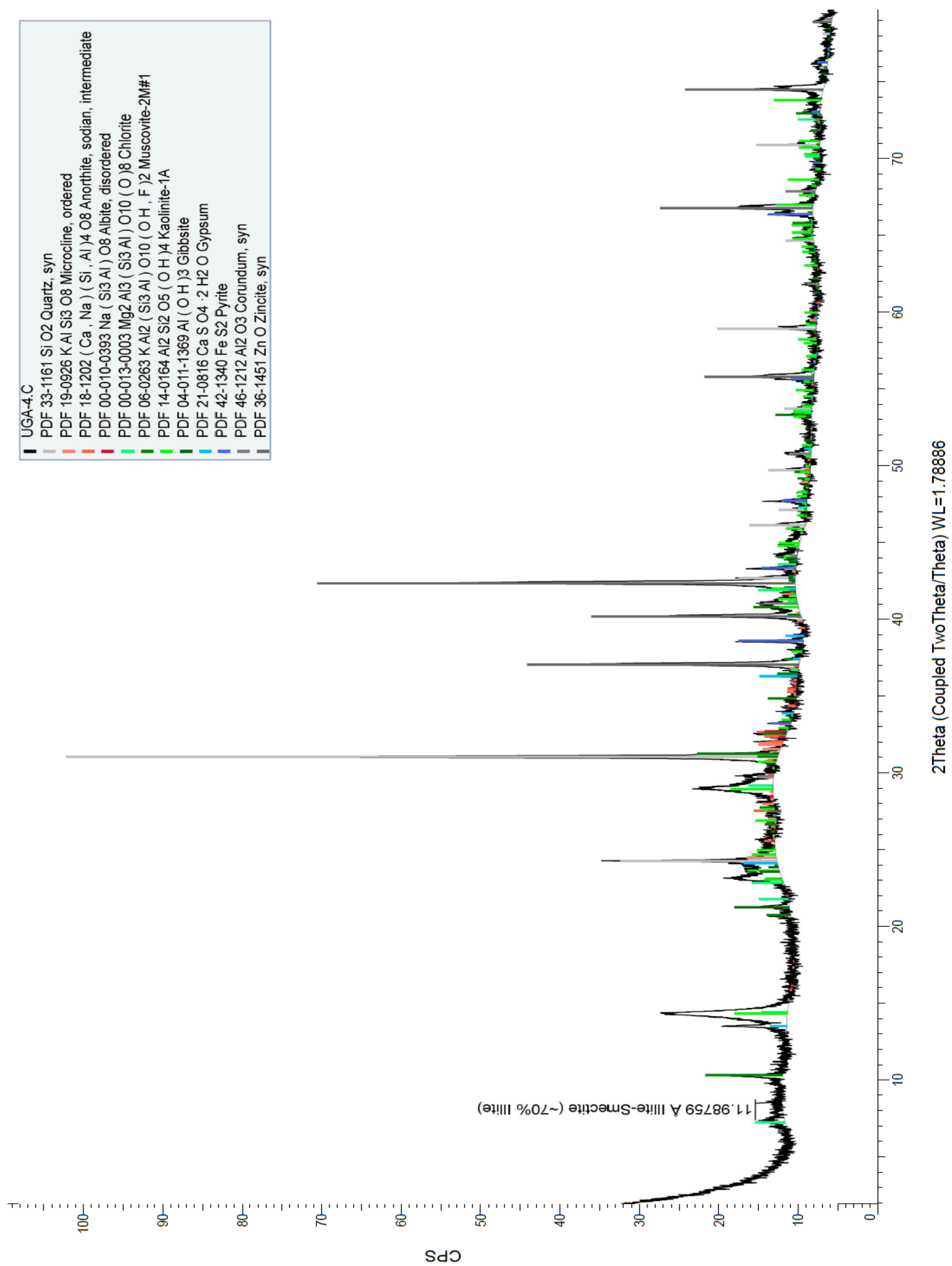


Figure 39 – XRD test result on soil sample of site 4.C.

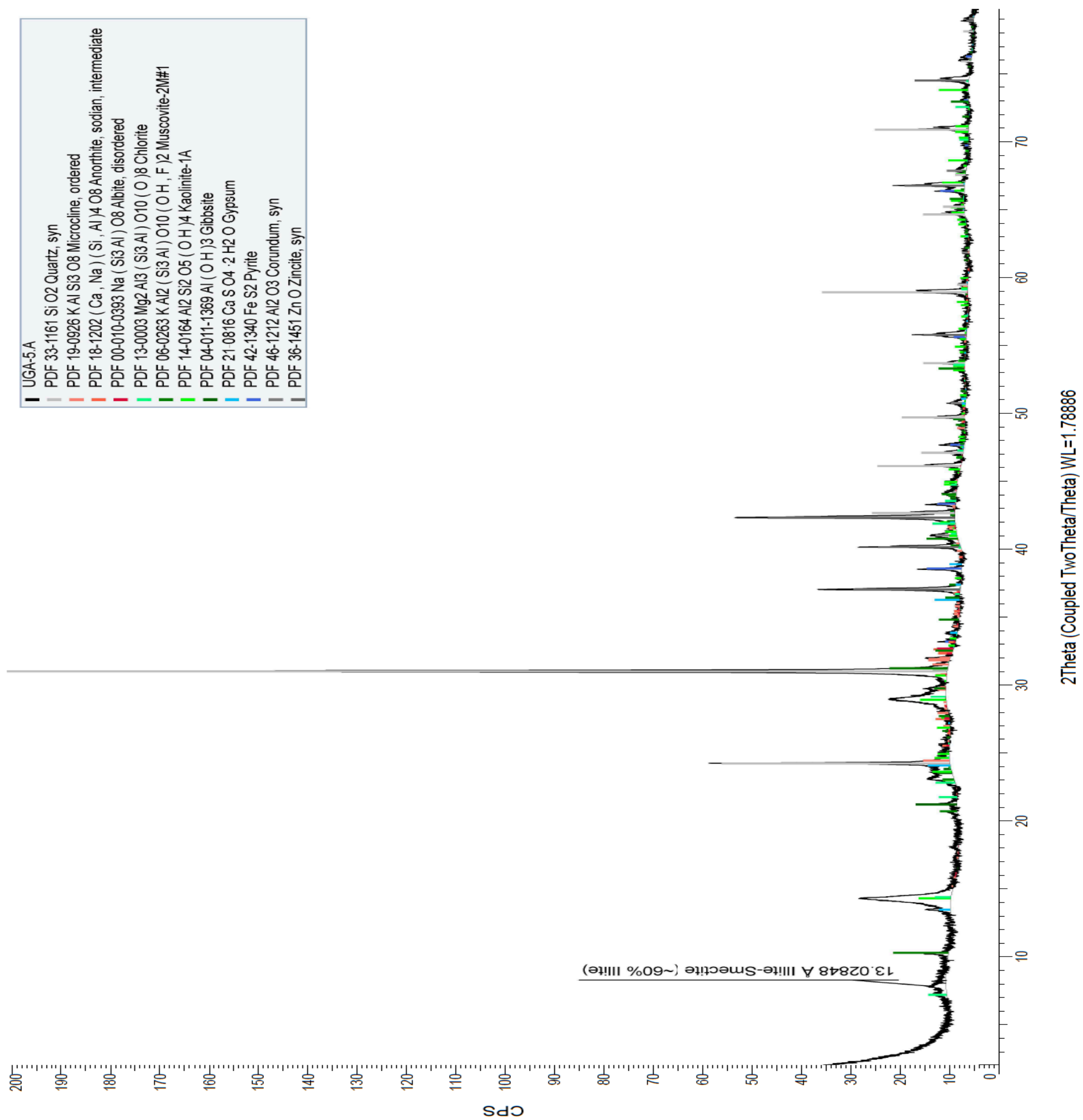


Figure 40 – XRD test result on soil sample of site 5.A.

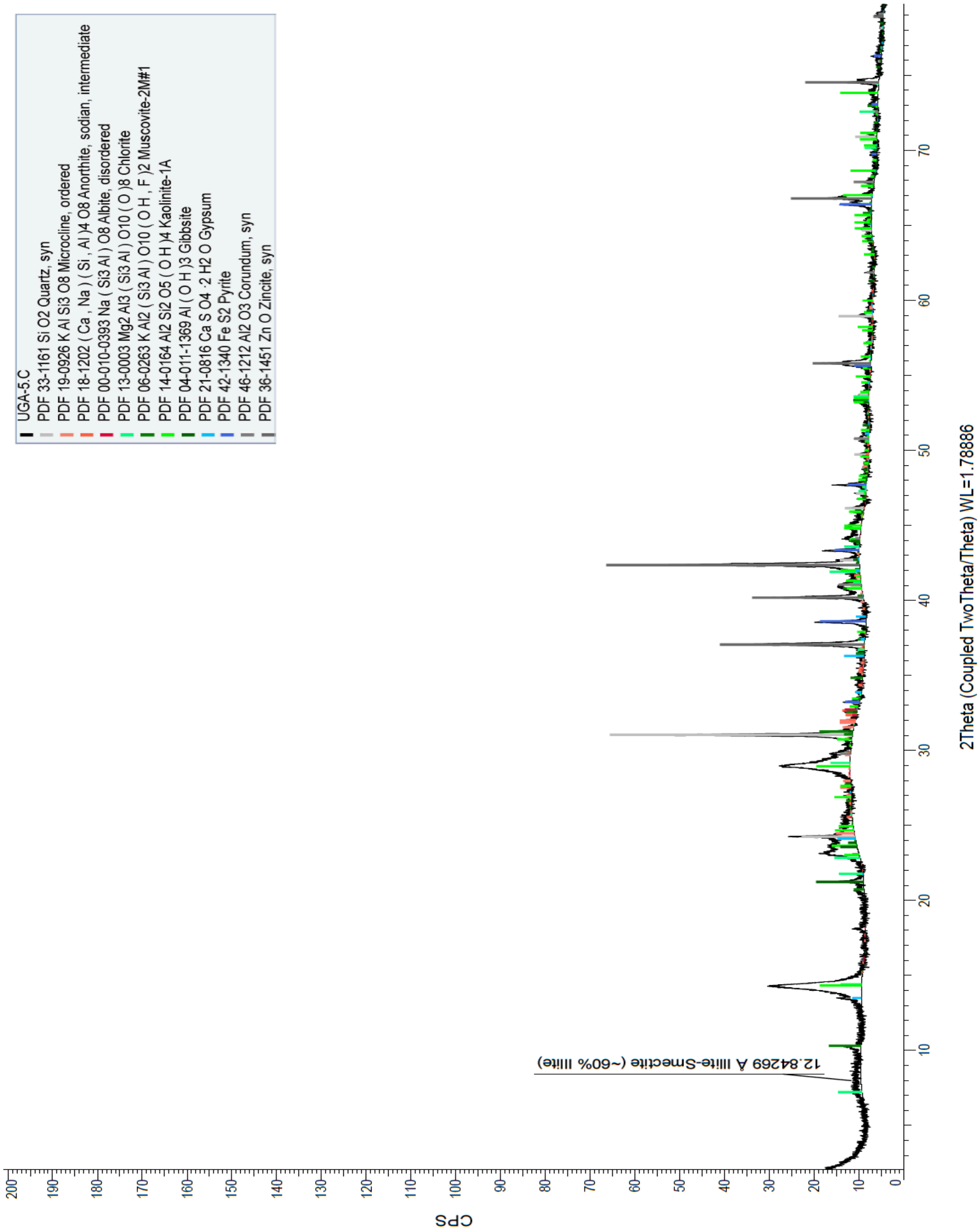


Figure 41 – XRD test result on soil sample of site 5.C.

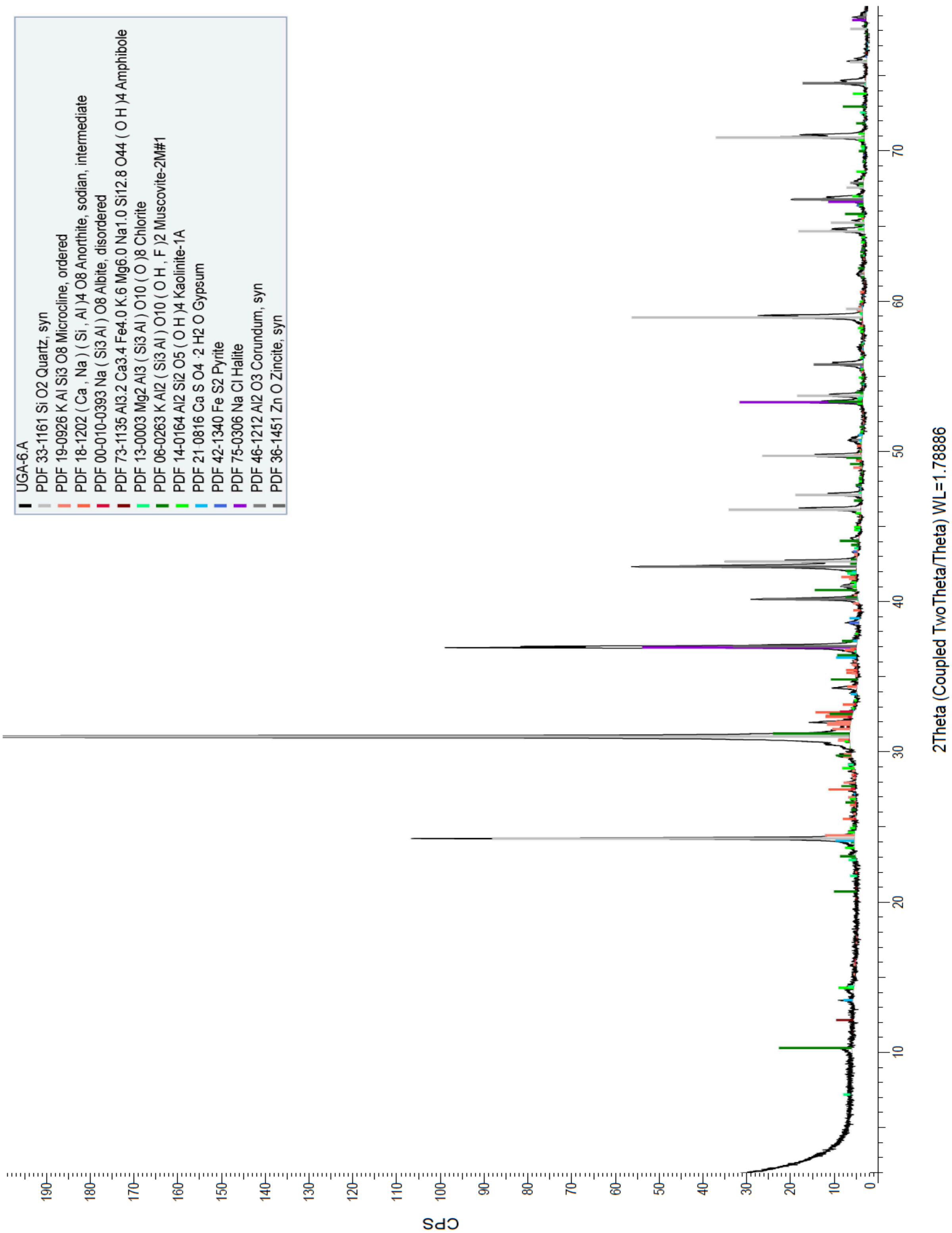


Figure 42 – XRD test result on soil sample of site 6.A.

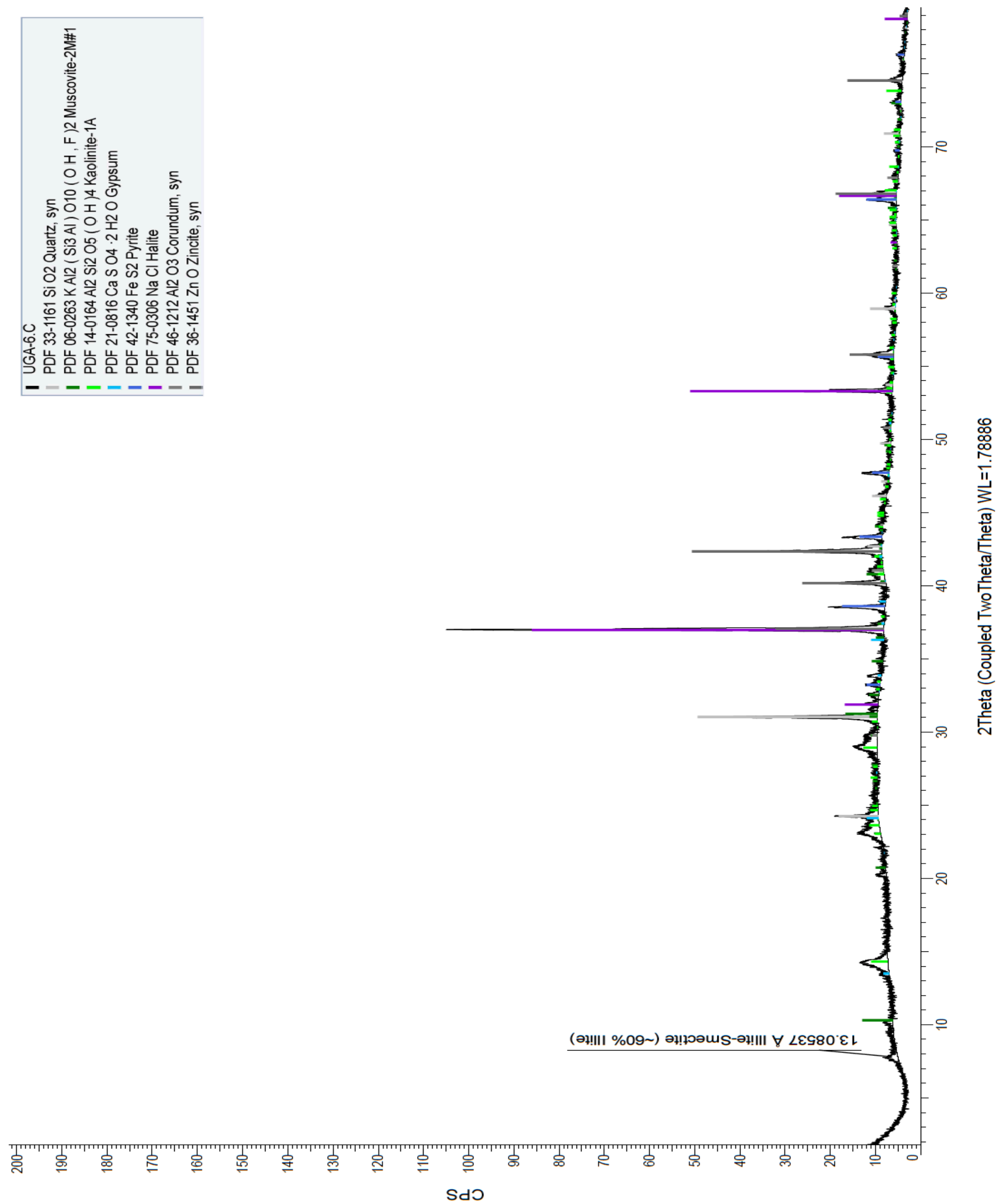


Figure 43 – XRD test result on soil sample of site 6.C.

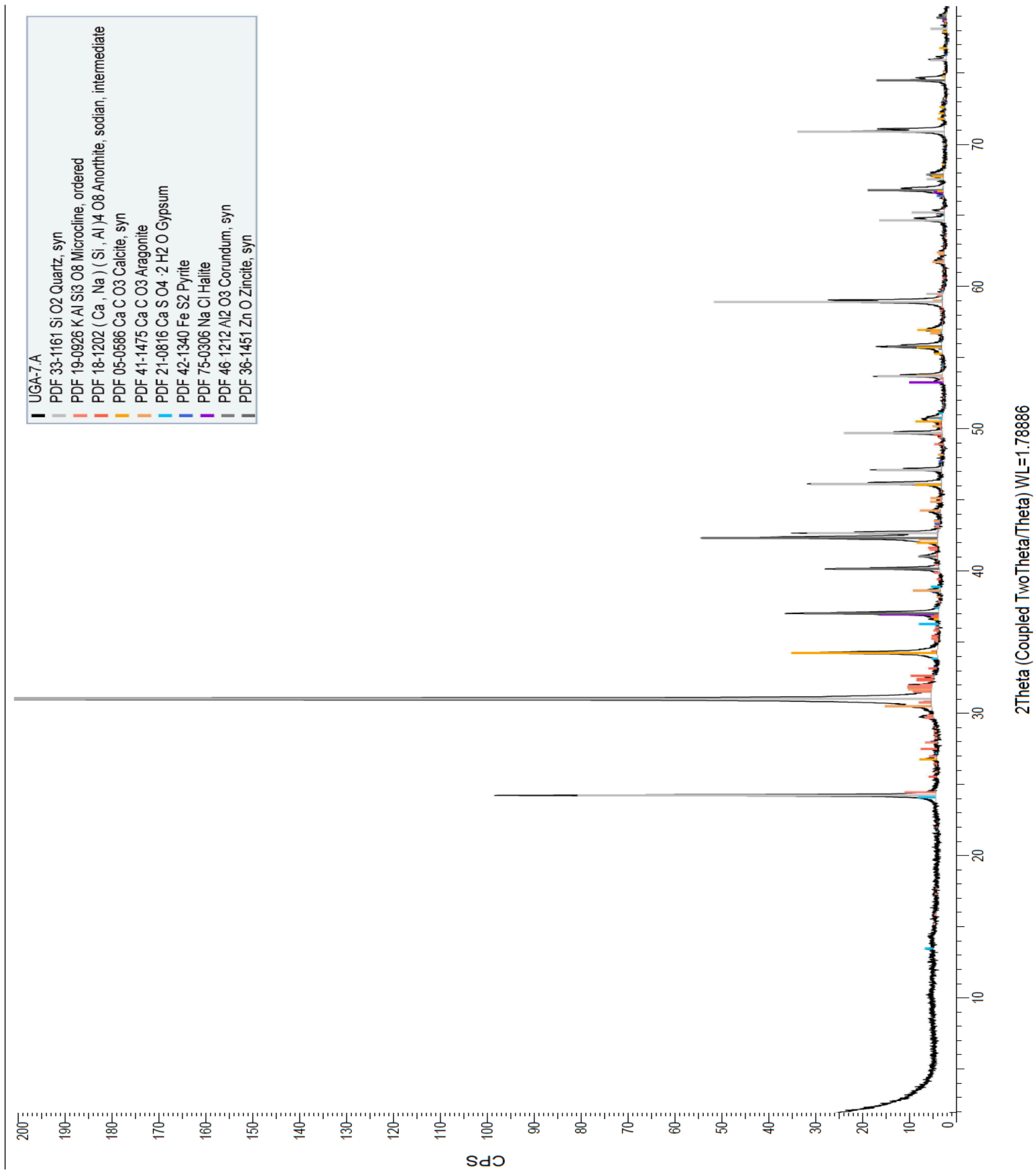


Figure 44– XRD test result on soil sample of site 7.A.

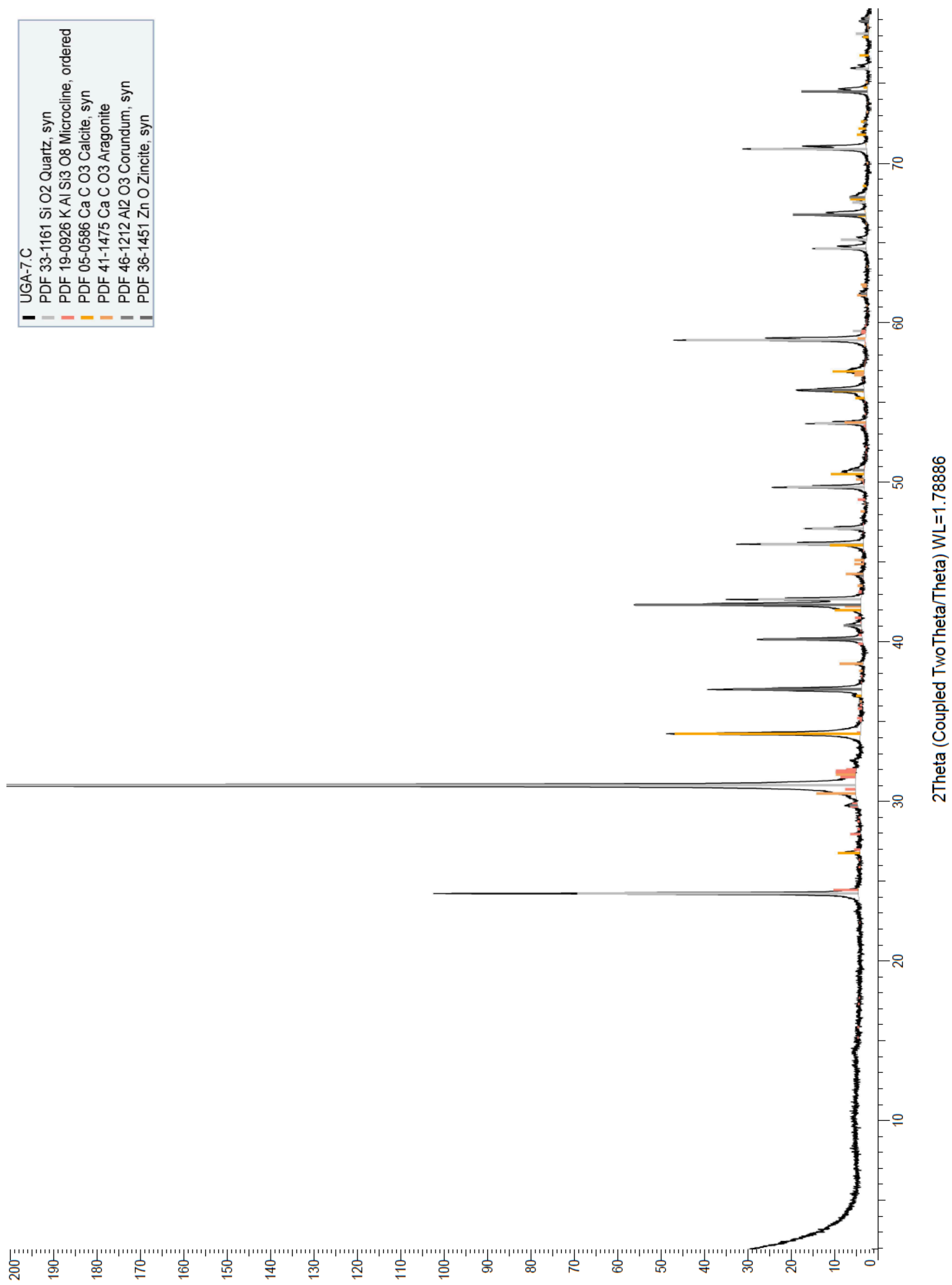


Figure 45 – XRD test result on soil sample of site 7.C.

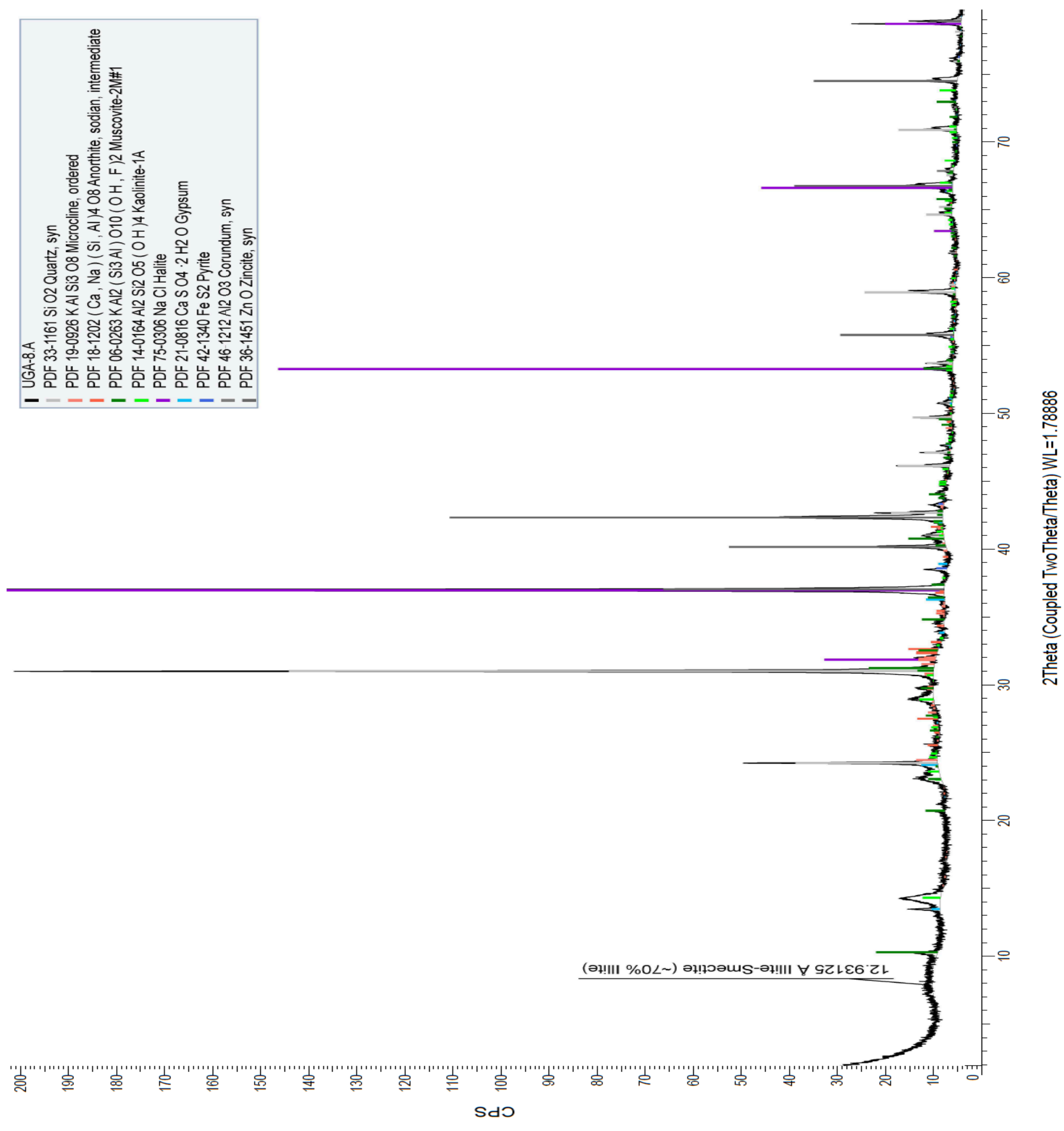


Figure 46 – XRD test result on soil sample of site 8.A.

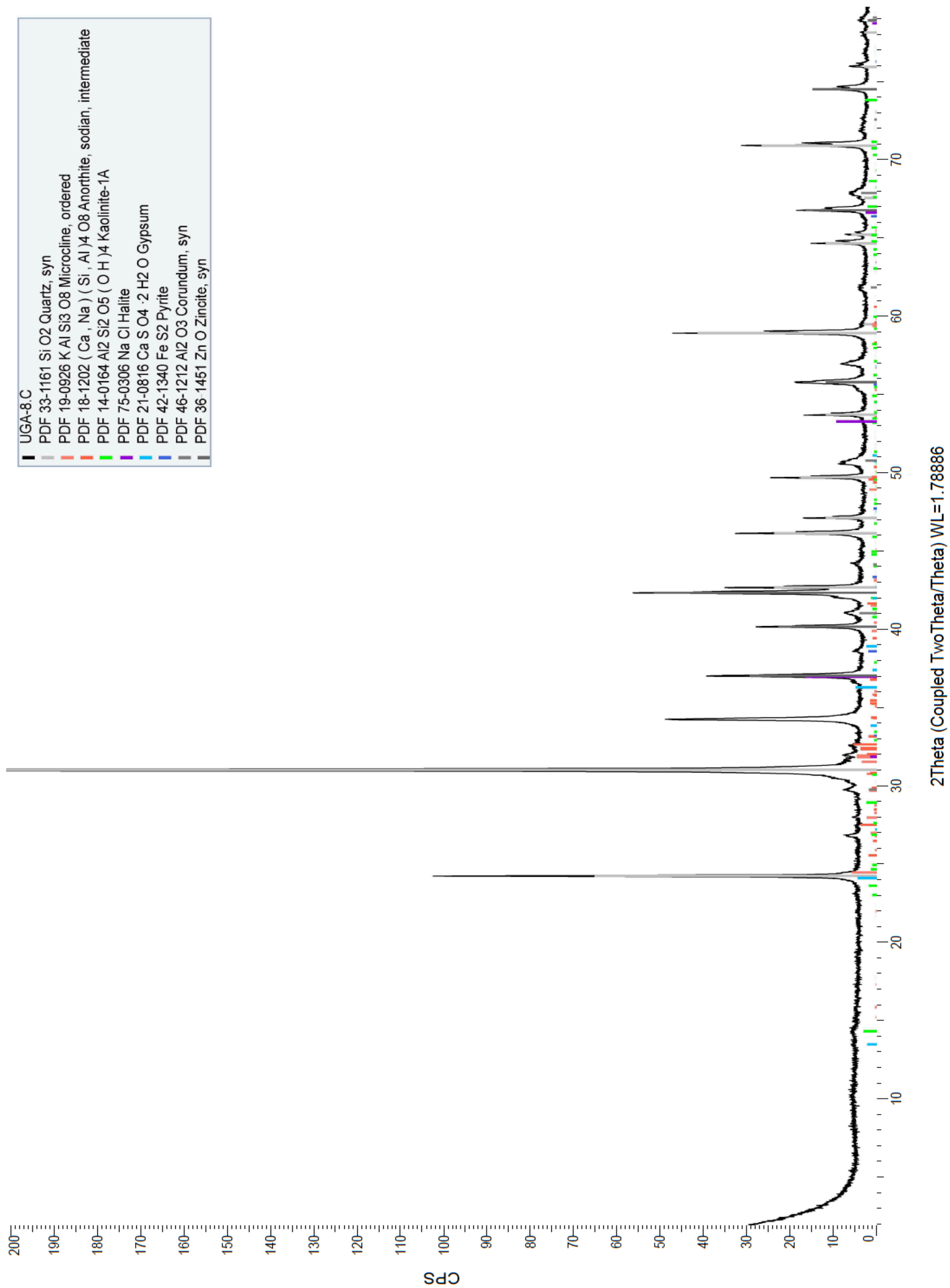
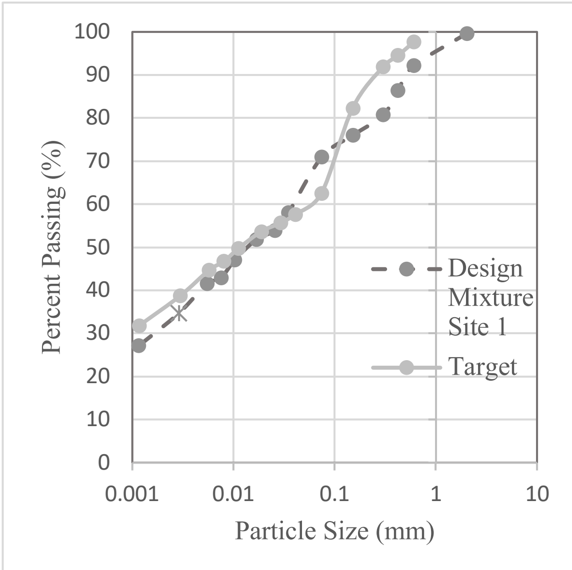


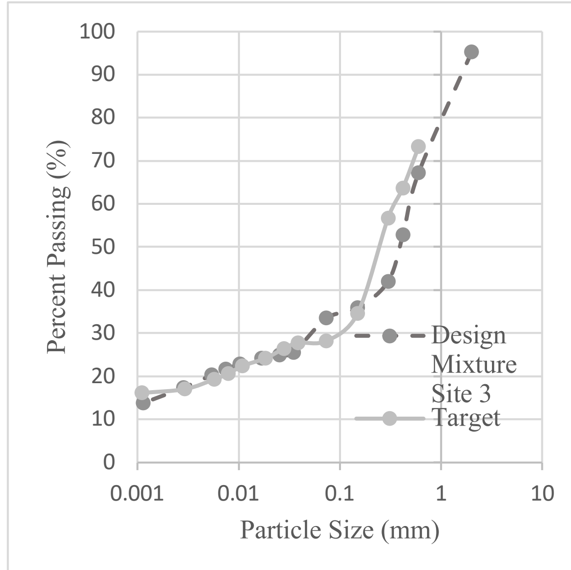
Figure 47 – XRD test result on soil sample of site 8.C.

Part 2: Particle size distribution curves for engineered soils

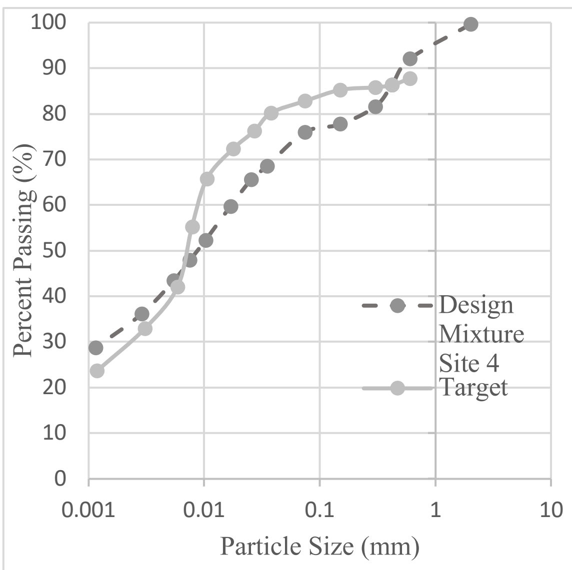
The following sections show the particle size distribution curves for the first and second mixture designs of engineered soils.



Percent Passing (%)
Particle Size (mm)
Design Mixture Site 1
Target



Percent Passing (%)
Particle Size (mm)
Design Mixture Site 3
Target



Percent Passing (%)
Particle Size (mm)
Design Mixture Site 4
Target

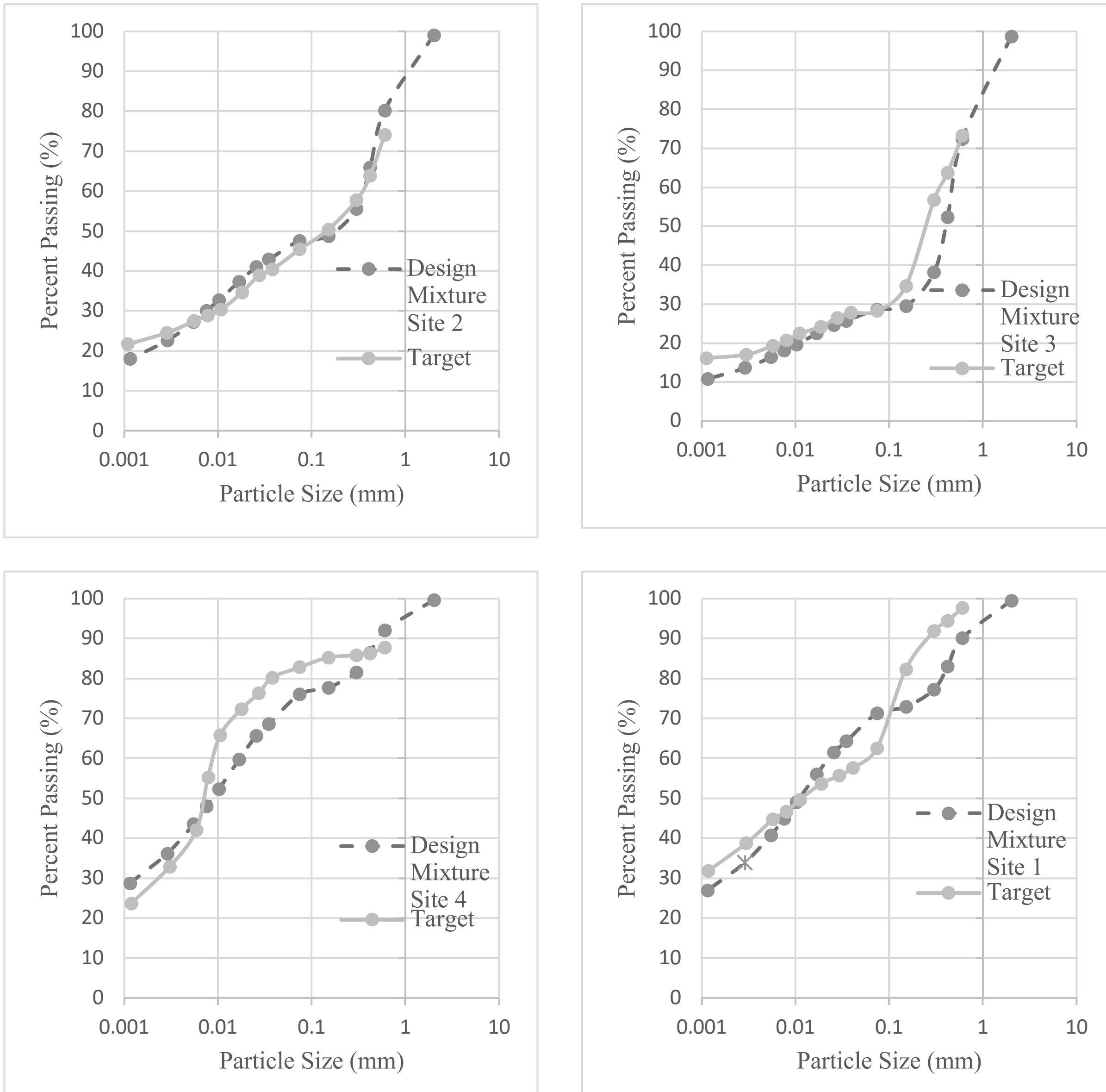


Figure 48. Particle size distribution curves for first mixture designs.

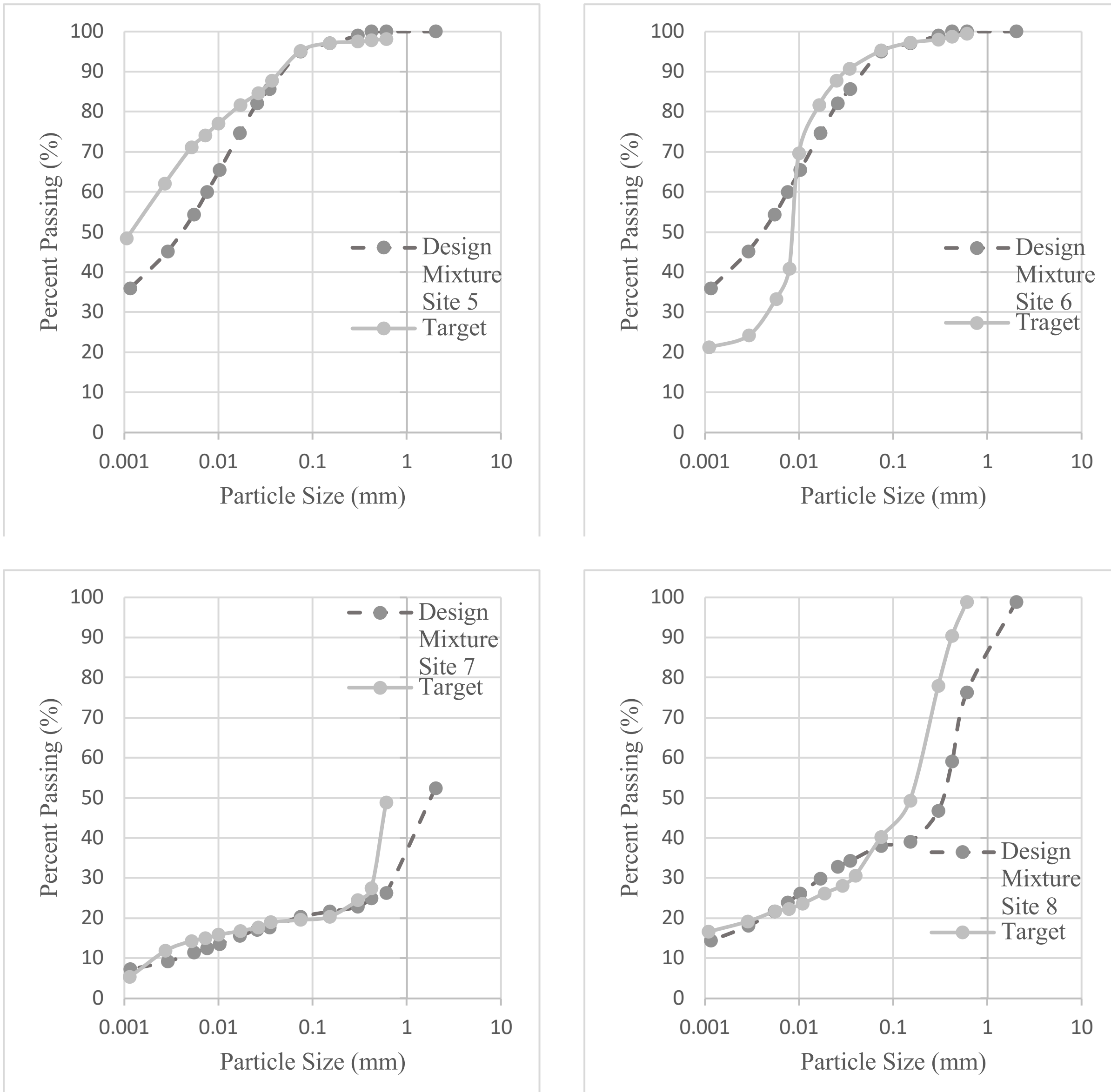


Figure 49. Particle size distribution curves for second mixture designs.

Part 3: Site description and some results

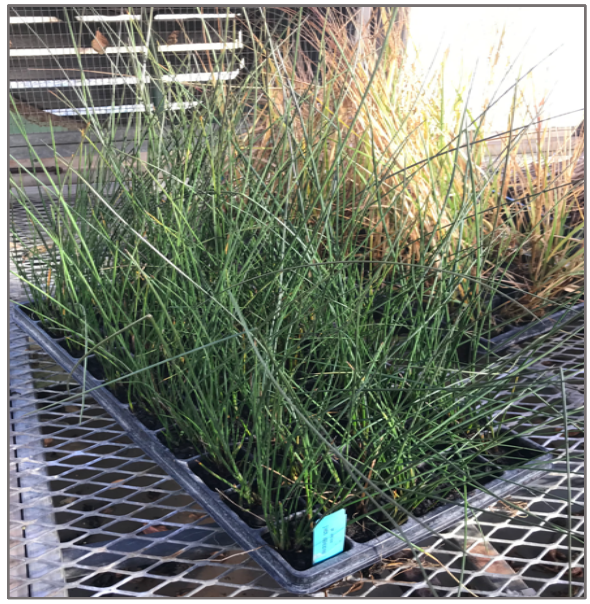
Figure 50 – An example of common flora, *Spartina alterniflora,* in Georgia's saltmarshes (Source: GDOT, June 2018).

Figure 51 – An example of common fauna, fiddler crab, in Georgia's saltmarshes (Source: GDOT, June 2018).

Figure 52 – An example for anthropogenic alterations in Georgia's saltmarshes (June 2018).

Figure 53 – An example of construction and wrack accumulation at a saltmarsh site in Georgia, Tybee Island (June 2018).

(a) *S. alterniflora*



(b) *J. roemerianus*

(c) *B. frutescens*

(d) *S. tabernaemontani*

Figure 54 – Vegetation: (a) *S. alterniflora*, (b) *J. roemeria*nus, (c) *B. frutescens*, and (d) *S. tabernaemontani* (Christian, J. et al. 2020).

(a) (b) (c) (d)

Figure 55 – Root structure for: (a) *S. alterniflora*, (b) *J. roemerianus*, (c) *B. frutescens*, and (d) *S. tabernaemontani* (Christian, J. et al. 2020).

Figure 56 – Aerial photograph of site 1 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 57 – Aerial photograph of site 2 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 58 – Aerial photograph of site 3 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 59 – Aerial photograph of site 4 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 60 – Aerial photograph of site 5 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 61 – Aerial photograph of site 6 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 62 – Aerial photograph of site 7 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

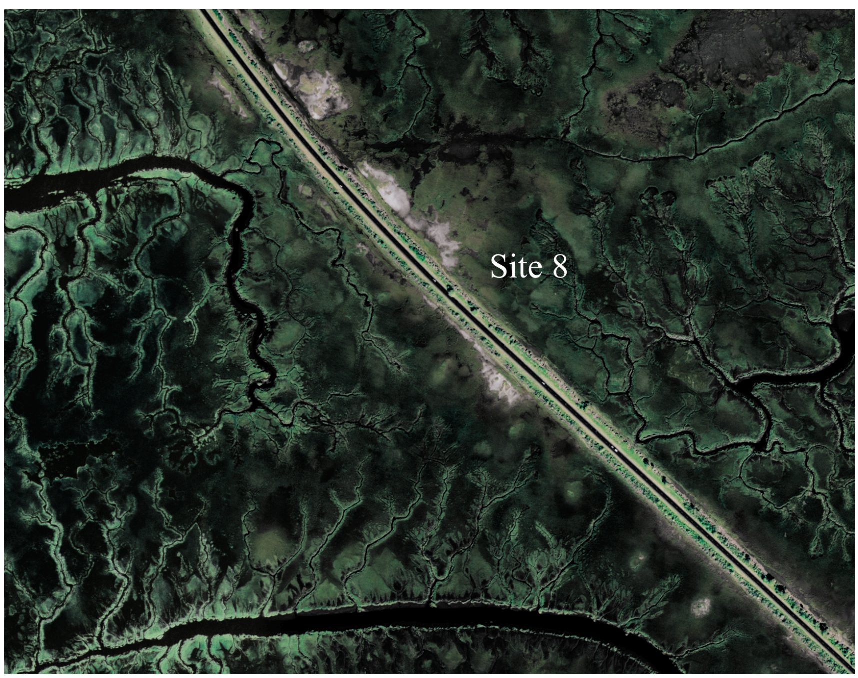


Figure 63 – Aerial photograph of site 8 acquired by the National Agriculture Imagery Program (NAIP) in October 2017.

Figure 64 – Two sampling sites adjacent to the GODT's infrastructures (June 2018).

Figure 65 – The unvegetated area adjacent to a bridge infrastructure at sampling site 7 (June 2018).

Figure 66 – Porewater withdrawn from halophytes root zone at saltmarsh sites in Georgia (June 2018).

Figure 67 – HI98194 portable meter (Hanna Instruments).

Figure 68 – Soil particle size distribution test.

Figure 69 – Collecting an undisturbed soil sample from the root zone to determine the bulk density.

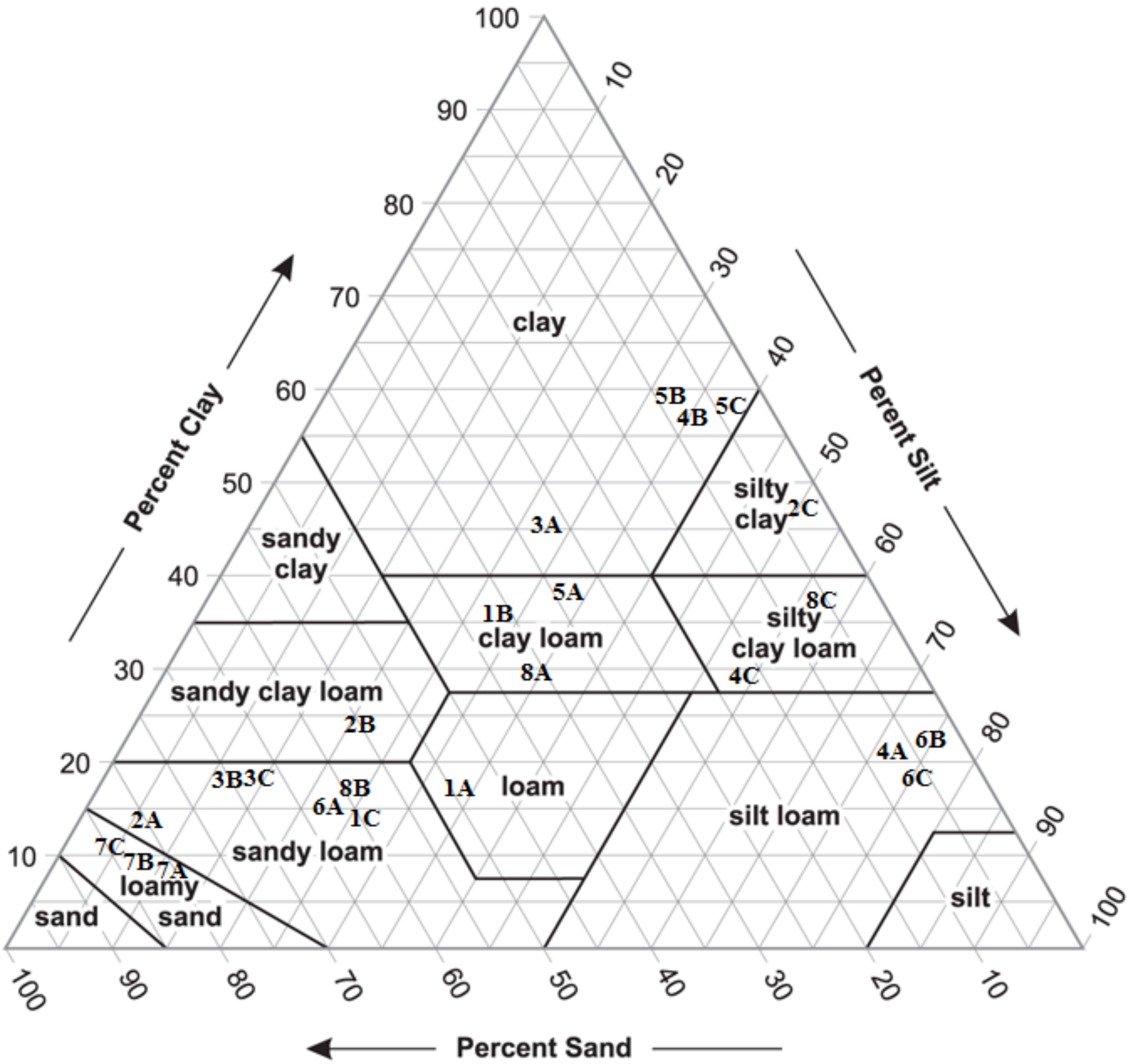


Figure 70 – Sampling soils texture according to the United States Department of Agriculture (USDA) soil classification (NRCS, U. 1993).

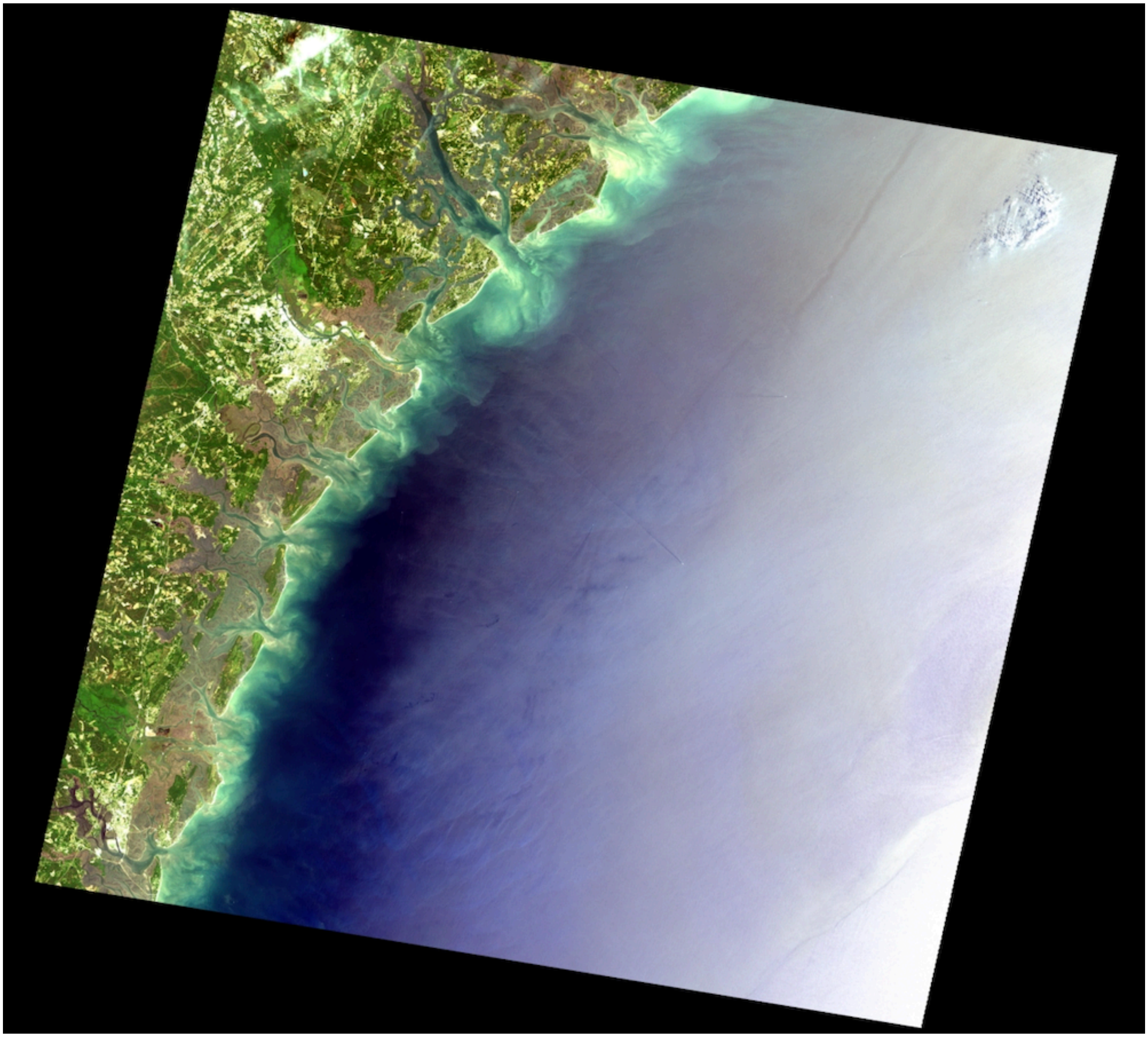


Figure 71 – Satellite image of Georgia coast acquired by LandSat-7 (ETM+).

Part 4: Inductively Coupled Plasma (ICP) Test Results and Threshold Effects Levels (TELs) and Probable Effects Levels (PELs) for heavy metals

Table 10 – ICP test results on soil samples

Sample	Al mg/kg	As mg/kg	B mg/kg	Ca mg/kg	Cd mg/kg	Cr mg/kg	Cu mg/kg	Fe mg/kg	K mg/kg	Mg mg/kg	Mn mg/kg	Mo mg/kg	Na mg/kg	Ni mg/kg	P mg/kg	Pb mg/kg	S mg/kg	Zn mg/kg
1A	2951	<1.52	7.25	1281	<0.50	5.21	<2.50	4841	421	897	66.2	<0.50	2747	1.05	202	3.88	3983	6.20
1B	9741	3.59	18.87	1366	<0.50	13.41	3.87	13567	1214	2492	105.5	1.75	11109	4.26	250	6.40	11385	14.63
1C	20082	9.71	46.52	1954	0.99	29.32	8.38	28354	3125	6118	161.7	5.67	24490	9.71	336	15.28	23262	35.12
2A	6025	2.83	13.07	3489	<0.50	8.20	7.56	8137	742	1544	103.9	0.55	4661	2.26	99	7.90	6479	15.92
2B	10181	6.69	21.01	1625	0.57	13.90	5.09	15996	1240	2477	158.1	0.85	6920	4.75	199	12.52	12275	21.44
2C	22792	16.64	42.85	1946	1.03	34.98	9.38	29426	3388	6358	106.5	2.04	17524	11.94	214	15.57	18686	34.95
3A	13854	4.91	20.62	1994	0.75	26.25	4.49	15172	1858	3763	72.9	0.95	9033	6.61	767	10.71	5129	21.34
3B	2884	<1.52	6.23	517	<0.50	6.97	<2.50	3762	487	823	7.7	<0.50	2409	0.86	163	2.48	2402	5.56
3C	3368	1.71	7.66	578	<0.50	6.48	<2.50	5010	649	1146	11.0	<0.50	3707	1.38	189	2.32	3756	7.70
4A	20287	<4.19	26.00	3093	<1.37	44.56	15.11	22655	1482	4488	182.2	1.75	8550	10.09	451	35.23	17547	57.51
4B	32137	5.11	28.66	5544	1.29	55.92	20.17	28582	1994	6284	334.4	1.31	8396	13.03	1061	33.76	11234	70.22
4C	23887	4.76	34.94	3867	1.26	66.77	22.89	31495	1457	5935	301.0	1.79	9457	12.75	454	44.13	24359	67.56
5A	16536	4.26	16.29	1453	0.75	19.68	8.18	17642	942	2416	82.5	1.02	3301	6.72	189	13.48	13895	30.14
5B	42571	11.16	28.44	1845	1.55	39.88	19.93	35039	2058	4926	176.1	1.51	4347	15.46	393	25.58	23455	59.09
5C	18091	5.40	17.81	17042	0.78	18.78	7.94	16845	1127	2555	83.0	1.09	4031	7.03	456	10.82	11217	26.10
6A	5699	2.55	11.93	10270	<0.50	8.01	<2.50	7047	872	1976	101.1	1.09	6955	2.59	765	3.65	6635	12.98
6B	18441	7.47	45.36	3308	0.93	26.06	8.83	29230	3350	9179	278.7	2.54	41414	8.12	389	27.61	29045	40.79
6C	9755	5.40	23.70	20306	<0.50	13.03	3.68	14954	1593	3254	82.2	4.09	13764	4.69	358	7.22	14006	17.39
7A	4229	<1.52	11.09	29222	<0.50	6.32	<2.50	5374	708	1717	75.2	<0.50	5507	1.89	899	2.61	1802	8.44
7B	3341	1.69	9.10	25734	<0.50	5.49	<2.50	4142	545	1111	28.1	<0.50	3073	1.27	1213	2.00	925	6.88
7C	2111	1.76	7.25	32470	<0.50	3.33	<2.50	3771	442	897	28.3	0.74	3147	0.79	457	1.21	1708	4.08
8A	17267	4.40	29.76	5631	0.71	24.51	6.10	18340	2589	5632	276.9	0.81	18913	7.18	469	12.57	14760	30.66
8B	5289	3.77	10.94	10301	<0.50	8.12	<2.50	7969	785	1987	85.9	0.82	4129	2.36	557	2.91	6681	8.27
8C	17991	8.27	29.02	26691	0.79	21.02	6.00	19688	2318	4719	140.7	1.42	18063	7.04	388	10.92	13839	26.45

Table 11 – Threshold Effects Levels (TELs) and Probable Effects Levels (PELs) for heavy metals.

	As	Cd	Cr	Cu	Pb	Zn
TELs (mg/kg)	7.24	0.68	52.3	18.7	30.2	12.4
TPLs (mg/kg)	41.6	4.21	160	108	112	271