MONITORING GREENHOUSE GAS FLUX AND SOIL MOISTURE IN THE GREAT DISMAL SWAMP NATIONAL WILDLIFE REFUGE

by

Laurel Wood Gutenberg
A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Earth Systems and GeoInformation Sciences

Committee:

_________________________________________  Dr. John J. Qu, Dissertation Director
_________________________________________  Dr. Changwoo Ahn, Committee Member
_________________________________________  Dr. Dianna Hogan, Committee Member
_________________________________________  Dr. Ruixin Yang, Committee Member
_________________________________________  Dr. Dieter Pfoser, Department Chairperson
_________________________________________  Dr. Donna M. Fox, Associate Dean, Office of Student Affairs & Special Programs, College of Science
_________________________________________  Dr. Ali Andalibi, Interim Dean, College of Science

Date:  ________________________________  Spring Semester 2020
George Mason University
Fairfax, VA
Monitoring Greenhouse Gas Flux and Soil Moisture in the Great Dismal Swamp National Wildlife Refuge

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

by

Laurel Wood Gutenberg
Master of Science
University of Wisconsin, 2009
Bachelor of Science
Juniata College, 2007

Director: John J. Qu, Professor
Department of Geography and GeoInformation Sciences

Spring Semester 2020
George Mason University
Fairfax, VA
DEDICATION

This is dedicated to my mother, Lisa, who helped with the field work by ensuring I was properly outfitted, and my daughter, Juniper, who didn’t help exactly.
ACKNOWLEDGEMENTS

Thank you to my advisor Dr. John J. Qu, all coauthors, my committee members Dr. Dianna Hogan, Dr. Ruixin Yang and Dr. Changwoo Ahn, and my reviewers who helped with planning, research, analysis, writing and editing. Thank you to the ESTC team, especially Dr. Xianjun Hao and Chenyang Xu.

Funding for this project was provided by USGS Land Carbon program. Thank you to the many amazing GDS Carbon Project scientists who have given me so much valuable input and experience, especially Dr. Zhiliang Zhu, and to the Refuge staff for their advice and assistance. Also, thanks to Christopher Wright, Joshua Simon, Christina Musser, Timothy Larson, and Alexander Jonesi for the many hot and buggy months assisting with data collection.

Thanks to my friends and family for their support, including my husband, James, and I would like to especially thank my father, Jeff, for all the indispensable support and help.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Tables</td>
<td>vii</td>
</tr>
<tr>
<td>List of Figures</td>
<td>viii</td>
</tr>
<tr>
<td>List of Abbreviations</td>
<td>ix</td>
</tr>
<tr>
<td>Abstract</td>
<td>x</td>
</tr>
<tr>
<td><strong>Chapter One: Introduction</strong></td>
<td>1</td>
</tr>
<tr>
<td>The Great Dismal Swamp Carbon Project</td>
<td>1</td>
</tr>
<tr>
<td>Study site</td>
<td>1</td>
</tr>
<tr>
<td>The GDS carbon project</td>
<td>3</td>
</tr>
<tr>
<td>Study questions</td>
<td>4</td>
</tr>
<tr>
<td>Overview</td>
<td>5</td>
</tr>
<tr>
<td><strong>Chapter Two: Literature review</strong></td>
<td>7</td>
</tr>
<tr>
<td>Forest classification</td>
<td>7</td>
</tr>
<tr>
<td>Greenhouse gas flux</td>
<td>13</td>
</tr>
<tr>
<td>Soil moisture</td>
<td>14</td>
</tr>
<tr>
<td><strong>Chapter Three: Forest classification</strong></td>
<td>17</td>
</tr>
<tr>
<td>Forest classification summary</td>
<td>17</td>
</tr>
<tr>
<td>Introduction to forest classification</td>
<td>17</td>
</tr>
<tr>
<td>Forest classification methods</td>
<td>18</td>
</tr>
<tr>
<td>Forest classification results</td>
<td>23</td>
</tr>
<tr>
<td><strong>Chapter Four: Carbon dioxide and methane flux</strong></td>
<td>27</td>
</tr>
<tr>
<td>CO₂ and CH₄ flux summary</td>
<td>27</td>
</tr>
<tr>
<td>Introduction to CO₂ and CH₄ flux</td>
<td>28</td>
</tr>
<tr>
<td>CO₂ and CH₄ flux methods</td>
<td>29</td>
</tr>
<tr>
<td>Study design and site description</td>
<td>29</td>
</tr>
<tr>
<td>Gas flux measurements</td>
<td>33</td>
</tr>
<tr>
<td>Chambers and sampling procedure</td>
<td>33</td>
</tr>
</tbody>
</table>
Data collection and processing ................................................................. 34
CO₂ and CH₄ flux results ........................................................................ 35

Chapter Five: Monitoring surface soil moisture and greenhouse gas flux through synthetic aperture radar ........................................................... 50
Soil moisture summary ................................................................. 50
Introduction to soil moisture .......................................................... 51
Soil moisture materials and methods .............................................. 52
Results ............................................................................................... 58

Chapter Six: Technical Discussion ........................................................ 64
Forest classification discussion ...................................................... 64
Forest classification conclusions ................................................... 66
Greenhouse gas flux discussion ....................................................... 67
Drivers of flux .................................................................................. 67
Increased sampling efficiencies .................................................... 71
Implications of the study ............................................................... 73
Greenhouse gas flux conclusions .................................................... 74
Soil moisture discussion ................................................................. 75
Remote sensing of greenhouse gas flux .......................................... 77
Soil moisture conclusions ............................................................... 82

Chapter 7: ConclusionS .............................................................. 84
Overall discussion ............................................................................. 86
Scientific and management contributions ...................................... 86
Future applications ............................................................................ 86
Future study ...................................................................................... 87
Ground sampling ............................................................................ 87
Data combinations ............................................................................ 87
Conclusions ..................................................................................... 88
References ......................................................................................... 89
LIST OF TABLES

Table 1. Ground calibration and validation sites .......................................................... 22
Table 2. Confusion matrices for unsupervised classification using a) multispectral only; b) multispectral and radar; c) radar only; and d) multispectral and NDVI ........................................ 25
Table 3. Basic statistics and distribution of measurements by site .................................. 38
Table 4. Results of regression analysis of relationships between variables. Values in bold are statistically significant at a 95% confidence level ........................................... 44
Table 5. Paired t-test for two sample means showing that the three populations are likely separate, with statistically significant results in bold ........................................... 54
Table 6. Data collection dates ......................................................................................... 57
Table 7. Site data from the three dates closest to satellite overpass. Soil moisture content (SMC) is (wet weight - dry weight) / dry weight ........................................... 58
Table 8. Linear regression results for each combination of variables with 14 observations each time ........................................................................................................... 58
Table 9. A. Multiple regression results for maple forest (A), cedar forests (B) and pocosin forest (C) ........................................................................................................... 81
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1. Project workflow.</td>
<td>5</td>
</tr>
<tr>
<td>Figure 2. Forest classification sampling sites by forest type with synthetic aperture radar background.</td>
<td>20</td>
</tr>
<tr>
<td>Figure 3. Calibration areas in orange (45% angle) and validation in blue (135% angle).</td>
<td>23</td>
</tr>
<tr>
<td>Figure 4. Map showing the Great Dismal Swamp with forest types (Fleming 2001), the locations of the 9 study sites, and the location within the mid-Atlantic of the US.</td>
<td>31</td>
</tr>
<tr>
<td>Figure 5. A) Distribution of CO\textsubscript{2}; B) Distribution of CH\textsubscript{4}; C) Distribution of CH\textsubscript{4} with outliers removed.</td>
<td>36</td>
</tr>
<tr>
<td>Figure 6. Water depth at the study sites, precipitation record, and soil moisture content at the sites over time.</td>
<td>40</td>
</tr>
<tr>
<td>Figure 7. a) Relationship between CO\textsubscript{2} flux and soil moisture (0-5 cm). b) Relationship between CH\textsubscript{4} flux and soil moisture (0-5 cm).</td>
<td>41</td>
</tr>
<tr>
<td>Figure 8. a) Relationship between CO\textsubscript{2} flux and air temperature. b) Relationship between CH\textsubscript{4} flux and air temperature.</td>
<td>42</td>
</tr>
<tr>
<td>Figure 9. Relationships between CO\textsubscript{2} and CH\textsubscript{4} and soil moisture and soil temperature for each site.</td>
<td>45</td>
</tr>
<tr>
<td>Figure 10. SAR backscattering map over GDS on February 15, 2017 with sampling sites.</td>
<td>55</td>
</tr>
<tr>
<td>Figure 11. Graph showing how well SAR alone predicts litter moisture.</td>
<td>59</td>
</tr>
<tr>
<td>Figure 12. Surface soil moisture on February 15, 2017 based on equation 1. Clipped at 0 and 8.21, showing the histogram in red of values before clipping.</td>
<td>61</td>
</tr>
<tr>
<td>Figure 13. Scatter plot of expected vs observed SSM and LM values.</td>
<td>63</td>
</tr>
<tr>
<td>Figure 14. a) Map of CO\textsubscript{2} flux in (\mu g) CO\textsubscript{2}-C/m\textsuperscript{2}/hr on 15 February 2017. b) Map of CH\textsubscript{4} flux in (\mu g) CH\textsubscript{4}-C/m\textsuperscript{2}/hr on 15 February 2017.</td>
<td>79</td>
</tr>
</tbody>
</table>
**LIST OF ABBREVIATIONS**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AWC</td>
<td>Atlantic white cedar</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon dioxide</td>
</tr>
<tr>
<td>DF</td>
<td>Degrees of Freedom</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital elevation model</td>
</tr>
<tr>
<td>DSSP</td>
<td>Dismal Swamp State Park</td>
</tr>
<tr>
<td>ESA</td>
<td>European Space Agency</td>
</tr>
<tr>
<td>FIREMON</td>
<td>Fire Effects Monitoring and Inventory Protocol</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic information system</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GDS</td>
<td>Great Dismal Swamp</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse gas</td>
</tr>
<tr>
<td>LM</td>
<td>Litter moisture</td>
</tr>
<tr>
<td>CH₄</td>
<td>Methane</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>NWR</td>
<td>National Wildlife Refuge</td>
</tr>
<tr>
<td>N₂O</td>
<td>Nitrous oxide</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized difference vegetation index</td>
</tr>
<tr>
<td>RFDI</td>
<td>Radar Forest Degradation Index</td>
</tr>
<tr>
<td>REDD+</td>
<td>Reducing emissions from deforestation and forest degradation</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l’Observation de la Terre</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle radar topography mission</td>
</tr>
<tr>
<td>SLC</td>
<td>Single look complex</td>
</tr>
<tr>
<td>SM</td>
<td>Soil moisture</td>
</tr>
<tr>
<td>SMC</td>
<td>Soil moisture content</td>
</tr>
<tr>
<td>SSM</td>
<td>Surface soil moisture</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic aperture radar</td>
</tr>
<tr>
<td>UGGA</td>
<td>Ultra-portable Greenhouse Gas Analyzer</td>
</tr>
<tr>
<td>USFWS</td>
<td>United States Fish and Wildlife Service</td>
</tr>
<tr>
<td>USGS</td>
<td>United States Geological Survey</td>
</tr>
</tbody>
</table>
ABSTRACT

MONITORING GREENHOUSE GAS FLUX AND SOIL MOISTURE IN THE GREAT DISMAL SWAMP NATIONAL WILDLIFE REFUGE

Laurel Wood Gutenberg, Ph.D.
George Mason University, 2020
Dissertation Director: Dr. John J. Qu

This dissertation seeks to quantify the relationships between soil carbon gas flux, surface soil moisture and forest class in the Great Dismal Swamp, and to map these variables by combining satellite remote sensing and in situ measurements with model simulation. Forest type classification is done using freely available multispectral and synthetic aperture radar data combined with ground sampling. This study finds a 79% accurate classification of six classes of interest (maple-gum, Atlantic white cedar, pocosin, cypress, open water and disturbed habitat) using multispectral bands combined with the Normalized Difference Vegetation Index (NDVI). Two years of monthly carbon dioxide and methane flux were measured in nine sites across three forest types (maple-gum, Atlantic white cedar and pocosin) along with temperature and soil moisture. On average, as soil moisture increased by 1 unit of soil moisture content, CH₄ flux increased by 457 μg CH₄-C/m²/hr. On average, as soil temperature increased by 1 μC, CO₂ flux increased
by 5,109 μg CO₂-C/m²/hr. The total area of Atlantic white cedar in the study boundary has an average yearly flux of 8.6 metric tons (t) of carbon from CH₄ and 3,270 t of carbon from CO₂; maple-gum has an average yearly flux of 923 t of carbon from CH₄ and 59,843 t of carbon from CO₂; pocosin has an average yearly flux of 431 t of carbon from CH₄ and 15,899 t of carbon from CO₂. Total Cha-1yr-1 ranged from 1,845 kg of Cha-1yr-1 in maple-gum to 2,024 kg Cha-1yr-1 for Atlantic white cedar. The driest sites lost the most carbon (up to 817 g C/m²/y), while the wettest sites lost the least (down to 575 g C/m²/y). These results show that soil carbon gas flux depends on soil moisture, temperature and forest type, which are all affected by anthropogenic activities in these peatlands. Soil moisture from 0-5 cm was a better fit with CH₄ flux than soil moisture 5-10 cm. Satellite data products were derived from Sentinel-1 C-band synthetic aperture radar (SAR). For validating the satellite surface soil moisture data products, ground measurements were taken on three dates at 9 sites and include: surface soil moisture content, litter moisture content, soil density, aboveground biomass density, and forest type. The results indicate that up to 38% of the variation in backscatter values is explained by biomass, soil density, and surface litter moisture. Despite biomass reducing SAR interaction with the soil, we found it is still possible to model surface soil moisture. Given the ability to measure surface soil moisture and forest class using multispectral and synthetic aperture radar data, as well as the relationships derived from the ground sampling of greenhouse gas flux, it is possible to estimate total soil carbon gas flux over the Great Dismal Swamp. This has implications for management of the Great Dismal Swamp and other forested peat wetlands, as well as other similar ecosystems globally.
The major contributions of this study include the relationships between: multispectral data and ground measurements of forest type; soil carbon gas flux, soil temperature and soil moisture; and synthetic aperture radar and soil moisture, as well as the methods for measuring these relationships and monitoring conditions in the Great Dismal Swamp in the future. Remote sensing of soil carbon gas is one important application of mapping surface soil moisture, which itself is essential for mapping of soil carbon gas flux.
CHAPTER ONE: INTRODUCTION

The Great Dismal Swamp Carbon Project

Study site

The Great Dismal Swamp (GDS) is located in southeastern Virginia and northeastern North Carolina and is one of the largest remaining forested wetlands on the Southeastern Coastal Plain of the US at around 111,203 acres. The GDS is bounded by the Suffolk Scarp on the west, the Dismal Swamp Canal on the east, and Highways 58 and 158 on the north and south; the area of the Scarp is a gradual transition with mixed forest, while the other three sides are sharp boundaries with agriculture and other development (Carter et al., 1994; USFWS, 2006). The GDS includes Lake Drummond, covering 3,108 acres with a maximum depth of just 6 to 7 feet, and elevation drops at about one foot per mile from the Scarp in the west across the swamp to the eastern boundary (USFWS, 2006). The GDS is composed of the Great Dismal Swamp National Wildlife Refuge (GDS NWR) mostly in Virginia managed by the US Fish and Wildlife Service (USFWS), and the North Carolina Dismal Swamp State Park (DSSP). The GDS is a peat wetland, with up to several meters of peat accumulated over thousands of years above the mineral soil surface.

The GDS contains several distinct forest community types, with about 340 different vascular plant species, and overall represents the interface between northern and
southeastern type swamps (USFWS, 2006). One of these types of wetland is known as pocosin, which refers to pine palustrine wooded wetlands with a dense shrub understory and organic soils. Pocosins are fire-adapted and are classified as forested non-tidal wetlands (Richardson, 2003) and are now a globally uncommon forest type. Another globally rare vegetation community found at the GDS is Atlantic white cedar (AWC) forest, which may be mixed with other species but often forms pure stands (USFWS, 2006). These pure stands of cedar were targeted for timber harvesting historically, and are also susceptible to high winds. The AWC may also have difficulty replacing themselves in the GDS, since places dry enough for germination in the spring, such as mossy logs and hummocks, may be too dry for seedlings to reach water as they mature later; water levels that are too high can also drown seedlings and seeds (Akerman, 1923). Fire can exacerbate this as peat at the surface burns away, lowering the soil surface in relation to the water table. The third forest type of interest for this study is a maple-gum hardwood assemblage. This community has largely replaced the above-mentioned species after logging and storms have removed the formerly dominant trees.

After European colonization of the east coast, swamp lands were drained, logged and farmed. Attempts were made to make the interior of the GDS suitable for agriculture, but this was unsuccessful and instead the timber was harvested. Ditches were dug across the current GDS area, which drain the top layers of peat, feeding the ground water into the Dismal Swamp Canal and other surface water. The area continued to be logged and drained into the mid-20th century, until a forest products company donated over 49,000 acres to the Nature Conservancy who then transferred that land plus over 50,000
additional purchased acres to the US Fish and Wildlife Service in 1974 (http://www.fws.gov/refuge/Great_Dismal_Swamp/about.html). Currently, the Fish and Wildlife Service manages the land in accordance with their stated goals to protect the animal and plant diversity of the ecosystem in a natural state and secondarily to promote public use when not in conflict with the main objectives.

**The GDS carbon project**

The GDS Carbon Project is a collaboration between the US Geological Survey (USGS), US Fish and Wildlife Service, and several universities. The goal of the project is to study the carbon balance of the refuge ecosystem, understand the effects or possible effects of management activities on carbon storage, and estimate the effects of management, fire and ecosystem change on carbon sequestration. To accomplish this, studies have been conducted measuring carbon loss due to fire (Reddy et al., 2015), looking at carbon stored in the peat soil over time (Drexler et al., 2017), measuring carbon in the ground and surface water as well as water level and soil moisture (Speiran and Wurseter, 2016; Kim et al., 2017) monitoring tree growth, looking at species composition and below and aboveground biomass, as well as modeling ecosystem level carbon balance (Sleeter et al., 2017). This effort is important to quantify the causes and effects of climate change adaptation, ecosystem restoration and management, and to potentially apply methods learned here to other similar ecosystems.

This part of the carbon project in the GDS focuses on greenhouse gas flux from the soil to the atmosphere. In order to study this on a meaningful scale across the GDS ecosystem, remote sensing is paired with ground-based measurements. The relationship
between carbon dioxide and methane flux and ground variables is determined, and then these variables are mapped using satellite remote sensing data to model GHG across the GDS. This makes it possible to get an idea of GHG flux over time and space that would be prohibitively intensive otherwise.

**Study questions**

In order to gain information about carbon gas flux in the GDS, in order to learn more about the ecosystem functions, to inform management activities in the GDS as well as around the world in similar environments, and to quantify the effects of global climate change, this paper asks several main research questions:

1. What are the relationships between environmental conditions (soil moisture, temperature, forest type) and carbon gas flux into and out of the peat soil? Is CO$_2$ or CH$_4$ more important in the GDS? How much carbon is lost or gained for each forest type over time?

2. Can readily available satellite data be used to classify the forest types of the GDS sufficiently to map the forest communities of interest in the GDS?

3. Can readily available c-band synthetic aperture radar be used to measure surface soil moisture despite the relatively high amount of biomass in the GDS?

This study contributes to the current science by providing answers to important questions about carbon loss and sequestration, how soil gas flux can be monitored remotely; providing information on the relationship between climate variables and gas
flux that can be used for future study and for management; and demonstrates the advantages of remote sensing on this scale, showing how remote sensing is useful to monitor conditions, estimate carbon loss and gain, and potentially identify future problem areas.

**Figure 1. Project workflow.**

**Overview**

In chapter three, this dissertation will cover forest classification using synthetic aperture radar and multispectral satellite images. In chapter four, ground measurements are analyzed to determine the relationship between soil carbon gas flux and environmental conditions. In chapter five, the relationship between synthetic aperture
radar backscatter intensity and ground based surface soil moisture measurements is determined. This information is then combined to look at refuge wide soil carbon gas flux in chapter six.

For forest classification, aerial photography allows for detailed spectral analysis of tree species but is very expensive. This study uses satellite data, which allows for the more frequent and less expensive mapping of forest type. Here, multispectral WorldView 2 images and Sentinel-1 SAR data from 2014 are used to map forest classes using supervised classification and validation to determine which data sources are most useful for this area.

For greenhouse gas flux, this study focuses on carbon soil gas flux. This study observes two years of CO$_2$ and CH$_4$ soil flux within the forest communities of interest to study the relationship between current conditions and carbon soil gas flux. Chapter four reports the effects of soil temperature and moisture increases on CO$_2$ and CH$_4$ flux in each forest type, as well as the total estimated amount of carbon flux across the refuge. The results show that soil carbon gas flux depends on soil moisture, temperature and forest type, which are all affected by anthropogenic activities in these peatlands.

For soil moisture, this study uses a combination of ground measurements and satellite data to model the radar backscatter response to surface soil moisture (SSM) in the GDS. Analysis of ground measurements (surface soil moisture content, litter moisture content, soil density, aboveground biomass density, and forest type) plus Sentinel 1 C-band synthetic aperture radar indicates that up to 38% of the variation in backscatter values is explained by biomass, soil density, and surface litter moisture.
CHAPTER TWO: LITERATURE REVIEW

The GDS today contains remnants of native ecosystems and vegetation communities, but ditching, fires, logging have reduced the once dominant cypress-gum forests of the area to mere fragments (Whitehead, 1972). Other important local ecosystems that have been greatly reduced and are part of the US Fish and Wildlife Service’s management goals for the refuge include AWC and pocosin. Maple-gum is also important forest class in this study because it covers the majority of the refuge due mainly to human impacts; today, the maple-gum assemblage is the only forest type that is naturally expanding in the GDS, replacing cypress-gum, which was formerly the most extensive, and also replacing other rarer forest types which may be affected negatively by the hydrological changes, changes in fire regime, or past selective logging (USFWS, 2006). Aside from pocosin, maple-gum, AWC, and remnants of cypress-gum, the other, smaller classes that are part of the refuge area include open water (Lake Drummond in the center of the refuge), and marsh or disturbed land.

Forest classification

In supervised forest classification, the signature extraction process involves locating calibration sites with known forest cover of each class to use as training data (Xie et al, 2008). Pattern recognition software then assigns each pixel a most likely classification based on these signatures. Early attempts to use remote sensing to map
forest class in the GDS include Messmore in 1975 using Landsat and Gammon and Carter in 1979 using infrared (Levy, 1991). In addition to improved data and availability since that time, many factors can improve the classification results including texture measures (Johansen et al., 2007), resolution (Hansen et al., 2008), ancillary data such as slope or elevation (Xie et al., 2008; Murphy et al., 2007; Li et al., 2005; Mitchard et al., 2012), NDVI (Jiang et al., 2012), temporal changes (del Castillo et al., 2015; Townsend, 2002), or advanced processing (Esbah et al., 2010).

Multispectral remote sensing of forest type has some limitations, such as dealing with spectral similarity of different forest species. This can be addressed by increasing temporal resolution which may allow behavioral differences to emerge (i.e. leaf on and off times for species with similar spectral characteristics may be different) or by including relevant ancillary data such as average yearly temperature limit differences between species. Saturation is also a problem in remote sensing of biomass and vegetation in general. For example, measurement of leaf area index gets saturated quickly in dense vegetation. Reflectance is mainly composed of the upper layer of leaves in the canopy; not much light reaches and is reflected back from understory plants or the soil surface. The exception to this is longwave radar remote sensing which can penetrate some layers of vegetation and even soil before all of the radiation has been attenuated or backscattered. Since the GDS is relatively small in scale and climatically and topographically uniform, causes of variation in vegetation can be narrowed down more easily by excluding many factors that can shape vegetation cover in other, more
topographically complex or diverse areas (Levy, 1991). For example, the soil type and average yearly temperature don’t vary enough to cause species zones within the GDS.

Early attempts to map forest class in the GDS include Messmore in 1975, who used Landsat 1 to map GDS vegetation; this result was very coarse. In 1979, Gammon and Carter used IR photography to map vegetation including 10 forest canopy classes (Levy, 1991). With good multispectral satellite data readily available, remote sensing of forest class based on spectral signature is now easier to accomplish. Specific bands can be selected based on known areas of reflectance characteristics due to physical differences in vegetation, or all bands can be used to create a signature or profile. The signature extraction process involves locating calibration sites with known forest cover in the images and selecting the area as training data (Xie et al, 2008). This is done for multiple instances of each class. This requires knowledge of some of the study area, as training data is required to initially produce the signatures, and validation data is required to test the resulting classification to see what the rate of error is, both producer’s and consumer’s error.

More specifically, radiance measurements at different bandwidths for each pixel are broken down into patterns; spatial relationships such as shape and size can be added, as can temporal patterns (Pal, 2012). These patterns can be found through automated classification processes, but knowledge of what they signify must come from knowledge of the land surface and vegetation. The pattern recognition software then assigns each pixel a most likely classification based on training labels. Smoothing out the resulting
classification maps so that land cover types are contiguous and more or less solid shapes is a common practice.

Texture measures have also been shown to improve forest remote sensing by looking at structural difference. Johansen et al. found that using spectral and textural bands gave better accuracy than either spectral or texture alone for riparian forest (Johansen et al., 2007). Spatial resolution is another consideration; often the data with the highest temporal frequency will have lower spatial resolution. Combining different sources of multispectral data, even at different resolutions, can be used to detect forest class and forest change or loss (Hansen et al., 2008).

Where spectral signatures do not produce enough distinction between classes, other data can be added to improve accuracy (Xie et al., 2008). This additional data should come from a dataset that is continuous or extrapolated across the study area, and could be slope or elevation information from a digital elevation model (DEM), soil type from a soil map, etc. This would be used to create a decision rule to rule out certain wetland species above a certain slope, for example, or when found in non-hydric soils, and could be used to model relationships between the different variables that would not otherwise be obvious (Murphy et al., 2007). Wetland composition is dependent on duration, frequency, extent, and seasonality of inundation and soil saturation. Presence of a species in a wetland depends on its tolerance for inundation and high soil moisture as well as periods of dryness. Carter et al. studied different vegetation groups in upland, transitional, and wetland areas of the GDS. Along four east-west transects, 127 species were found, 15 of which were considered obligate wetland species, and 37 of which were
considered facultative wetland species. Sweet bay, red bay, holly, and inkberry were found in all three areas and were considered mainly facultative wetland species. Red maple, pawpaw, holly, gum, and pine were considered generally facultative species that did not favor wet conditions. Sweet bay and red bay were considered facultative wetland plants, and cypress was considered an obligate wetland species (Carter et al., 1994). Knowing these habits of the different plants can lead to creation of decision rules to classify the forest types. Knowledge of the landscape can also be used to determine processing steps that will add additional information to the analysis or will prevent certain errors. For example, using segmentation can avoid misclassified pixels when the landscape is full of ecotones, transition zones and different classes (Esbah et al., 2010).

Addition of a DEM can also improve accuracy (Li et al., 2005). These are not known issues in the GDS, however.

Time series of remote sensing data or data products, such as NDVI, can be helpful for capturing seasonal differences in plant growth, for greenness that can be used to look for overall health or for looking at plants that are evergreen (or at the soil) during leaf-off season. Even in tropical environments with no specific leaf off period, seasonal changes in growth patterns can be significant enough to allow for species presence and abundance detection. For example, NDVI from SPOT and MODIS data, combined with field sampling, has been used to separate broadleaf evergreen forest into classes and determine epiphyll presence (Jiang et al., 2012). When seasons are more defined, it can be effective to use spring, summer, and fall data points when the land cover is deciduous trees (del Castillo et al., 2015).
Mitchard et al. studied the use of radar to map aboveground biomass in tropical forest to prepare for projects for the Clean Development Mechanism and REDD+ in the future. They found that active remote sensing has an advantage over optical where there is high cloud cover, but that the radar and lidar they used tended to saturate with high biomass. They reported good accuracy when using a DEM to correct for terrain; however, with low relief in the GDS this would not be necessary. They also found that using Radar Forest Degradation Index (RFDI) which is a ratio index between HH and HV polarization, was useful for differentiation vegetation type (Mitchard et al., 2012). The Radar Forest Degradation Index (RFDI) is an example of exploiting the polarization of the radar radiation and using the physical properties of forest biomass to add to the data that can be gathered. This ratio, where $\text{RFDI} = \frac{\text{HH} - \text{HV}}{\text{HH} + \text{HV}}$, can be made a layer in addition to other radar layers and can add additional utility and decrease error.

Polarization and wavelength also contribute to the saturation point of radar when looking at biomass; longer wavelength synthetic aperture radar (SAR) can differentiate between differing levels of biomass until a saturation point around 40 tons per hectare (Lu, 2006).

Many studies have demonstrated the use of radar in estimating forest properties, including forest cover and biomass (Koch, 2010) though SAR is limited by availability of data (temporal frequency, bands, and polarization) and by surface properties and interactions. Radar data depends on forest structure characteristics, which can be related to species composition. In the GDS, the maple-gum forest is characterized by a relatively thin shrub layer under a closed canopy, whereas the AWC and pocosin forests have dense shrub layers and open conifer canopy above. Townsend shows that adding multitemporal
data (especially leaf off and leaf on), and multifrequency when available, is much more effective than using single date, co-polarized data for mapping forest type. Adding NDVI also improves this model (Townsend, 2002). Though one might expect SAR, with the benefit of cloud and vegetation penetration, to outperform optical approaches in dense vegetation, especially in cloudy regions, Englhart et al. found that a combination of optical (RapidEye) and SAR did not outperform their optical only iteration.

**Greenhouse gas flux**

Many factors affect GHG flux from soil in forests and wetlands. These include presence of phenolics (Wang et al., 2015), waterlogged conditions, water table height and soil moisture (Harriss & Sebacher, 1982; Beringer et al., 2013; Batson et al., 2014; Moore and Knowles, 1989; Swails et al. 2019), leaf area index, soil nitrogen and tree height (Berryman et al., 2016), irradiance and temperature (Lohila et al., 2011; Miao et al., 2012).

CH₄ flux was measured in the Great Dismal Swamp in 1980-1981, finding that waterlogged soil was a CH₄ source and soils during drought acted as a sink, while normally-dry forest soil did not act as a sink; temperature, season and soil water content were used to determine CH₄ flux within a maple-gum site in the Great Dismal Swamp (Harriss & Sebacher, 1982). In Pocosin Lakes National Wildlife Refuge, a pocosin habitat relatively near the Great Dismal Swamp, consisting of natural, restored and degraded pocosins, phenolics present in the peats, which are found in higher concentrations in shrubs than herbaceous vegetation, protect against peat oxidation during short term droughts, mitigating the increase in CO₂ emissions found in sphagnum
wetland areas. Phenolics were found to be inversely related to soil respiration, protecting peat in shrub communities during droughts (Wang et al., 2015).

Soil moisture

This study of soil moisture is part of a larger project to model carbon, land cover and ecosystem services in the GDS (Sleeter et al. 2017, Kim et al. 2017, Parthum et al. 2017, Drexler et al. 2017, and Pindilli et al. 2018). Synthetic aperture radar is the most useful of several soil moisture remote sensing techniques since radar backscatter relates to the dielectric constant of soil which in turn is related to soil moisture. Other factors that affect SAR backscatter include texture, as well as vegetation including height, density, texture and water content of vegetation (Ulaby et al. 1996; Wang et al. 2009). These vegetation structure effects are strong and biomass can also be measured using SAR (Beaudoin et al. 1994; Kasischke et al. 2011). Vegetation water also effects remote sensing of soil moisture, but can be measured at high spatial and temporal resolution by fusing various remote sensing data sources (Xu et al. 2020). These vegetation effects are less important with longer wavelength sensors (Englhart et al. 2012; Kasischke et al. 2009). When monitoring at soil moisture in forests, SAR is the most useful of several soil moisture remote sensing techniques. The backscattering coefficient of active radar remote sensing as well as passive microwave radiation can be used to detect soil moisture because in bare soil, dielectric properties of the soil (including surface soil moisture (SSM)) and the soil roughness are the two main variables that determine radar backscatter response. The dielectric constant of soil increases as the soil increases in water content. For soil that is not bare, the backscatter is also affected by structure and
amount of vegetation cover. Specifically, height, density, texture and water content of vegetation provide an additional part of the signal effect (Ulaby et al. 1996). In addition to the contribution of vegetation reflectance, the vegetation canopy will also absorb or attenuate some of the soil reflectance (Wang et al. 2009) which will also be affected by vegetation moisture content. The conversion of measured microwave radiation into soil moisture can be done using statistical regression with ground data calibration, or can be based on a radiation transfer model (Wang et al. 2009). This study uses the regression approach which will be discussed below. A preliminary study in the GDS (Kim et al. 2017) found a strong correlation between groundwater levels and soil moisture, groundwater levels and SAR intensity, as well as interferometric SAR and inundation.

Due to the effect of biomass, it is helpful to first classify land cover when attempting to collect data on soil moisture for a given scene (Ulaby et al. 1996). This allows different surfaces including woody vegetation, herbaceous vegetation, water and bare soil to be distinguished initially, as they have different radar responses. This study uses forest cover as determined in a 2014 forest survey. In the GDS, the areas of interest are forested so longer wavelength sensors are ideal, as the signal will penetrate further into the vegetation and then into the soil surface (Englhart et al. 2012). Kasischke et al. (2011) found a positive relationship between SAR backscatter and soil moisture in herbaceous wetlands, a negative relationship in 6 cm or more of standing water, and no relationship in a wetland forested with spruce. This particular study used C-band SAR; the study period for this research also did not have a wide range of soil moisture values for the spruce wetland, so a wider range of values may have revealed a different pattern.
Studies have also shown that it is possible to model forest characteristics using SAR (Beaudoin et al. 1994). While looking at monitoring biomass, one study (Kasischke et al. 2011) found soil moisture also had a significant influence particularly interfering in biomass modeling with lower biomass and longer wavelength. Beaudoin et al. (1994) found strong relationships between radar backscatter and forest characteristics, determining that horizontal-horizontal (HH) polarized returns respond to both tree trunk and crown biomass, while vertical-vertical (VV) and horizontal-vertical (HV) responded mainly to crown biomass. HV polarization backscatter responds to vegetation cover (Tanase et al. 2011) while co-polarization passes though vegetation canopy and brings out the effect caused by soil moisture.
CHAPTER THREE: FOREST CLASSIFICATION

Forest classification summary

Monitoring carbon dioxide and methane emissions requires wall to wall forest cover data to model across the refuge. While specially-collected aerial photography allows for detailed spectral analysis of tree species, this is very expensive and thus difficult to replicate for monitoring change over time. Using multiple sources of readily available and temporally and spatially high-resolution satellite data allows for the more frequent and less expensive mapping of forest type. Using readily available data will allow this process to be repeated as necessary to monitor changes in forest type across the refuge in response to climate change or in response to management activities. Here, multispectral WorldView 2 images and Sentinel-1 SAR data from 2014 are used to map maple-gum, Atlantic white cedar, pocosin and cypress forest, as well as open water and disturbed areas of the Great Dismal Swamp, using supervised classification and validation to determine which data sources are most useful in this case.

Introduction to forest classification

This study aims to map forest type over the entire refuge by using ground measurements to train remote sensing data, since satellite products allow for wall to wall repeated mapping of the study site. Ground measurements can only cover a small percentage of the area, especially in dense forest such as the GDS. This map will later be
used to model current greenhouse gas flux across the refuge and to inform other studies and potential management activities.

This study uses supervised classification, including spectral signatures and training data gathered from available ground study and high-resolution aerial photos, to classify satellite remote sensing data. While forest type can be divided into many increasingly specific classes in the GDS, the classes of focus in this study are Atlantic white cedar (AWC), pocosin, and maple-gum, which together cover most of the refuge. Creating spectral signatures from each dataset means that atmospheric correction is not necessary. In order to obtain the highest accuracy, different combinations of data are tested. These inputs include multispectral data, normalized difference vegetation index (NDVI), and synthetic aperture radar (SAR) which responds to texture, structure, and amount of biomass. Biomass density and structure are important aspects of forest classes in the GDS, including differentiating disturbed and planted areas from natural second growth forest. Error matrices for different combinations of bands show the result with the highest accuracy. If forest structure, texture and biomass is a strong factor in differentiating forest types, the SAR should improve the classification result. If biomass amounts and health of vegetation differs between the first types, then NDVI should improve the classification result.

**Forest classification methods**

This study makes use of established research sites from 2014-2015 where aboveground biomass was surveyed. Random points within walking distance of roads were surveyed including species composition, which was used for this study. These sites
are examples of known forest types, since they have been visited and cataloged, or, in the case of several sites, chosen specifically for their good representation of a given forest class. These sites, with known GPS locations (see Fig. 3), were used for calibration and validation of supervised forest classification. These data points were used to train an algorithm that extracts a pixel based spectral signature for each forest class and uses maximum likelihood to assign classes to each pixel in the image. Then, some reserved ground truth points were used to determine the success of the classification.
Figure 2. Forest classification sampling sites by forest type with synthetic aperture radar background.
The ground data were used to create polygons of known land cover, including 4 forest types as well as disturbed area and water. Seventy percent of the known areas were used to extract signatures across all of the pixels in these polygons. The remaining thirty percent were reserved for validation. The signature is made up of data from each band of multispectral images that are included in the analysis, and can include not just single wavelength bands, but also NDVI layers and radar data. First, multispectral data using 4 bands- 3 visible and 1 IR- from WorldView 2 were used to produce a classification map, then validated using the ground data, and an error matrix produced showing user’s and producer’s accuracy for each class. Next, the same was done using 5 bands- 3 visible, 1 IR and 1 radar. Another was made using the radar only. The fourth repetition used the 4 multispectral bands and an NDVI layer emphasizing the weight of the part of the spectrum indicating healthy vegetation.

Satellite data that was used for signature extraction includes readily available WorldView images and Sentinel-1 radar data, (Fig. 10). Spatial resolution for data sources must be fine enough to allow for detail on the scale of the sample plots, which are in the 10s of meters in radius. The Worldview 2 data is composed of 4 bands- red, green, blue and near infrared. The resolution is 1.84 meters. The images were taken on October 22nd, 2015 which is during the leaf-on season. The Sentinel 1 c-band synthetic aperture radar data was taken on February 15, 2017, with approximately 30-meter resolution.

For signature extraction, several polygons of each type are required and each polygon must contain many pixels, ideally hundreds. Meter sized pixels work well for the 2014 sites which were established with a radius of 10 m (though the forest type can be
extrapolated beyond this 10 m radius in some cases). Table 1 shows the number and types of ground sites used for calibration and validation, see Fig. 4 for locations.

Table 1. Ground calibration and validation sites

<table>
<thead>
<tr>
<th>Ground Sites</th>
<th>AW Cedar</th>
<th>Maple-Gum</th>
<th>Pocosin-Gum</th>
<th>Cypress-Gum</th>
<th>Disturbed</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>10</td>
<td>28</td>
<td>17</td>
<td>10</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Calibration</td>
<td>7</td>
<td>20</td>
<td>12</td>
<td>7</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Validation</td>
<td>3</td>
<td>8</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

These ground points were derived from study plots established in 2014-15 using a protocol adapted from the FIREMON: Fire Effects Monitoring and Inventory Protocol (www.frames.gov/firemon). Some of the ~80 plots were found to be of indeterminate class and were not used. Others had an obvious forest cover, and some were double checked with commercial aerial photography which had been classified into very fine categories. Known sites of other land cover were also created, including sites in disturbed land, open water and marsh (land disturbed by fire) based on known locations. In the end, 65 known forest cover ground truth sites were created and located in a geographic information system (GIS). Polygons around each location were drawn in the GIS software, each one used to create a signature using software classification tools, and then the maximum likelihood parametric rule was used to classify all pixels.
Forest classification results

Visually, the multispectral combined with NDVI iteration provided the most promising classification map, although there are clear differences between the areas.
covered by the different WorldView images. Indeed, the confusion matrix of user’s and producer’s accuracy (Table 2) shows that this combination had the highest percentage of correctly identified pixels of the four at 79%, as well as tied with the radar-only test for the most classes with the majority of pixels correctly classified (4 out of 6 classes). The water class had very few false positives or false negatives in any of the iterations.
Table 2: Confusion matrices for unsupervised classification using a) multispectral only; b) multispectral and radar; c) radar only; and d) multispectral and NDVI.

### a) multispectral

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>maple-gum</td>
<td>cedar</td>
<td>Pocosin</td>
<td>Cypress</td>
<td>Disturbed</td>
<td>Water</td>
<td></td>
</tr>
<tr>
<td>predicted maple-gum</td>
<td>113056</td>
<td>35978</td>
<td>81169</td>
<td>51892</td>
<td>1727823</td>
<td>14289</td>
<td>2024207</td>
</tr>
<tr>
<td>cedar</td>
<td>3026</td>
<td>4605</td>
<td>7003</td>
<td>205</td>
<td>492</td>
<td>1</td>
<td>15332</td>
</tr>
<tr>
<td>pocosin</td>
<td>3346</td>
<td>1170</td>
<td>4203</td>
<td>1496</td>
<td>354</td>
<td>0</td>
<td>10569</td>
</tr>
<tr>
<td>cypress</td>
<td>6453</td>
<td>2374</td>
<td>1858</td>
<td>1937</td>
<td>115951</td>
<td>17</td>
<td>128590</td>
</tr>
<tr>
<td>disturbed</td>
<td>161</td>
<td>6</td>
<td>130</td>
<td>50</td>
<td>1422</td>
<td>16</td>
<td>1785</td>
</tr>
<tr>
<td>water</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>696932</td>
</tr>
<tr>
<td>sum</td>
<td>126043</td>
<td>44133</td>
<td>94363</td>
<td>55580</td>
<td>1846042</td>
<td>711255</td>
<td>2877416</td>
</tr>
</tbody>
</table>

### b) radar and multispectral

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>maple-gum</td>
<td>cedar</td>
<td>Pocosin</td>
<td>Cypress</td>
<td>Disturbed</td>
<td>Water</td>
<td>Sum</td>
</tr>
<tr>
<td>predicted maple-gum</td>
<td>966</td>
<td>182</td>
<td>448</td>
<td>792</td>
<td>32115</td>
<td>0</td>
<td>34503</td>
</tr>
<tr>
<td>cedar</td>
<td>113</td>
<td>247</td>
<td>187</td>
<td>7</td>
<td>27</td>
<td>0</td>
<td>581</td>
</tr>
<tr>
<td>pocosin</td>
<td>1340</td>
<td>440</td>
<td>1378</td>
<td>336</td>
<td>1125</td>
<td>4364</td>
<td>8983</td>
</tr>
<tr>
<td>cypress</td>
<td>385</td>
<td>113</td>
<td>95</td>
<td>104</td>
<td>7786</td>
<td>0</td>
<td>8483</td>
</tr>
<tr>
<td>disturbed</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>66</td>
<td>1</td>
<td>72</td>
</tr>
<tr>
<td>water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11470</td>
</tr>
<tr>
<td>sum</td>
<td>2806</td>
<td>982</td>
<td>2110</td>
<td>1240</td>
<td>41119</td>
<td>15835</td>
<td>64092</td>
</tr>
</tbody>
</table>

### c) radar only

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>maple-gum</td>
<td>cedar</td>
<td>Pocosin</td>
<td>Cypress</td>
<td>Disturbed</td>
<td>Water</td>
<td>Sum</td>
</tr>
<tr>
<td>predicted maple-gum</td>
<td>101</td>
<td>41</td>
<td>62</td>
<td>40</td>
<td>419</td>
<td>0</td>
<td>663</td>
</tr>
<tr>
<td>cedar</td>
<td>18</td>
<td>14</td>
<td>36</td>
<td>3</td>
<td>808</td>
<td>0</td>
<td>879</td>
</tr>
<tr>
<td>pocosin</td>
<td>108</td>
<td>44</td>
<td>91</td>
<td>25</td>
<td>1193</td>
<td>0</td>
<td>1461</td>
</tr>
<tr>
<td>cypress</td>
<td>177</td>
<td>34</td>
<td>67</td>
<td>109</td>
<td>255</td>
<td>0</td>
<td>642</td>
</tr>
<tr>
<td>disturbed</td>
<td>12</td>
<td>12</td>
<td>52</td>
<td>4</td>
<td>3377</td>
<td>0</td>
<td>3457</td>
</tr>
<tr>
<td>water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2333</td>
</tr>
<tr>
<td>sum</td>
<td>416</td>
<td>145</td>
<td>308</td>
<td>181</td>
<td>6052</td>
<td>2333</td>
<td>9435</td>
</tr>
</tbody>
</table>
Table 2 shows the user’s accuracy and producer’s accuracy for these four different classifications. Each performed differently for different classes based on the strengths of that type of classification. The columns show the actual classification of each pixel, and the rows show how those categories of pixels were classified by the algorithm. The multispectral classification frequently overclassified pixels as maple-gum and cypress, and this was also reflected in the classification using multispectral and NDVI although the effect was reduced. Multispectral alone had an accuracy rate of 28.57%. Multispectral and NDVI had an accuracy rate of 78.83%. Multispectral and radar had an accuracy rate of 22.20% and radar alone had an accuracy rate of 63.86%.
CHAPTER FOUR: CARBON DIOXIDE AND METHANE FLUX

**CO₂ and CH₄ flux summary**

The Great Dismal Swamp has accumulated massive amounts of soil carbon since the postglacial period. Logging, ditching, and draining have severely altered the hydrology and forest composition, leading to drier soils, accelerated oxidation, and vulnerability to disturbance. This study observes two years of CO₂ and CH₄ soil flux within these forest communities to study the relationship between current conditions and carbon soil gas flux. On average, as soil moisture increased by 1 unit of soil moisture content, CH₄ flux increased by 457 µg CH₄-C/m²/hr. On average, as soil temperature increased by 1°C, CO₂ flux increased by 5,109 µg CO₂-C/m²/hr. The total area of Atlantic white cedar in the study boundary has an average yearly flux of 8.6 metric tons (t) of carbon from CH₄ and 3,270 t of carbon from CO₂; maple-gum has an average yearly flux of 923 t of carbon from CH₄ and 59,843 t of carbon from CO₂; pocosin has an average yearly flux of 431 t of carbon from CH₄ and 15,899 t of carbon from CO₂. Total Cha⁻¹yr⁻¹ ranged from 1,845 kg of Cha⁻¹yr⁻¹ in maple-gum to 2,024 kg Cha⁻¹yr⁻¹ for Atlantic white cedar. These results show that soil carbon gas flux depends on soil moisture, temperature and forest type, which are all affected by anthropogenic activities in these peatlands.
Introduction to CO$_2$ and CH$_4$ flux

Forested peat wetlands store large quantities of carbon in the form of organic biomass, largely in the soil pool. Human alteration of the wetland hydrology can lead to drying of the soil, which leads to oxidation, changes in plant species composition, altered ecosystem health, increased fire risk, and potentially large emissions of greenhouse gases. Forest degradation and land use change is an important contributor to climate change globally. This study aims to quantify the differential greenhouse gas (GHG) fluxes of carbon from the soil matrices occurring in maple-gum, Atlantic white cedar (Chamaecyparis thyoides), and pocosin habitats at the Great Dismal Swamp. In all, we tested the hypotheses that the GHG flux of carbon differs between soils under maple-gum, Atlantic white cedar, and pocosin habitats, and that carbon flux is dependent on soil temperature and soil moisture. We also explore other possible variables contributing to differences in flux rates. The main drivers of carbon flux are generally soil and vegetation characteristics, including soil moisture and flooding, wetland or forest type, and soil chemistry.

In this study, we measured carbon-based GHG emissions (CO$_2$, CH$_4$) from soils present within three forested wetland habitat types that differ in peat chemistry, carbon density and peat accretion (Drexler et al., 2017) and hydrologic patterns. CO$_2$ and CH$_4$ flux respond to changes in soil temperature and soil moisture as well as forest community type. The Great Dismal Swamp has experienced massive peat loss facilitated not only by chronic oxidation from perennially lower water tables, but also from dry-condition-induced fires which burn through thousands of years of peat deposition in relative short
periods of time to reduce elevations, and further promote forest habitat shifts. We evaluate the consequence of these shifts on the fluxes of carbon-based GHGs.

**CO$_2$ and CH$_4$ flux methods**

**Study design and site description**

The Great Dismal Swamp has an area of over 54,000 ha, and is less than 64 km from the Atlantic coast. Currently, the US Fish and Wildlife Service manages the Great Dismal Swamp National Wildlife Refuge, while the small section in the southeast is managed by North Carolina Dismal Swamp State Park (Fig. 4). Before European settlement, the forested wetland was estimated to occupy over 404,000 ha in extent but has been reduced to its current size through anthropogenic pressures for development and clearing for agriculture (Laderman et al., 1989; Oaks and Whitehead, 1979). There are still ~ 250 km of ditches and roads running through the Great Dismal Swamp, making hydrologic restoration a challenge. The native forest types once dominating the Great Dismal Swamp were bald cypress (Taxodium distichum) and Atlantic white cedar (Chamaecyparis thyoides) (Barrd, 2006), with bald cypress in the wetter areas and Atlantic white cedar in the slightly higher areas. Today, Atlantic white cedar and bald cypress still remain in remnant populations along with pond pine (Pinus serotina), but red maple (Acer rubrum), black gum (Nyssa sylvatica) and sweet bay (Liquidambar styraciflua) (referred to as “maple-gum”) have become a major part of the contemporary forest composition, comprising over 60% of the current Great Dismal Swamp extent (Laderman, 1989) due to their resilience and ability to compete with other species in the new, drained conditions. Pine pocosin (hereafter, pocosin) is a type of fire-adapted
wetland of the Atlantic coastal plain characterized by nutrient poor, often saturated peat soils inhabited by pond pine (Pinus serotina) and loblolly pine (Pinus taeda), and a mix of dense shrubs (e.g., sweet pepperbush [Clethra alnifolia], inkberry [Ilex glabra] and greenbriar [Smilax rotundifolia]). Here, we focus on Atlantic white cedar and pocosin which are vulnerable to alternative succession by maple-gum.
Figure 4. Map showing the Great Dismal Swamp with forest types (Fleming 2001), the locations of the 9 study sites, and the location within the mid-Atlantic of the US.

Data were collected at three sites in each of the three forest types, using four sampling plots within each site, for a total of 9 sites and 36 sampling plots. Sites were
chosen as good representatives of the target forest types in the Great Dismal Swamp, within accessibility constraints, based on mix of species within each forest type (maple-gum, Atlantic white cedar, and pocosin), canopy cover, inundation and moisture regime, and disturbance. To determine the rate of soil CO$_2$ and CH$_4$ flux in the Great Dismal Swamp and the driving factors for these rates, two years of monthly CO$_2$ and CH$_4$ flux measurements over 10-minute durations, soil temperature at 10 cm, and ambient air temperature were collected. Gas fluxes (CO$_2$ and CH$_4$) were measured from chambers (adapted from Krauss and Whitbeck (2012) for use with tubes instead of syringes), which were installed in each sampling plot, for a total of 12 chambers per forest type.

Monthly site-level moisture measurements included litter, soil of 0-5 cm depth, and soil of 5-10 cm depths within each site. Soil temperature was recorded from all sites over 2+ years using continuous loggers (model HOBO Pro v.2, Onset Computer Corp., Bourne, MA, USA). We minimized impact on the study site as much as possible by not walking near the chambers except to place the equipment, and by placing equipment from a bench to distribute the weight of the researcher. We also used an in situ portable cavity ring-down spectroscopy analyzer (Los Gatos Research Ultra Portable Greenhouse Gas Analyzer [UGGA], San Jose, California) to detect smaller concentrations of CH$_4$ than the traditional gas chromatography technique (Christiansen et al., 2015), since CH$_4$ is found in much lower concentrations than CO$_2$ at these sites. Using the spectroscopy analyzer also allows for a short sampling time, which reduces the buildup of pressure inside the chamber which can reduce the diffusive flux of the system (Parkin et al., 2012) but still
provides hundreds of data points at the sampling rate of over one measurement per second, enough to establish the flux rate.

**Gas flux measurements**

**Chambers and sampling procedure**

Each gas flux measuring chamber base was set and left for the duration of the study. Chamber bases measure 29.4 cm by 29.4 cm (864 cm² area), and are 12.7 cm deep, composed of straight sides forming an open top with a square trough in which to set the chamber top, which added 30.5 cm to the chamber height during sampling. This trough was filled with water before sampling so that the chamber top and base form an air tight seal. Gas exchange was also blocked from below the chamber base by insertion to 12 cm into the soil, which was deep enough to avoid leakage during the sampling time (Rochette et al., 2008).

Chambers were sampled during the daytime in the same order each month by placing the chamber top into the bottom trough with the UGGA running. The chambers were left in place for 10 minutes and then removed and the analyzer was allowed to return to baseline by remaining open to the air for 4 minutes in between each sample. Air temperature sometimes varied by several degrees over the sampling period at each site.

In order to minimize disturbance of the soil caused by the sampling process, wide footed stools were placed near each point before sampling and the chamber top was lowered onto each base from a plank set between the stools rather than from standing on the ground. Where the points were close enough together, multiple points could be measured without setting foot on the soil in between. Where this was not possible, the
stools were moved gently during the resting phase. This mitigates against negative measurement impacts (c.f., Winton et al., 2016). Leaving the chambers for one month – or greater in our case – before sampling also avoids errors based on soil disturbance from insertion (Muñoz et al., 2011).

Data collection and processing

The UGGA intakes gas from a tube connected to the chamber top and returns it to the chamber after it is run through a cavity enhanced laser spectrometer through a second tube connected back to the chamber top. The UGGA sampling rate is once every 0.975 seconds and measurements are recorded in parts per million for both CO₂ and CH₄. The chamber volume was calculated by measuring the inner sides and top of the chamber, accounting for compaction and water volume. With no standing water, the chamber volume is approximately 27 liters. Flux is determined by calculating the slope of the increasing concentration of gas inside the chamber in ppm/0.975 seconds and converting that into CO₂ or CH₄ (and then into carbon) per square meter of ground surface. Unless otherwise noted, yearly data from this study is made up of measurements throughout all months of the year sampled, averaged and added together so that seasonal fluctuations are represented.

The paired two sample t-test of CO₂ and CH₄ fluxes in each forest type is used to show if two means come from the same statistical population. Linear regression is used to show the relationships between measured variables and gas flux.
**CO₂ and CH₄ flux results**

CO₂ flux averaged across all measurements and individually at the different sites varied in response to the changing seasons and temperatures, as well as by forest type. Average CO₂ flux in the peak growing season (April-September over 120.95 mg CO₂-C/m²/hr) was almost three times higher than CO₂ flux in October - December (42.84 mg CO₂-C/m²/hr) and January – March (34.76 mg CO₂-C/m²/hr). CH₄ flux also varied throughout the year but in response to soil moisture and other variables as well as season and temperature (Tables 3 and 4).

The CO₂ flux measurement distribution is positively skewed (Fig. 5), with the greatest number of flux values between 7,000 and 200,000 µg CO₂-C/m²/hr, with values ranging up to 567,897 µg CO₂-C/m²/hr. The distribution of CH₄ flux measurements is also positively skewed, but to a greater extent with many very high outliers, with the greatest number of flux values between 0 and 50 µg CH₄-C/m²/hr, and a right tail of values ranging up to 56,686 µg CH₄-C/m²/hr. CO₂ flux showed a more consistent range of values, whereas range of CH₄ flux measurements varied by site (Table 3).
Linear regression shows that much of the variation in CO$_2$ flux is explained by changes in air and soil temperature (Table 4). Much of the variation in CH$_4$ flux is
explained by soil moisture from 0 to 5 cm, but less of the overall variation in CH$_4$ flux is accounted for.

CO$_2$ flux across all the sites shows a statistically significant relationship with air temperature (P < 0.001) and soil temperature (P < 0.001), as well as a relationship with soil moisture content in the top 5 cm of soil (P = 0.074) and in the litter layer (P = 0.081) that is significant at a 90% confidence level. The slopes and R$^2$ values for CO$_2$ flux plotted against soil temperature varied by forest type. Atlantic white cedar sites had the best fit (R$^2$ = 0.6419) followed by pocosin (R$^2$ = 0.5588) and then maple-gum (R$^2$ = 0.488). Increasing soil temperature caused a generally greater increase in CO$_2$ flux on Atlantic white cedar sites than in pocosin or maple-gum sites, and a generally greater increase in CO$_2$ flux in pocosin sites than in maple-gum sites (Atlantic white cedar slope 10,320 μg C/m$^2$/hr/°C, pocosin slope 8,183 μg C/m$^2$/hr/°C, maple-gum slope 6,693 μg C/m$^2$/hr/°C).

CH$_4$ flux shows a statistically significant relationship with soil moisture content in the top 5 cm of soil (P = 0.027), and a relationship with water depth (P = 0.090) which is statistically significant at a 90% confidence level. Average age of trees and average diameter of trees at breast height sampled at the sites do not show a significant relationship to CH$_4$ (P-values 0.209 and 0.279 respectively) or CO$_2$ (P-values 0.225 and 0.901 respectively) flux. The relationship between CH$_4$ flux and soil moisture is not linear. Second degree polynomial fit pocosin and maple-gum measurements better than Atlantic white cedar (pocosin R$^2$ = 0.1758, maple-gum R$^2$ = 0.1256, cedar R$^2$ = 0.0045). The differences between the forest types are less pronounced when possible statistical
outliers are removed, with outliers determined as values above the 3rd quartile value plus 1.5 x the middle quartile range, and less than the 1st quartile value minus 1.5 x the middle quartile range, in this case -83 to 120 µg CH₄-C/m²/hr.

Table 3. Basic statistics and distribution of measurements by site.

<table>
<thead>
<tr>
<th>site</th>
<th>Carbon dioxide net emissions (µg CO₂-C/m²/hr)</th>
<th>Methane net emissions (µg CH₄-C/m²/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>C1</td>
<td>8.3×10³</td>
<td>3.0×10⁵</td>
</tr>
<tr>
<td>C2</td>
<td>8.4×10³</td>
<td>2.8×10⁵</td>
</tr>
<tr>
<td>C3</td>
<td>1.1×10⁴</td>
<td>2.8×10⁵</td>
</tr>
<tr>
<td>M1</td>
<td>1.0×10⁴</td>
<td>5.7×10⁵</td>
</tr>
<tr>
<td>M2</td>
<td>7.0×10⁴</td>
<td>2.9×10⁵</td>
</tr>
<tr>
<td>M3</td>
<td>7.3×10⁴</td>
<td>1.9×10⁵</td>
</tr>
<tr>
<td>P1</td>
<td>7.8×10³</td>
<td>3.5×10⁵</td>
</tr>
<tr>
<td>P2</td>
<td>1.5×10⁴</td>
<td>3.1×10⁵</td>
</tr>
<tr>
<td>P3</td>
<td>1.2×10⁴</td>
<td>2.7×10⁵</td>
</tr>
</tbody>
</table>
Table 4. Results of regression analysis of relationships between variables. Values in bold are statistically significant at a 95% confidence level.

<table>
<thead>
<tr>
<th></th>
<th>CO&lt;sub&gt;2&lt;/sub&gt;</th>
<th></th>
<th>Soil moisture, litter layer</th>
<th>Soil moisture, 0-5 cm</th>
<th>Soil moisture, 5-10 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>P values</td>
<td>All sites</td>
<td>&lt;0.001</td>
<td>0.081</td>
<td>0.074</td>
<td>0.211</td>
</tr>
<tr>
<td>Air temp</td>
<td>Maple-gum</td>
<td>0.056</td>
<td>&lt;0.001</td>
<td>0.104</td>
<td>0.758</td>
</tr>
<tr>
<td>Soil temp</td>
<td>Pocosin</td>
<td>0.258</td>
<td>&lt;0.001</td>
<td>0.024</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>Cedar</td>
<td>&lt;0.001</td>
<td>0.001</td>
<td>0.065</td>
<td>0.211</td>
</tr>
<tr>
<td>Growing season (Apr.-Sept.)</td>
<td>0.011</td>
<td>&lt;0.001</td>
<td>0.143</td>
<td>0.466</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>Non growing season (Oct.-Mar.)</td>
<td>0.099</td>
<td>0.001</td>
<td>0.758</td>
<td>0.570</td>
</tr>
<tr>
<td>CH&lt;sub&gt;4&lt;/sub&gt;</td>
<td>All sites</td>
<td>0.518</td>
<td>0.266</td>
<td>0.388</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>Maple-gum</td>
<td>0.647</td>
<td>0.289</td>
<td>0.013</td>
<td>0.564</td>
</tr>
<tr>
<td></td>
<td>Pocosin</td>
<td>0.458</td>
<td>0.474</td>
<td>0.351</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>Cedar</td>
<td>0.576</td>
<td>0.542</td>
<td>0.579</td>
<td>0.574</td>
</tr>
<tr>
<td>Growing season (Apr.-Sept.)</td>
<td>0.060</td>
<td>0.848</td>
<td>0.678</td>
<td>0.011</td>
<td>0.755</td>
</tr>
<tr>
<td></td>
<td>Non growing season (Oct.-Mar.)</td>
<td>0.836</td>
<td>0.062</td>
<td><strong>0.012</strong></td>
<td><strong>0.048</strong></td>
</tr>
</tbody>
</table>

Soil moisture varied by time and by site during this study, including fully saturated or flooded soil at most of the sites at some point during the year. Precipitation accounted for some of the water depth and soil moisture variation, but not all (Fig. 6); the highest water depth measurements occurred after a high precipitation event, but some of the other higher water depth measurements appear to be unrelated to precipitation and may be due to water management. However, samples where water depth was measured have no SMC
measurements because it was not possible to measure soil moisture content under standing water.

Figure 6. Water depth at the study sites, precipitation record, and soil moisture content at the sites over time.
Soil moisture content (SMC) varies spatially more than temporally, although soil moisture and water depth were generally higher in winter. SMC is defined as (wet weight - dry weight) / dry weight.

Figure 7. a) Relationship between CO2 flux and soil moisture (0-5 cm). b) Relationship between CH4 flux and soil moisture (0-5 cm).
CO₂ flux decreased as soil moisture increased (Fig. 7). CH₄ flux increased with increasing soil moisture. Temperature varied by season during the duration of this study. CO₂ flux increased with increasing temperature, and CH₄ flux showed little relationship with temperature (Fig. 8). Over the year, CO₂ flux varies with temperature but CH₄ responded to soil moisture and water depth as well as temperature.

A.

\[
y = 5109.2x - 27229
\]

\[R^2 = 0.408\]

\[P = < 0.000\]
Statistical analysis showed that the three different forest communities studied have different rates of carbon gas flux. There is a 16% chance that cedar and maple-gum CO$_2$ flux measurements come from the same population, so an 84% chance that maple-gum and cedar have statistically different flux rates (Table 5). The statistics showed that there is a 27% chance that Atlantic white cedar and pocosin CO$_2$ flux measurements come from the same population, so a 73% chance that they are different populations. There is a 38% chance that maple-gum and pocosin CO$_2$ flux measurements come from the same population, so a 62% chance that they are different populations. For CH$_4$ flux, there is a 3% chance that Atlantic white cedar and maple-gum are from the same population, a 2% chance that Atlantic white cedar and pocosin are from the same population, and a 16% chance that pocosin and maple-gum are from the same population.
The differences between Atlantic white cedar and the other two forest types in terms of 
\( \text{CH}_4 \) flux were the only statistically significant values at a 95% confidence level, but all 
tests tended toward separation between the three populations in both measurements. 
Atlantic white cedar is the forest type with flux measurements most different from the 
other two, and maple-gum and pocosin are the populations with the most similar 
measurements. This shows that forest type has an effect on flux, in addition to the effects 
of moisture and temperature.

Table 5. Paired t-test for two sample means showing that the three populations are likely separate, with 
statistically significant results in bold.

<table>
<thead>
<tr>
<th>CO(_2)</th>
<th>Chance same pop.</th>
<th>T-stat</th>
<th>DF</th>
<th>P value</th>
<th>CH(_4)</th>
<th>Chance same pop.</th>
<th>T-stat</th>
<th>DF</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar and Maple-gum</td>
<td>16%</td>
<td>1.26</td>
<td>105</td>
<td>0.21</td>
<td>Cedar and Maple-gum</td>
<td>3%</td>
<td>-2.01</td>
<td>80</td>
<td>0.05</td>
</tr>
<tr>
<td>Maple-gum and Pocosin</td>
<td>38%</td>
<td>-0.90</td>
<td>112</td>
<td>0.37</td>
<td>Maple-gum and Pocosin</td>
<td>16%</td>
<td>-1.02</td>
<td>74</td>
<td>0.31</td>
</tr>
<tr>
<td>Cedar and Pocosin</td>
<td>27%</td>
<td>0.40</td>
<td>106</td>
<td>0.69</td>
<td>Cedar and Pocosin</td>
<td>2%</td>
<td>-2.02</td>
<td>57</td>
<td>0.05</td>
</tr>
</tbody>
</table>

The relationships between soil gas flux and soil temperature and soil moisture at 
each site are shown in Fig. 9.
9a) Cedar 1

9b) Cedar 2
9c) Cedar 3

9d) Maple 1
9e) Maple 2

9f) Maple 3
9g) Pocosin 1

9h) Pocosin 2
9i) Pocosin 3

Figure 9. Relationships between CO₂ and CH₄ and soil moisture and soil temperature for each site.
CHAPTER FIVE: MONITORING SURFACE SOIL MOISTURE AND GREENHOUSE GAS FLUX THROUGH SYNTHETIC APERTURE RADAR

Soil moisture summary

Remotely measuring surface soil moisture is important for monitoring climate change effects in large areas of remote ecosystems that cannot be effectively measured in situ. Radar remote sensing can penetrate clouds and biomass that prevent the use of other remote sensing techniques. This study uses a combination of ground measurements and satellite data to model the radar backscatter response to surface soil moisture (SSM), in the forested peat wetland of the Great Dismal Swamp (GDS). Ground measurements were taken at 9 sites and include: surface soil moisture content and litter moisture content on three dates, soil density, aboveground biomass density, and forest type. Satellite data was derived from Sentinel-1 C-band synthetic aperture radar (SAR). The major finding of this study is that it is feasible to retrieve surface soil moisture with SAR measurements despite the dense forest biomass causing the majority of variation in Sentinel-1 backscattering. Regression analysis results indicate that up to 38% of the variation in backscatter values is explained by average forest type biomass, average soil density, and surface litter moisture (R² = 0.375). Based on statistical analysis, we established an equation to estimate soil moisture with SAR backscattering measurements, average biomass and average soil density at the 9 sites, then generated a soil moisture map over the whole GDS. In the future, we expect that more ground samples, longer wavelength
SAR data, more detailed biomass data (potentially through LiDAR modeling), as well as a satellite-based vegetation moisture content product, would also likely improve the soil moisture retrieval model.

**Introduction to soil moisture**

Surface soil moisture monitoring and modeling from satellite observations is important for many environmental applications, especially when access to obtain extensive ground measurements is not feasible due to practical considerations. Surface soil moisture is an important variable in many ecosystems including agro-ecosystems, restored areas, and natural habitats such as peatlands. In this study, we investigate surface soil moisture in the Great Dismal Swamp (GDS), a forested peat wetland that has been timbered, drained and altered over the past three centuries, but still retains some fragmented original forest community types. Peatlands globally contain a large amount of stored organic carbon (Yu et al. 2010). Drying of peat soils through drainage eliminates anoxic conditions required for peat formation and maintenance, and also makes the soil more susceptible to fire, which can remove significant amounts of carbon as has happened in the GDS in the past (Reddy et al. 2017). In the GDS ecosystem, monitoring soil moisture is especially important for assessing fire risk, build up or loss of organic material in the peat soil, and conditions that help or hinder the regrowth of native plant species.

This study of soil moisture is part of a larger project to model carbon, land cover and ecosystem services in the GDS (Sleeter et al. 2017, Kim et al. 2017, Parthum et al. 2017, Drexler et al. 2017, and Pindilli et al. 2018). The purpose of this part of the study
is to determine if radar remote sensing can be used to monitor surface soil moisture in the GDS despite the high biomass that rules out other remote sensing techniques. This soil moisture data can then be used to model greenhouse gas emissions, fire risk, and other ecosystem services and research topics. This is significant because in situ measurements are difficult to obtain in the dense and remote terrain. It is much cheaper, faster and more replicable to monitor soil moisture conditions from space, if possible.

Although SAR has been used to model SSM under low to moderate biomass, and to model forest characteristics, this study found a significant relationship between backscatter and SSM under high biomass by using forest cover to account for varying levels of aboveground biomass. Factors shown to affect backscatter in this study are biomass, SSM, litter moisture, and soil density.

**Soil moisture materials and methods**

The active radar data used in this study is Sentinel-1 C-band synthetic aperture radar (SAR) with VV polarization at approximately 30-meter resolution, as it was readily available over the study location during the time period of the ground sampling. All the Sentinel data were provided by the European Space Agency (ESA)’s Copernicus Programme via Alaska Satellite Facility Distributed Active Archive Center’s Vertex and processed through high-performance computing utilizing Southern Methodist University’s supercomputer (ManeFrame II). Single Look Complex (SLC) of Sentinel-1 datasets are multi-looked and geocoded using both Shuttle Radar Topography Mission (SRTM) and LiDAR digital elevation models (DEMs). The ground data (see Table 7) used in this study includes soil moisture, soil density, and biomass. Soil density of the top
6 cm is taken from Drexler et al. (2017), in which core samples of peat were taken at each of the same sites used in this study. The sites were chosen to be representative of the forest types of interest, far enough from the roads to be beyond the obvious edge effects, and yet close enough to a road to allow several sites to be sampled per day. Three sites were chosen for each forest type, but not all samples could be used in this study due to seasonal flooding and satellite overpass timing. Biomass is taken from the study by Duberstein et al. (2016), in which aboveground biomass was calculated using in situ sampling of plant species, concentration, stem height and diameter at randomized locations in the GDS using a protocol adapted from the FIREMON: Fire Effects Monitoring and Inventory Protocol (www.frames.gov/firemon). Biomass at locations sampled that fit within the three idealized forest types used in this study were averaged to get an estimate of aboveground biomass for each forest type. The forest cover classes of focus in this study are AWC, pocosin, and maple-gum, which together cover most of the refuge.
Table 6. Data collection dates.

<table>
<thead>
<tr>
<th>Site name</th>
<th>SAR overpass date</th>
<th>Ground measurement date</th>
</tr>
</thead>
<tbody>
<tr>
<td>maple1</td>
<td>2/15/2017</td>
<td>2/17/2017</td>
</tr>
<tr>
<td>maple2</td>
<td>2/15/2017</td>
<td>2/17/2017</td>
</tr>
<tr>
<td>maple3</td>
<td>2/15/2017</td>
<td>2/18/2017</td>
</tr>
<tr>
<td>pocosin1</td>
<td>2/15/2017</td>
<td>2/18/2017</td>
</tr>
<tr>
<td>pocosin2</td>
<td>2/15/2017</td>
<td>2/18/2017</td>
</tr>
<tr>
<td>pocosin3</td>
<td>2/15/2017</td>
<td>2/17/2017</td>
</tr>
<tr>
<td>cedar1</td>
<td>4/28/2017</td>
<td>4/28/2017</td>
</tr>
<tr>
<td>cedar2</td>
<td>4/28/2017</td>
<td>4/28/2017</td>
</tr>
<tr>
<td>cedar3</td>
<td>4/28/2017</td>
<td>4/29/2017</td>
</tr>
<tr>
<td>maple1</td>
<td>4/28/2017</td>
<td>4/27/2017</td>
</tr>
<tr>
<td>maple2</td>
<td>4/28/2017</td>
<td>4/27/2017</td>
</tr>
<tr>
<td>maple3</td>
<td>4/28/2017</td>
<td>4/27/2017</td>
</tr>
<tr>
<td>pocosin1</td>
<td>4/28/2017</td>
<td>4/29/2017</td>
</tr>
<tr>
<td>pocosin2</td>
<td>4/28/2017</td>
<td>4/28/2017</td>
</tr>
<tr>
<td>pocosin3</td>
<td>4/28/2017</td>
<td>4/28/2017</td>
</tr>
<tr>
<td>maple3</td>
<td>6/15/2017</td>
<td>6/15/2017</td>
</tr>
<tr>
<td>pocosin2</td>
<td>6/15/2017</td>
<td>6/15/2017</td>
</tr>
</tbody>
</table>
Figure 10. SAR backscattering map over GDS on February 15, 2017 with sampling sites.
The AWC and pocosin forest types are native forest communities that are adapted to the fire and hydrological conditions of the swamp, while the maple-gum forest type has increased in extent due to the logging of the more desirable timber species (e.g., AWC) and changing hydrological and environmental conditions. Since no pure stands of AWC were sampled for biomass, a literature-derived biomass value for a similar environment is used (Dable and Day 1977). The 2016 study mentioned above (Duberstein et al. 2016) and the 1977 study produced similar biomass values for maple-gum and cypress, although the 1977 paper did not measure pocosin and the 2016 study did not include AWC. Dable and Day (1977) found 195,000 kg/ha for maple-gum, 345,500 kg/ha for cypress, and 220,500 kg/ha for AWC, and the calculations by Duberstein et al. (2016) gave 184,700 kg/ha for maple-gum, 389,200 for cypress, and 225,400 for pocosin. When available, the most recent data are used in this study. Therefore, this study uses the 2016 study for the pocosin and maple-gum classes. The AWC biomass estimate from the 1977 study is used here as there was none in 2016 study.

In situ soil moisture samples were collected at each site, including a 5 cm² sample of the litter layer (depth varied based on location and time of year) and two 5 cm³ samples of the soil, from 0-5 cm deep (Table 2). Gravimetric soil moisture of each sample was measured using standard procedures of weighing and drying each sample separately at 60°C until constant mass was observed. Surface soil moisture (0-5 cm) and root zone soil moisture are important for ecological functions, but the leaf litter layer covering the ground in the GDS and other forests is the first layer to interact with active
microwave remote sensing. Therefore, we sampled this litter layer separately instead of removing it to sample the soil only. In situ measurements were timed to coincide with Sentinel-1 overpass dates and times as closely as possible (Table 1).

Linear regression was used to determine which independent variables significantly contribute to the variation in radar backscatter (Table 6).

Linear regression was used to determine which independent variables significantly contribute to the variation in radar backscatter (Table 8). The independent variables include soil density, biomass, surface soil moisture (0-5 cm), and litter moisture.

Table 7. Site data from the three dates closest to satellite overpass. Soil moisture content (SMC) is (wet weight - dry weight) / dry weight.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Average backscatter coefficient</th>
<th>SMC, 0-5 cm</th>
<th>SMC, litter</th>
<th>Biomass (kg/m²)</th>
<th>Soil density (g/cm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>maple1 (February)</td>
<td>-7.290</td>
<td>2.75</td>
<td>1.24</td>
<td>18.47</td>
<td>0.15</td>
</tr>
<tr>
<td>maple2 (February)</td>
<td>-7.585</td>
<td>3.11</td>
<td>0.72</td>
<td>18.47</td>
<td>0.11</td>
</tr>
<tr>
<td>maple3 (February)</td>
<td>-6.836</td>
<td>4.18</td>
<td>0.81</td>
<td>18.47</td>
<td>0.12</td>
</tr>
<tr>
<td>pocosin2 (February)</td>
<td>-10.904</td>
<td>2.71</td>
<td>0.20</td>
<td>22.54</td>
<td>0.11</td>
</tr>
<tr>
<td>pocosin3 (February)</td>
<td>-10.758</td>
<td>3.11</td>
<td>0.86</td>
<td>22.54</td>
<td>0.12</td>
</tr>
<tr>
<td>cedar1 (April)</td>
<td>-9.224</td>
<td>2.12</td>
<td>1.55</td>
<td>22.05</td>
<td>0.15</td>
</tr>
<tr>
<td>cedar2 (April)</td>
<td>-9.993</td>
<td>2.38</td>
<td>1.14</td>
<td>22.05</td>
<td>0.09</td>
</tr>
<tr>
<td>cedar3 (April)</td>
<td>-9.664</td>
<td>3.84</td>
<td>1.54</td>
<td>22.05</td>
<td>0.07</td>
</tr>
<tr>
<td>maple1 (April)</td>
<td>-6.362</td>
<td>2.80</td>
<td>1.25</td>
<td>18.47</td>
<td>0.15</td>
</tr>
<tr>
<td>maple2 (April)</td>
<td>-9.219</td>
<td>3.31</td>
<td>2.95</td>
<td>18.47</td>
<td>0.11</td>
</tr>
<tr>
<td>pocosin2 (April)</td>
<td>-10.349</td>
<td>2.98</td>
<td>2.08</td>
<td>22.54</td>
<td>0.11</td>
</tr>
<tr>
<td>pocosin3 (April)</td>
<td>-7.888</td>
<td>3.06</td>
<td>1.50</td>
<td>22.54</td>
<td>0.12</td>
</tr>
<tr>
<td>maple3 (June)</td>
<td>-9.546</td>
<td>12.62</td>
<td>9.82</td>
<td>18.47</td>
<td>0.12</td>
</tr>
<tr>
<td>pocosin2 (June)</td>
<td>-8.533</td>
<td>1.67</td>
<td>0.37</td>
<td>22.54</td>
<td>0.11</td>
</tr>
</tbody>
</table>
**Table 8. Linear regression results for each combination of variables with 14 observations each time.**

<table>
<thead>
<tr>
<th>Variables</th>
<th>R squared value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>For soil moisture:</strong></td>
<td></td>
</tr>
<tr>
<td>Radar</td>
<td>0.008</td>
</tr>
<tr>
<td>Biomass</td>
<td>0.157</td>
</tr>
<tr>
<td>Soil density</td>
<td>0.001</td>
</tr>
<tr>
<td>Radar, soil density</td>
<td>0.008</td>
</tr>
<tr>
<td>Radar, biomass</td>
<td>0.364</td>
</tr>
<tr>
<td>Soil density, biomass</td>
<td>0.194</td>
</tr>
<tr>
<td>Radar, soil density, biomass</td>
<td>0.365</td>
</tr>
<tr>
<td><strong>For litter moisture:</strong></td>
<td></td>
</tr>
<tr>
<td>Radar</td>
<td>0.021</td>
</tr>
<tr>
<td>Biomass</td>
<td>0.127</td>
</tr>
<tr>
<td>Soil density</td>
<td>0.001</td>
</tr>
<tr>
<td>Radar, soil density</td>
<td>0.034</td>
</tr>
<tr>
<td>Radar, biomass</td>
<td>0.370</td>
</tr>
<tr>
<td>Soil density, biomass</td>
<td>0.139</td>
</tr>
<tr>
<td>Radar, soil density, biomass</td>
<td>0.375</td>
</tr>
</tbody>
</table>
Among other variables, SAR backscatter depends on and soil and/or litter moistures (Fig. 11), biomass and soil density. In the GDS, these parameters vary by forest type and were measured at each site. With the available measurements for radar, soil moisture, soil density and aboveground biomass, a linear regression model is built as:

$$SM = 16.452 - 1.052*R - 1.046*B - 4.564*D$$  \hspace{1cm} (1)$$

where SM is soil moisture, R is backscatter, B is above-ground biomass (AGB), and D is soil density. The $R^2$ value for this relationship is $R^2 = 0.365$. Depending on application, the relationship for litter moisture could also be modeled using the following equation, with $R^2 = 0.375$:

$$LM = 9.98 - 1.109*R - 0.917*B + 8.777*D$$  \hspace{1cm} (2)$$

Surface soil moisture and litter moisture content are related since the two layers are in proximity. If litter moisture is added as an independent variable in the soil moisture
regression, $R^2 = 0.909$; if soil moisture is added as an independent variable in the litter moisture regression, $R^2 = 0.910$. Although the two variables are related, the relationship is not always positive or negative. If the area experienced rain and then a day of dry conditions, the soil would be wetter than the litter. If the area had been dry for a few days and a small amount of rain fell, the litter would be moist but the precipitation may not penetrate much into the soil surface. On a coarser scale, the two layers’ moisture content will vary together.
Figure 12. Surface soil moisture on February 15, 2017 based on equation 1. Clipped at 0 and 8.21, showing the histogram in red of values before clipping.
As expected, due to the spatial biophysical interactions of radiation and ground conditions, biomass characteristics have a strong effect on backscatter intensity, as do surface properties including soil and litter moisture. SAR interacts with the aboveground biomass before reaching the soil and then again as the return signal; the vegetation in the GDS is very dense, forming one or more leaf canopies and preventing much radar radiation from directly reaching the soil surface and returning to the sensor, as biomass intercepts and attenuates radar radiation. However, given the wavelength of C-band SAR, some radiation penetrates the canopy and interacts with the soil surface, responding to the texture and dielectric constant of the soil. Among the iterations, all of the measured variables together account for the highest percentage (38%) of variation in radar backscatter. See Figure 13 for expected vs observed values.
Figure 13. Scatter plot of predicted vs observed SM and LM values.
CHAPTER SIX: TECHNICAL DISCUSSION

Forest classification discussion

The information gathered from this process will help inform refuge management as to the current state of the forest as well as allow them to repeat this classification in the future to monitor the effects of management, climate change, and other potential impacts. As the USFWS manage for their different priorities, including plant and wildlife communities and fire risk, they may choose to increase water levels within the refuge while balancing other concerns such as flooding downstream, recreation and accessibility, endangered species etc. The effects of this water management using water control structures may impact the hydrology and soil of the refuge, which may impact forest communities over the long term. Changes in forest class may be monitored using the techniques described in this paper. The techniques may also be useful for monitoring health and other characteristics.

It is unexpected that combining multispectral bands with SAR has a worse classification accuracy than either dataset alone. This may be due to the way ArcMap treats pixels of different sizes which are not aligned. In addition, since the maximum likelihood classification tool uses averages and covariances across all the signature bands, it seems to dilute the accurate predictive power of the process. This could be improved by adding a workflow to the classification algorithm where whatever combination of bands
has the best accuracy for a given class is used to make a mask of each class. For example, water was accurately classified by SAR, so the SAR-water result could be applied as a mask before running the next classification. The forest classification process could also be improved by adding more ground data samples, potentially in different types of forest cover to increase the number of classes. If different forest classes show strong differences in temporal spectral reflectance, adding a second multispectral image from a different season may improve the classification result. Further statistical analysis and techniques may also be able to improve the accuracy of this classification. The large margins of error seen in these classifications may be due in part to deficiencies in the site selection and allocation of calibration and validation pixels. At the time of study design, it was not possible to ensure a wide range of conditions were sampled for each forest class due to lack of information and for time and budgetary reasons. It would have been ideal to sample several wet and several dry sites for each forest class, but this proved impractical to arrange. Radar in particular responds to standing water or differences in soil moisture, so classification would probably be improved if both biomass structure and soil moisture regimes were being classified. Unfortunately, soil moisture was not measured for all of the sampling sites.

It is clear visually that using multispectral data from multiple images has negatively affected the classification. Although these images come from approximately the same time, it would be ideal to use a single image covering the entire area so that angle of observation and atmospheric conditions would be consistent across the image. Obtaining coverage of the entire refuge in one image would be preferable. In this study,
all six images were required to include all of the training and validation samples. Any one of the images would not have had enough known ground sites to create training and validation data.

**Forest classification conclusions**

The classification using multispectral WorldView2 data combined with NDVI data provided the best result. This suggests that NDVI varies biophysically between the forest classes of interest. Since this result is better than multispectral combined with SAR, NDVI is a better distinguishing variable than aboveground biomass as measured by SAR, although other factors such as soil moisture, soil density and soil texture also impact SAR backscatter intensity. Accounting for these other factors by measuring soil moisture and texture and removing that effect could improve the multispectral and SAR classification combination. Combining more variables into the classification could also potentially improve the result, for example measuring leaf area index in addition to or instead of using NDVI, or refining the SAR parameter by using different wavelengths and polarizations, as well as adding ancillary data such as inundation, soil properties, etc.

The result of 78% accuracy is promising for mapping forest type. Smoothing the edges of clusters may also improve the map’s utility and/or accuracy. Adding mixed classes or further differentiating classes with different biophysical properties that can be remotely sensed could also improve the mapping capability.

This study shows that NDVI is useful in distinguishing forest classes in the GDS and provides a forest classification map that has many applications. For example, the
following chapters use this forest classification result to map surface soil moisture and greenhouse gas flux over the refuge.

**Greenhouse gas flux discussion**

**Drivers of flux**

Drivers behind soil respiration and carbon gas flux in other studies include groundwater or surface water level and source, vegetation type, water-filled pore space, restoration status, temperature and pH. In this study, soil moisture and temperature were the main drivers for CH$_4$ flux and CO$_2$ flux respectively, with some influence from forest type (Table 5). Pore-filled water space, depth to groundwater, and soil moisture are related variables. However, in this study, soil moisture from 0-5 cm deep was more highly correlated to CH$_4$ flux than soil moisture 5-10 cm deep, indicating the relationship to depth to ground water may be a measure of field capacity or water retention of the soil and time since last rewetting. CO$_2$ flux decreasing as soil moisture increases is expected and may be related to the biogeochemical chain of electron acceptors as oxygen is depleted in flooded conditions. This may also be related to reduced metabolic activity and increased soil moisture in the colder months. Refuge management activity affects water level in the ditches and therefore depth of the water table, especially closer to the roads and ditches. Of the sites sampled in this study, two were flooded frequently, the northernmost pocosin site and the northernmost maple-gum site. The Atlantic white cedar and pocosin sites that are closest to the highest concentration of ditches were least often flooded.
Many studies have quantified carbon flux in forest, peat and wetland soils. Different variables affect carbon flux in different ecosystems. In subalpine forests of the Rocky Mountains in the US, leaf area index, soil nitrogen and tree height were found to account for much of the variability in positive total belowground carbon flux (Berryman et al., 2016). In a drained forested peatland in Finland, GHG flux (carbon uptake) was found to depend on season (irradiance and temperature), vapor pressure deficit and water table, but did not correlate with plant community composition or soil micro topography (Lohila et al., 2011). In the wet-dry topics of Australia, GHG soil flux was found to be controlled by soil moisture (Beringer et al., 2013). On a floodplain in the mid-Atlantic region of the US, carbon flux was found to depend on water filled pore space and mass of deposited mineral sediment, clay fraction and particle size, temperature, pH and soil redox (Batson et al., 2014). In open water and emergent vegetation, ebullition and diffusion of CH4 and CO2 flux were found to depend on season and wetland structure (McNicol et al., 2017). Different forests and wetlands can also act as a source or a sink. Snow-covered northern wetlands in China were found to act as a source or sink at different times of the year, depending on snow pack density, temperature, and type of wetland (Miao et al., 2012).

Other studies of soil respiration in forests and wetlands have reported a wide range of values. For CO2 flux, high values were seen in a Canadian peatland, with very high values when the water table was 70 cm below the surface (239,805.00 to 341,540.45 g C-CO2/m²/yr), and still fairly high when the water table was 10 cm above the surface (10,900 to 18,167 g C-CO2/m²/yr) (Moore and Knowles, 1989). Moderate levels of CO2
flux were seen in North Carolina peatlands and pocosins, with short pocosin ranging from 438 to 1,314 g C/m²/yr, tall pocosin (which is closer to the pocosin in the Great Dismal Swamp) ranging from 788 to 1,095 g C/m²/yr, and maple-gum ranging from 657 to 2,190 g C/m²/yr (Bridgham and Richardson, 1992). Peak soil respiration in the subalpine Rocky Mountains was also moderately high at 1,654 g C/m²/yr (Berryman et al., 2016). A floodplain in Virginia saw similar levels of soil respiration, with 1,091 g C-CO₂/m²/yr (Batson et al., 2014). Chambers in the water of a restored wetland in California also showed similar levels of 915 g C-CO₂/m²/yr (McNichol et al., 2017). Low levels of CO₂ soil flux were seen in peatlands during snow cover in the winter in China, with 3 to 12 g C-CO₂/m²/yr in the peat and 20 g C-CO₂/m²/yr in a marsh (Miao et al., 2012). A natural site in Pocosin Lakes National Wildlife Refuge measured only 14 g C-CO₂/m²/yr (Wang et al., 2015). A tropical peatland that had been burned, losing 0.7 meters of soil, showed 382 g C/m²/yr in 2004-2005 and 362 g C/m²/yr in 2005-2006 (Hirano et al., 2014).

Peatland in Australia and forestry drained peatland in Finland showed net uptake of CO₂, -308 g C-CO₂/m²/yr (Beringer et al., 2013) and -237 g C-CO₂/m²/yr (Lohila et al., 2011) respectively.

For CH₄, Great Dismal Swamp measurements in the maple-gum forest type from 1982 showed high flux rates of 130 g C-CH₄/m²/yr to 1,968 g C-CH₄/m²/yr (Harriss and Sebacher, 1982). The high CH₄ values may be due to ebullition from pockets in the soil air space or below the water table or water surface in the case of flooded conditions. Other measurements are relatively low; 2.9 g C-CH₄/m²/yr in restored California wetland water chambers (McNichol et al., 2017), 0.01 to 0.04 g C-CH₄/m²/yr in snow covered
peatlands in China (Miao et al., 2012), 7.67 g C-CH₄/m²/yr in an inundated fen in Canada, and 0.19 g C-CH₄/m²/yr in an inundated bog in Canada (Moore and Knowles, 1989).

These measurements were either reported in, or were converted to, grams of carbon, per square meter, per year (g C/m²/yr-1). Measurements were converted based on units only, from hours or days to years. CH₄ flux in the Great Dismal Swamp in this study was 0.05 g C/m²/yr for the cedar forest type, 1.29 g C/m²/yr for maple-gum, and 3.81 g C/m²/yr for pocosin. This is lower than the 1982 CH₄ measurements above, which were taken over a 17-month period in maple-gum forest cover, but more in line with the low to moderate results in other study areas. CO₂ flux in the Great Dismal Swamp in this study was 740 g C/m²/yr for cedar, 684 g C/m²/yr for maple-gum, and 711 g C/m²/yr for pocosin, or 7,397 kg C/ha/yr for cedar, 6,844 kg C/ha/yr for maple-gum, and 7,113 kg C/ha/yr for pocosin. The individual sites ranged from the lowest CO₂ fluxes in the wettest, most frequently inundated sites (low of 575 g C/m²/yr at the wettest maple-gum site), to the highest in the dryer sites (817 g C/m²/yr at a dry pocosin site). These CO₂ flux measurements are within the ranges reported in the studies above.

The forest cover of the Great Dismal Swamp is 61% maple-gum, 15% pocosin, 12% cypress-gum, 3% Atlantic white cedar and 9% other with a total study area of 54,000 ha (Fleming et al., 2001). Using these figures as a guideline, the total area of Atlantic white cedar in the study area (1,620 ha) has an average yearly flux of 0.75 metric tons carbon from CH₄ and 11,983 metric tons of carbon from CO₂. The total area of maple-gum in the study area (32,940 ha) has an average yearly flux of 425 metric tons of
carbon from CH₄ and 225,457 metric tons of carbon from CO₂. The total area of pocosin
in the study area (8,100 ha) has an average yearly flux of 309 metric tons of carbon from
CH₄ and 57,617 metric tons of carbon from CO₂. The total yearly carbon loss (not
including uptake due to plant productivity and carbon burial) from the study area made
up of these three forest types (54,000 ha minus the 21% that is cypress-gum or other is
42,660 ha) would then be 295,792 metric tons of carbon per year, from soil flux alone.

**Increased sampling efficiencies**

In an attempt to minimize error due to sampling, the techniques were designed to
minimize researcher impact on the system. This included reducing impact on the chamber
area by keeping the bases in place over the duration of the study and not stepping on the
ground near the chambers unless unavoidable (for example, in the case of disturbance by
wildlife which required replacing the chamber bottom, after which that chamber would
not be sampled until the next month). The sites were left as natural as possible, with no
removal of vegetation except that which made it impossible to place a chamber top with
an air tight seal. The 12-foot long tubes connecting the chambers to the analyzer made it
possible to keep field equipment away from the chambers. Despite these precautions, it
is possible that motion above the ground could have caused some ebullition of CH₄ from
below ground during sampling. For example, bubbles rising through the standing water
were often visible when approaching flooded sites. However, these small bubbles seemed
to be restricted to the paths used for walking and were not seen in the chamber areas.

Hutchinson and Livingston (2001) provide several recommendations for reducing
error during chamber sampling. They recommend an air tight chamber base, in our case
achieved using the water trough seal. They also recommend sufficient chamber base installation depth, based on soil porosity and sampling time; our chamber bottoms, about 12.7 cm deep, were installed as fully as possible given small terrain differences to about 12 cm deep. This also helped to reduce the attention of bears. This is easily sufficient according to that study’s calculations, given a short sampling time of 10 minutes, even at the highest calculated porosity (requiring at least 8.6 cm depth). Their recommendation that all chambers include a vent near ground level aims to reduce error due to sudden changes in pressure during sampling - for example, when the chamber top is placed and when gas is extracted as a sample. However, since we used continuous sampling, there were no disturbances to pressure leading to the disturbances that they observed in their study. Also, the short sampling time and reflective white chamber tops eliminate risk of pressure change due to increasing temperature inside the chamber as compared with the outside temperature. Additionally, our continuous sampling allows us to see if any large disturbances occur in real time. Some small deviation from the overall linear trends at the very beginning of sampling may indeed be due to the pressure change of placing the chamber top. However, these are usually very small, perhaps due to the controlled and gradual lowering of the chamber top edge by edge, which was possible due to the bench and stool set up providing access to the chamber.

Although studying N\textsubscript{2}O soil emissions in agricultural land, Smith and Dobbie (2001) found mostly statistically insignificant differences between sampling several days apart interpolating, and sampling every 8 hours, as well as between samplings at different times of the day. Also studying N\textsubscript{2}O, Rochette and Eriksen-Hamel (2008) found that
many methods were sufficient for treatment comparison, but insufficient for comparison with other studies at other sites due to the limitations of their physical techniques. However, our study avoids many of these common pitfalls; although our chambers are unvented and uninsulated, our deployment duration was only 10 minutes. In addition, we had sufficient insertion depth, chamber height greater than 10 cm, no sample handling or storage, no use of plastic syringes, and no delay between sampling and analysis. We did not, however, use quality control gas standards (Rochette and Eriksen-Hamel, 2008).

**Implications of the study**

Since soil moisture is responsive in part to manageable conditions, there is the possibility of management activities influencing future carbon gas flux. Prior to the 1970’s, when the Great Dismal Swamp National Wildlife Refuge was established, land use decisions (i.e. ditch construction and forestry) led to drier soil conditions and ecosystem vulnerability, which, given these findings, could have not only reduced CH$_4$ flux, but also changed the characteristics of the soil and plant communities in addition to the changes caused directly by harvesting select species of timber. For example, fire susceptibility in terms of ignition success, burn depth and total combustion depends on factors including soil moisture, bulk density, organic matter component and species composition (Benscoter et al., 2011). In the Great Dismal Swamp, wetter areas with higher mean water levels were found to have thicker peat and higher species richness than drier areas, and while conditions in wetter areas did not meet fire risk conditions, drier areas were found to be always at risk of burning (Schulte, 2017). CH$_4$ flux, however, is a small fraction of net carbon flux. Future rewetting of the swamp may
change plant communities once again, favoring wetland species that are tolerant of frequent flooding, overall moister conditions, and anoxic root zones. This may lead to increased CH₄ flux and decreased CO₂ flux. Rewetting may also cool the soil through evapotranspiration, further reducing CO₂ flux and possibly mitigating some temperature increase due to changing global temperatures.

The limitations of this project suggest opportunities for future study such as sampling over greater temporal resolution or sampling over the length of a 24-hour period to determine the effect of sunlight hours to see whether the same patterns persist. Such measurement disparity can be seen when eddy covariance measurements occurring over 24-hour periods are compared with chamber methods; CH₄ flux were 2-4 times higher from chambers (Krauss et al., 2016). Sampling differences from one day to the next with minimal changes in temperature or moisture would also be informative, since sampling each chamber only once a month means we do not have a full seasonal picture either. Sampling before, during and after a weather event would also be useful and could show the effect of rising groundwater on flux as air is replaced with water in soil air pockets.

**Greenhouse gas flux conclusions**

CH₄ flux increased as temperature increased for pocosin, but decreased with temperature for cedar and maple. All of the CH₄ fluxes increased as soil moisture increased. On average, as soil moisture increased by 1 unit of soil moisture content, CH₄ flux increased by 457 μg C-CH₄/m²/hr (Fig. 7). On average, as temperature increased by 1°C, CO₂ flux increased by 5,109 μg C-CO₂ m²/hr (Fig.8). Cedar average CH₄ flux was
significantly different from both maple and pocosin. These results show that soil carbon
gas flux depends on soil moisture, temperature and forest type, all as affected by
anthropogenic activities in these peatlands.

Overall, CO₂ flux occurred at much higher concentrations than CH₄ flux in the
Great Dismal Swamp. CH₄ uptake sometimes outpaced production, but the soil was
usually a net source, while CO₂ flux always showed a net source. Different forest types
showed somewhat different trends. CO₂ was primarily associated with soil temperature,
and CH₄ flux was primarily associated with soil moisture in the top 5 cm (surface soil
moisture).

This study shows the relationship between surface soil moisture and temperature
and gas flux. More variables could be studied to determine their relationship with soil
carbon gas flux. The forests in the Great Dismal Swamp have been managed for
centuries, which has very likely influenced current conditions including hydrology and
soil conditions, since the peat soil is composed of organic matter accumulated over
thousands of years. Topography, water flow, and soil nutrients would also play a role.
While this study looked at sites situated in representative examples of three different
forest types, more replication of these sites in different conditions could provide more
information on gas flux in different hydrologic regimes, disturbed conditions, growth
stages and tree maturities, and combinations of these factors.

Soil moisture discussion

Given that this study has a relatively small sample size, that samples could not
logistically all be taken at the same moment of SAR collection, and that radar is prone to
speckling noise, accounting for 38% of variation in soil moisture under a dense canopy is a promising start. This study uses the average amount of aboveground biomass by forest type to estimate the impact of biomass on SAR backscatter, but other measures could also be used to improve this parameter. For example, the physical structure of the forest types differs in addition to the amount of biomass. Pocosin and AWC forest types have a tall, open canopy of conifers and a dense layer of shrubs 1-2 meters tall below, with the pocosin shrub layer particularly dense. The maple-gum forest type has a closed broad leaf canopy, smaller understory trees, and no dense shrub layer. Radar polarization or another data source such as LiDAR coverage could potentially be added as a measure of biomass structure by forest type. This study uses VV polarized SAR, as studies have found VV is subject to less canopy noise, although HH and HV polarized could also be potentially useful (Li and Wang, 2018).

While biomass intercepts a lot of the radiation, there is a clear soil surface interaction as well, both in terms of soil texture and soil moisture. As with biomass, soil texture measures could be improved in future studies, although there is no compounding linear effect as there is in row-planted agricultural settings (Brisco et al. 1991). For the soil density used in this study, there was some compression during sampling where voids in the soil strata were collapsed when the core severed the fine root structure holding the peat together; some core lengths were shorter than the depths that they measured (Drexler et al. 2017). More core samples may be helpful for obtaining more accurate soil characteristics. However, the void issue is probably negligible within the top 10 cm of the
core as the voids tend to occur below the surface root mat which is usually deeper than 10 cm.

Mapping and monitoring soil moisture (see Figure 4) has many possible applications. In the context of this larger research effort, this relationship (see equation 1) can be used to estimate SSM and carbon flux across the GDS if SAR data is available, as well as to study other issues impacted by SSM such as fire risk, vegetation health, habitat, etc. Soil moisture mapped across the refuge could be used by land managers to monitor rewetting program success, change over time due to management, as well as global climate change impacts, including before, during and after management activities and weather events.

This study shows that SAR can be combined with ground measurements even in high biomass forested areas to provide all-weather monitoring of surface soil moisture independent of day time satellite coverage, penetrating through clouds and leaf canopies. This is of particular importance in tropical forests which are often remote, often cloud covered, and have dense forest cover with high leaf area indices.

**Remote sensing of greenhouse gas flux**

Given the results of the previous analyses, it is possible to begin to estimate soil carbon gas flux across the GDS. Calculating GHG flux requires forest type, surface soil moisture and temperature. Forest type can be found using multispectral satellite imagery and supervised classification using signature extraction from calibration sites. The forest classification result along with surface soil moisture estimates by pixel and air
temperature records can then be used to calculate carbon dioxide and methane flux using relationships from a previous study (Gutenberg et al. 2019).

To map soil carbon gas flux, constants based on the average for each forest type were used for soil density and aboveground biomass (Gutenberg and Sleeter, 2018). For biomass, these values are 184,700 kg/ha for maple-gum, 220,500 kg/ha for AWC, and 225,400 kg/ha for pocosin. For soil density, these values are 0.124 g/cm³ for maple-gum, 0.105 g/cm³ for AWC, and 0.115 g/cm³ for pocosin. These were used to calculate surface soil moisture content for February 15, 2017, the date of the SAR data. Negative values indicate the soil acting as a carbon sink, and positive values indicate a carbon source. Multiple linear regression of any samples that had both a soil moisture and temperature measurement provided the equations used to model CH4 and CO2 flux. Forest class was included in the regression but was not a significant factor, so temperature and moisture are the only variables needed in the equations. The temperature of 9°C is based on the average daily temperature for 2/15/17 measured at Norfolk International Airport (www.wunderground.com accessed on 8 August 2019), and used to calculate CO2 and CH4 flux for that day given the regression equations:

\[
\text{CO}_2 \text{ flux} = 745.56 + 4689^\circ \text{T} - 4470^\circ \text{SM} \\
\text{CH}_4 \text{ flux} = -1358 + 36.35^\circ \text{T} + 248.22^\circ \text{SM}
\]

where T is air temperature in degrees Celsius (9°C) and SM is soil moisture content.
The resulting maps (see Figure 14) show wide variation in surface gas flux, including negative values that indicate a carbon sink, with clear artifacts from the image classification process (vertical striping effects show where the supervised classification was affected by combining two overlapping image swaths). Especially for CO2, these numbers range much lower than expected, indicating the map is not a good representation of actual CO2 flux. Within the eastern portion of the refuge without the classification artefacts, the model is likely more accurate and consistent.

Although forest class did not significantly impact the overall gas flux regression analysis, multiple regression (Table 9) shows that the different forest classes do show differences in gas flux. Air temperature was statistically significant (at p=.05 or lower).
for CO2 flux in all forest types but for CH4 in pocosin only, and soil moisture was
significant for both CH4 and CO2 in pocosin, only for CH4 in maple-gum, and only for
CO2 in AWC. The relationships split out by forest type are as follows, where SM is soil
moisture and T is temperature in °C:
Maple CH4 = -1154.3 + 430.3 SM
Maple CO2 = 18654.8 – 5099.5 SM + 3848.5 T
Cedar CH4 = 27.6 + 17.6 SM + 0.24 T
Cedar CO2 = -11241.9 SM + 6094.1 T
Pocosin CH4 = -5222.6 + 860.4 SM + 115.7 T
Pocosin CO2 = -19279.5 – 7211.1 SM + 5741.2 T
Table 9 shows the assessment values for the relationships among different forest
types of methane/carbon dioxide (dependent variables) and soil moisture and air
temperature (independent variables) which together represent seasonal variation.
Table 9. Multiple regression results for maple forest (A), cedar forests (B) and pocosin forest (C).

<table>
<thead>
<tr>
<th>Forest Type</th>
<th>Methane (CH₄)</th>
<th>Carbon Dioxide (CO₂)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Maple forest</td>
<td>CH₄: R-squared = 0.124; F(1,207)=29.396, p=0.000</td>
<td>CO₂: R-squared = 0.272; F(1,207)=77.438, p=0.000</td>
</tr>
<tr>
<td>B. Cedar forests</td>
<td>CH₄: R-squared = 0.001; F(2,209)=0.097, p=.91</td>
<td>CO₂: R-squared = 0.646; F(2,209)=190.907, p=0.000</td>
</tr>
<tr>
<td>C. Pocosin forests</td>
<td>CH₄: R-squared = 0.137; F(2,180)=14.234, p=0.000</td>
<td>CO₂: R-squared = 0.533; F(2,180)=102.709, p=0.000</td>
</tr>
</tbody>
</table>

These relationships may be biased due to the sampling locations chosen, as they did not represent a normally distributed range of hydrologic or soil moisture regimes. Therefore, the slightly drier cedar sites may not have included wet enough conditions to gather a full range of methane flux. However, it is also possible that different microbial communities, differences in organic matter or in historical disturbance could cause soil moisture to be unrelated to methane flux in the cedar sites.

In addition to management and research applications, the accuracy of this model could be improved in the future by increasing the level of detail of the independent variables by increasing the number of samples taken. More sample dates, more sample locations, and concurrent sampling of biomass and soil characteristics including moisture would likely improve the relationships. The ground data in this study was limited logistically; samples taken at the exact time of satellite overpass would remove any error.
due to the time difference. Samples spread randomly through the GDS rather than located along roads may also reduce bias, but would greatly limit the number of samples that could be collected in the same amount of time. Including more detailed soil and vegetation variables could also improve the accuracy of the model, for example litter texture, roughness and depth and vegetation moisture content. Data processing techniques such as smoothing and de-speckling may also help adjust for the natural speckling variation in radar backscatter values. Trials in other types of forest, peatlands and wetlands could also strengthen the wider applicability of this model in other areas.

**Soil moisture conclusions**

We found surface moisture does contribute to radar backscatter in the GDS. Accounting for biomass and soil density improved the calibration of the SAR to soil moisture relationship. Based on the results of this study, we conclude:

- forest biomass does not totally prevent remote sensing of surface soil moisture;
- leaf litter or other surface detritus is important for backscatter response and should be considered when sampling for surface moisture;
- Remote sensing of soil carbon gas is one important application of surface soil moisture and mapping of surface soil moisture is essential for mapping of soil carbon gas flux.

This study found that in the GDS, biomass impacted SAR backscatter intensity but that surface soil or litter layer moisture was also a measurable component of backscatter response. Even using categorical data based on three different forest types of
Atlantic white cedar, tall pocosin, and maple-gum, soil density and surface soil moisture were detectable through the multiple canopies and relatively high biomass of the Great Dismal Swamp National Wildlife Refuge. This data supports further study of related variables and processes such as carbon flux and management activities involving habitat and fire risk.
CHAPTER 7: CONCLUSIONS

Ecosystem carbon flux is important globally when studying the causes and effects of global climate change, as well as planning for management of these ecosystems. In the GDS, soil carbon gas flux monitoring has shown that CO$_2$ and CH$_4$ emissions depend on soil moisture and temperature, and vary by forest type. These relationships calculated from ground data can be used to map soil carbon gas flux using satellite remote sensing data. This study shows it is possible to make forest type, soil moisture and CO$_2$ and CH$_4$ flux using freely available multispectral reflectance and synthetic aperture radar backscatter.

To summarize, carbon dioxide flux is directly proportional to temperature and methane flux increases with increasing surface soil moisture. Amount of carbon lost over time varies by forest type. WorldView multispectral imagery combined with NDVI can be used to map forest type with relatively good accuracy. C-band SAR backscatter can be used to map surface soil moisture despite the high levels of biomass in the GDS. The resulting data can be used to look at ecosystem response to changing climate, to predict future conditions, including fire risk, given various management activities, and to demonstrate the WorldView multispectral imagery combined with NDVI can be used to map forest type with relatively good accuracy. C-band SAR backscatter can be used to
map surface soil moisture despite the high levels of biomass in the GDS. s technique for similar environments elsewhere in the region and across the world.

This study finds a 79% accurate classification of six classes of interest (maple-gum, Atlantic white cedar, pocosin, cypress, open water and disturbed habitat) using multispectral bands combined with NDVI. This study finds that soil carbon gas flux depends on soil moisture, temperature and forest type, which are all affected by anthropogenic activities in these peatlands. Specific results include:

- On average, as soil moisture increased by 1 unit of soil moisture content, CH4 flux increased by 457 μg CH4-C/m²/hr.
- On average, as soil temperature increased by 1°C, CO2 flux increased by 5,109 μg CO2-C/m²/hr.
- The total area of Atlantic white cedar in the study boundary has an average yearly flux of 8.6 metric tons (t) of carbon from CH4 and 3,270 t of carbon from CO2; maple-gum has an average yearly flux of 923 t of carbon from CH4 and 59,843 t of carbon from CO2; pocosin has an average yearly flux of 431 t of carbon from CH4 and 15,899 t of carbon from CO2.
- Total Cha-1yr-1 ranged from 1,845 kg of Cha-1yr-1 in maple-gum to 2,024 kg Cha-1yr-1 for Atlantic white cedar.

This study also finds up to 58% of the variation in backscatter values from synthetic aperture radar is explained by biomass, soil density, and surface litter moisture (p=0.029), with biomass being the most important variable.
The results of this study will be useful for management considerations as well as future studies, including fire prediction and management, habitat and species restoration, and applying these techniques in similar environments around the world as changing climate patterns and other human activities impact forested peatlands. Future temperature and soil moisture predictions can be used to predict GHG flux using the calculations in this study.

**Overall discussion**

**Scientific and management contributions**

This study contributes to the current science by answering relevant questions about carbon loss and sequestration and their relationship to climate variables, as well as possibilities for monitoring soil gas flux and soil moisture remotely in dense woody vegetation. This study demonstrates the advantages of remote sensing for this topic, showing how satellite data paired with ground measurements can be used to monitor forest and soil conditions, estimate carbon loss and gain, predict future issues, and assess the effects of management actions.

**Future applications**

Remotely mapping surface soil moisture and greenhouse gas flux in forested peat wetlands has applications in other areas, as well as in the GDS. For example, protected forests and forest agriculture in tropical peatlands are also subject to drying and fire; these same techniques could be applied to monitor fire risk and other conditions there. This in turn has climate change mitigation possibilities - as fires in peatlands release great quantities of carbon - as well as adaptation applications, where climate changes may
impact an area’s suitability for various wildlife and plant species. In the GDS, habitat concerns include Atlantic white cedar and red-cockaded woodpeckers.

**Future study**

**Ground sampling**

Improvements in ground sampling could benefit future study in this subject and area. For example, greater spatial and temporal resolution of ground samples could improve the strength of the analysis, or could reveal more detailed information. This could include daytime and nighttime sampling to provide more information on GHG respiration; sampling before, during and after precipitation so see how movement of the groundwater table affects GHG flux; sampling before, during and after either fire or management to see how these affect soil moisture and GHG conditions. The sampling methods from this study could also be compared with traditional sampling techniques to see if results are affected. More discrete forest types could be categorized and sampled to see if they are statistically relevant and distinct from those measured in this study. More samples could be taken timed with satellite SAR measurements. Lastly, more ecosystems could be sampled to provide a comparison, such as the Pocosin Lakes National Wildlife Refuge nearby which has some similar plant communities.

**Data combinations**

Additional sources of information could improve the understanding and accuracy of the results of this study. For example, study of plant roots, fungi and microorganisms in the soil as well as further chemical analysis of the soil and ground water could improve the understanding of the GHG flux results. Improved satellite data, including higher
resolution multispectral and SAR data, or L band or other band longer wavelength radar, could add to the accuracy of the soil moisture findings. This could also be improved with more ground measurements to quantify the contribution of different variables to overall backscatter. For example, adding a measure of surface texture as a variable, or improved measurements of aboveground biomass in each forest type or at each site. Additional advanced classification and statistical approaches could also potentially improve the modeling of forest class, soil moisture, or GHG flux. This could include processing techniques, using more images and more data points to increase the number of statistical options available, and novel ways of combining the data.

Conclusions

This study and the data made publicly available as part of this research will hopefully prove useful for future management considerations in the GDS, and in other research studies taking place there. Ideally this study will also be of use to researchers and managers working in similar environments around the world aiming to understand net carbon flux and to monitor surface soil moisture under dense forest canopy. This is of ever increasing urgency as these ecosystems experience the impacts of climate change as well as potentially contribute to overall atmospheric greenhouse gas content through oxidation of organic matter and emissions of CO₂ and CH₄.


90


Gesch, D.B. (2012). Global digital elevation model development from satellite remote-sensing data: Advances in mapping from remote sensor imagery techniques and


Laurel Wood Gutenberg graduated from Brighton High School, in Rochester, New York, in 2003. She received her Bachelor of Science from Juniata College in Huntingdon, Pennsylvania in 2007 and her Master of Science from the University of Wisconsin in Madison, Wisconsin in 2009. She currently works for the Army Geospatial Intelligence Battalion in Springfield, Virginia.