Assessing family forest landowners interest in forest carbon programs in the southern United States and predicting carbon content in loblolly pine using Near Infrared Spectroscopy

by

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Abstract

Over the past few decades, atmospheric carbon dioxide (CO_2) levels have increased from 300 to 416 ppm. Increased concentrations of atmospheric CO_2 affect forests and create an imbalance of carbon exchange between the atmosphere and natural sinks. A significant rise in CO_2 levels contributes to increased global temperatures and leads to climate change. Forests play a critical role in mitigating climate change by absorbing the carbon dioxide emitted into the atmosphere from individuals and industries burning fossil fuels for energy purposes into the terrestrial carbon sink. Strategies like maximizing forest carbon storage in forests and forest products by promoting sustainable forest management practices help reduce CO_2 levels. This study focuses on bringing market-based mechanisms to meet the greenhouse gas reduction targets to comply with the Kyoto Protocol and develop an advanced methodology (Near-Infrared Spectroscopy) to estimate carbon content for biomass/timber production. For the proposed study, there are two objectives. First, assess the awareness, attitudes, and willingness of family forest landowners in the southern United States on managing their forestland to increase carbon sequestration and participate in emerging voluntary forest carbon programs. Second, develop a non-destructive method for predicting the carbon content of loblolly pine using Near-Infrared Spectroscopy with an application of chemometrics.

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List of Abbreviations

ACES	Alabama Cooperative Extension System
AFOA	Alabama Forest Owners Association
CCB	Climate Community and Biodiversity Standards
CCX	Chicago Climate Exchange
CDM	Clean Development Mechanism
CER	Certified Emission Reduction
CLT	Cross-laminated timber
CO_2	Carbon dioxide
CRP	Conservation Reserve Program
CSP	Conservation Stewardship Program
DLT	Dowel-laminated timber
EQIP	Environmental Quality Incentives Program
ERUs	Emission Reduction Units
ET	Emission Trading
FFLs	Family Forest Landowners
FLA	Forest Landowner Association
GHG	Greenhouse Gas Emissions
Glulam	Glue-laminated timber
IFM	Improved Forest Management
IPCC	The Intergovernmental Panel on Climate Change
JI	Joint Implementation

LLC	Limited Liability Company
LLP	Limited Liability Partnership
NCX	National Capital Exchange
NIRS	Near-Infrared Spectroscopy
NLT	Nail-laminated timber and
NRCS	Natural Resource Conservation Service
PC	Principal Component
PCR+	Principal Component Regression
SEE	Standard Error of Estimate
SEP	Standard Error of Prediction
SREF	Southern Region Extension Forestry
UNFCCC	United Nations Framework Convention for Climate Change
U.S	United States
USDA	United States Department of Agriculture
VCS	Verified Carbon Standard

Chapter 1 : Introduction

Forests offer great services to humankind – including reliable, clean water, climate regulation, productive soils, food, medicine, and recreational, aesthetic, and spiritual benefits (Jenkins & Schaap, 2018). Forests also provide essential local environmental services to the forest landowners ranging from water quality and quantity regulation to providing wildlife habitat that protects biodiversity. In addition to providing numerous essential ecosystem services that forests offer, increasing the amount of carbon stored in forests and wood products can lower the quantity of carbon dioxide (CO_2) in the atmosphere (Dugan et al., 2021). However, there has been an increase in CO_2 levels due to an imbalance between carbon sources released into the atmosphere through human activity, such as burning fossil fuels and deforestation, and uptake by sinks in oceans and terrestrial systems (Friedlingstein et al., 2020). Over the past few decades, atmospheric CO_2 levels have increased from 300 to 416 ppm (Scripps Institute of Oceanography 2021). A significant rise in atmospheric carbon contributes to increased global temperatures and climate change.

Climate change poses an unprecedented challenge to human civilization, with both present and anticipated effects on various environmental systems. Forest productivity changes have been observed and are projected to intensify over time (Bottero et al., 2017). Recent studies have shown that climate change is having significant and diverse impacts on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States, with potential implications for the sustainability and resilience of these systems (Parmesan & Hanley, 2022; Gopalakrishna et al., 2021; Groffman et al., 2022). In the United States, the largest sources of greenhouse gas emissions (GHG) in 2020 were transportation (27%), electricity production

(25%), industry (24%), commercial and residential (13%), and agriculture (11%) (EPA, 2021). The forests and other land use practices in the United States can offset almost 16 percent of the country's domestic CO_2 emissions by sequestering approximately 866 million metric tons of CO_2 annually (EPA, 2021). These numbers suggest a great need to focus on including forests as a tool to mitigate climate change.

In a forest, carbon is continually changing. Planting and harvesting trees can help reduce atmospheric CO_2 and mitigate climate change (Domke et al., 2020). Trees sequester atmospheric CO_2 and constantly cycle from one pool to another, eventually returning to the atmosphere at different times. In natural forests, carbon pools are divided into five types. They are aboveground (trunk, branches, bark, leaves), belowground (roots), deadwood, litter (fallen leaves, stems), and soils (Hoover, 2020). In the context of forest carbon, it is also necessary to consider the relationship between the stored carbon in the forest and harvested carbon in wood products from the forest. As trees grow, they absorb more CO_2, so planting new trees and replanting harvested areas can help capture and store CO_2 while keeping the average carbon across the whole forest stable. When harvested, the carbon stored in wood products can displace emissions from fossil fuels by serving as biofuels for heating or electricity generation. Long-lived wood products like those used in construction also provide a source of long-term carbon storage.

Additionally, using wood products instead of building materials like concrete and steel can reduce the carbon footprint associated with those materials (Bergman et al., 2014). To ensure these benefits are realized over the long term, it is essential to practice sustainable forest management. This means managing forests to maintain their productivity and biodiversity while avoiding activities that could release stored carbon into the atmosphere, such as burning fossil fuels or deforestation.

Forests are crucial in mitigating climate change by reducing atmospheric CO_2 through sequestration and offsetting emissions (Federici et al., 2015). Considering the role of forests in mitigating climate change, it is crucial to understand further how to enhance the sequestration process. Carbon sequestration occurs by capturing carbon from the atmosphere through photosynthesis and converting it into living biomass such as roots, branches, leaves, and tree trunks (Brack, 2019). One of the approaches for recovering harmful CO_2 from the atmosphere would be enhancing carbon sequestration projects on forested lands by participating in market-based mechanisms (Fawzy et al., 2020).

The Intergovernmental Panel on Climate Change (IPCC) defined net CO_2 emissions as the difference between emissions from sources and removals by sinks. In 1997, the United Nations Framework Convention for Climate Change (UNFCCC) members in the Kyoto Protocol agreed to use three market-based mechanisms to meet the GHG emissions reduction targets to comply with the protocol (UNFCCC, 1998). They are clean development mechanism (CDM), joint implementation (JI), and emission trading (ET) (UNFCCC, 2022). CDM enables developed countries to earn Certified Emission Reduction (CER) credits by investing in clean energy and sustainable development projects in developing countries. JI allows a country with a GHG reduction project in another country to earn emission reduction units (ERUs) that can be used towards meeting their emission reduction targets. ET allows countries to trade their emissions allowances. A country that has reduced its emissions below its allowance can sell the excess to a country exceeding its allowance. The objective is to create a market for emissions allowances and to provide an economic incentive for countries to reduce their emissions.

Carbon markets are market-based mechanisms that put a price on carbon emissions, allowing industries and companies to buy or sell carbon credits (Kreibich & Hermwille, 2021).

These credits represent a reduction of one metric ton of CO_2 or equivalent GHG emissions. On the other hand, forest carbon programs focus on preserving and increasing the carbon storage capacity of forests (Badgley et al., 2022). They incentivize forest landowners to keep their forests intact or to plant new trees that absorb CO_2 from the atmosphere. These programs allow forest landowners to earn carbon credits for the carbon sequestered by their forests (Badgley et al., 2022). The credits can be sold on voluntary or compliance markets or used to offset the carbon emissions of other activities. Overall, while both carbon markets and forest carbon programs are two different mechanisms aimed at reducing GHG emissions, they operate differently and target different sources of emissions. These emerging forest carbon programs can provide an additional source of revenue from forestland by increasing carbon stored in trees (Alhassan, 2019; Sharma & Kreye, 2022).

The importance of forest carbon programs has been increasingly recognized over the past decade. However, great uncertainty persists about familiarity, interest level, and factors affecting the forest landowner's decision to participate in such programs (Kelly et al., 2017). Historically, forest carbon programs have not been available to all forest landowners because of vast acreage requirements, high upfront costs, and long-term commitments (Kerchner & Keeton, 2015; Pan et al., 2022). This is especially true for forest landowners who own and actively manage plantations for timber production (Wear and Greis, 2013; Chudy & Cubbage, 2020). However, the benefits these forests provide towards the objectives of increasing carbon sequestration are too great to ignore, specifically when considering sustainable forest management and the potential benefits of prolonged carbon storage in wood products (Shephard et al., 2022).

Apart from the forests that can act as carbon sinks, it is acknowledged that the energy contained in wood products also serves as a significant carbon sink (Amiri et al., 2020). The most effective strategy to exploit the forest ecosystem for atmospheric carbon sequestration is to increase the production of wood-based products on a sustainable basis, considering the productivity of the forest ecosystem (Verkerk et al., 2020; Shephard et al., 2022). While the beneficial role of forests in reducing the effects of climate change is generally widely acknowledged, the role of wood products in reducing the effects of climate change needs to be more well-known and understood (Leskinen et al., 2018). Wood products are the derivatives of trees as a result of any work or manufacturing process on the wood. Wood products consist of paper and paper products; dimensional lumber; engineered wood products such as particleboard, oriented strand board, medium-density fiberboard, and plywood; wood doors; wood windows; and biocomposite surface products (Chaowana & Barbu, 2017). Wood products offer a variety of economic and social advantages in terms of income and employment generation for forest landowners to replant, manage, and maintain forests against any disturbances (Leskinen et al., 2018).

Due to the increase in population, the demand for buildings, bridges, and other structures has drastically changed. According to an estimate, 40 percent of United States CO_2 emissions come from residential and commercial buildings (Robinson et al., 2017). On the contrary, wood is a natural, renewable, and sustainable material for building and acts as a substitute to reduce the effects of climate change (Gustavsson et al., 2017; Ramage et al., 2017). Hence much focus is emphasized on giving importance to wood in the construction industries and considered a tool to mitigate climate change. Considering the demand, mass timber constructions are gaining momentum and will likely play a significant role in the building sector (Ahmed & Arocho, 2020). Several kinds of massive wood planar or frame elements used for building walls, floors, and roofs are called Mass Timber Construction (Ahmed & Arocho, 2020). Mass timber has gained massive attention in the construction industry over the past decade due to its structural integrity, beauty, and sustainability (Gong, 2019). Depending on how the layers of wood are composed, four different types of mass timber include Cross-laminated timber (CLT), Nail-laminated timber (NLT), Dowel-laminated timber (DLT), and Glue-laminated timber (Glulam) (Sahoo et al., 2019). The benefits of mass timber are broader, considering the positive environmental impacts like a lighter carbon footprint than steel and concrete, faster construction, reduced shipping and installment costs, and its remarkable performance in fire and earthquakes (Sahoo et al., 2019).

The importance of considering forests, wood products, and mass timber in the construction industries to enhance biomass or timber production to increase carbon sequestration and carbon storage promotes the need for improved methodologies for measuring and tracking carbon utilizing cutting-edge technologies for innovative applications. Near-Infrared Spectroscopy (NIRS) has been reported as a non-invasive, rapid, and cost-effective technique, requiring minimal sample preparation and no chemicals, and can evaluate several properties with a single spectral (Manley, 2014). This thesis focuses on studying family forest landowners (FFLs) knowledge of forest carbon programs and bringing the best of the methodologies to estimate carbon in their forestlands. This thesis aims to assess the awareness, attitudes, and willingness of FFLs in the southern United States to manage their forestland to increase carbon sequestration and participate in emerging voluntary carbon offset programs. Also, develop a simple, user-friendly, non-destructive method for predicting the carbon content in wood samples in standing trees and wood products using NIRS coupled with chemometric models.

The ultimate objective of this research is to demonstrate the advantages of involving in forest carbon programs, which help generate supplemental income opportunities and spread the knowledge of NIR usage without the involvement of third parties to predict the carbon on their forestland. To achieve these research objectives, the thesis presents the results of a survey and a study involving building a chemometrics model to predict the carbon in trees, in which data is collected from various species. The study aims to develop consistent national volume, biomass, and carbon models by species.

Chapter 2 : Forest Carbon Programs: An Assessment of family forest landowners in the southern United States

2.1 Introduction

Forests play a critical role in mitigating climate change by absorbing atmospheric carbon dioxide (CO_2). Approximately 2.6 billion tons of CO_2 released from the burning of fossil fuels is absorbed by forests every year (IUCN 2021). However, the continued deforestation and degradation of forests could turn them from carbon sinks to the source of carbon emissions, further exacerbating climate change (Houghton & Nassikas, 2018). Therefore, it is crucial to prioritize efforts to protect, restore, and sustainably manage forests as part of global and local efforts to combat climate change. Forests throughout the United States serve as significant carbon offsets, storing approximately 16% of the country's annual carbon emissions, with southern forests alone absorbing approximately one-third of that carbon (Domke et al., 2020). Hence, forests in the southern United States play a significant role in addressing the effects of climate change.

Private ownership dominates the south on all fronts. Two hundred million acres, or 86 percent of the region's total forestland, are owned privately by more than 5 million people (Butler & Wear, 2013). Two-thirds of this area (127.6 million acres) is owned by families or individuals, which accounts for 63% of the forestland in the south, and the remaining one-third of the private land is owned by corporations, conservation groups, alliances, and tribes on average (Butler & Wear, 2013).

Family forests are forests owned by individuals, married couples, family estates & trusts, or other groups of individuals who are not incorporated or otherwise associated as a legal entity

(Butler, 2008). Family forest landowners (FFLs) are highly diverse regarding ownership motivation and management objectives, ranging from intensive timber production to preservation of non-timber interests like amenities and family legacy (Butler et al., 2016; Butler et al., 2020). FFLs have different motivations or objectives for owning their forestland, such as timber, maintaining wildlife habitat, recreation, aesthetics, and soil stabilization (Bengston et al., 2011; Butler et al., 2016; Poudyal et al., 2019; Singh, 2020). Despite having a significant portion of the overall forestland in the southern United States, it has been found that approximately 30 percent of FFLs have a good understanding of forest carbon sequestration programs (Khanal et al., 2016). Management actions by landowners that could help increase carbon sequestration on their lands include thinning, prescribed burnings, delayed harvest or implementing alternative forest management practices, afforestation, and reforestation through planting new trees and avoided conversions (Galik et al., 2013; Clay et al., 2019). Recently, many policies developed to reduce carbon emissions have been pursued using market–based mechanisms (Fawzy et al., 2020), often including opportunities for landowners compensation for managing their lands in ways that improve carbon sequestration (Alhassan, 2019).

Active forest management can increase the amount of carbon stored in a forest ecosystem and the rate at which carbon is sequestered (Verkerk et al., 2020). Harvesting, thinning, and replanting can increase tree growth rates and biomass accumulation, leading to greater carbon sequestration and storage (Di Sacco et al., 2021). Furthermore, these practices can enhance forest health and resilience, providing additional benefits to FFLs and the broader ecosystem (Ontl et al., 2020). Despite the potential benefits of including active FFLs in forest carbon programs, more research must be conducted on their interest and willingness to participate in such programs.

Landowners who actively manage their forestland for timber production have been identified as an important group for achieving carbon storage objectives and reducing atmospheric CO_2 (Sharma & Kreye, 2022). These landowners typically own larger forested properties, have a greater attachment to the land, and tend to be more engaged in forestry activities than non-managing landowners (Sharma & Kreye, 2022). In addition, they often have a greater awareness of the potential benefits of managing their forests for carbon sequestration and may be more willing to adopt sustainable management practices that enhance carbon sequestration and storage (Sharma & Kreye, 2022). Hence it is important to understand the interest and willingness of FFLs actively manage their forestlands for timber production, as it has often been overlooked in regard to forest carbon markets because of their harvesting characteristics.

There are different types of forest carbon projects that can generate carbon credits, such as afforestation, reforestation, and improved forest management (Van der Gaast et al., 2018). These projects involve planting trees or improving the management of existing forests to increase their ability to sequester CO_2 from the atmosphere. Afforestation involves planting trees on land that has not been forested before, while reforestation involves replanting trees on land that has been deforested or degraded. Improved forest management focuses on enhancing the growth and health of existing forests through sustainable forestry practices such as reducing deforestation, promoting forest regeneration, and avoiding land-use changes. Carbon credits generated from forest carbon projects are verified by independent third-party registries such as Verified Carbon Standard (VCS) or the Climate, Community, and Biodiversity Standards (CCB) (Pra & Brotto, 2018). These registries ensure that the carbon credits are accurately measured, verified, and accounted for and that the projects meet rigorous environmental and social standards.

Carbon markets can be categorized as regulated and voluntary. Regulated markets are based on a government regulatory framework related to climate change mitigation and account for companies' and governments' GHG emissions. Whereas voluntary markets, on the contrary, trade carbon voluntarily (Tjon Akon, 2023). The Chicago Climate Exchange (CCX) was the first voluntary carbon market in North America and Brazil, launched in 2003 as a trading exchange for voluntary greenhouse gas emission reductions and offsets (Gans & Hintermann, 2013). The CCX provided a formal market for businesses to cut GHC emissions, accounting for 43% of the voluntary carbon market transaction value globally (Sabbaghi & Sabbaghi, 2017). However, in 2010, the CCX ceased its operations because large investors were not interested in a voluntary market and had counted on U.S. legislation to enact a mandatory market (Havens, 2022). Since then, many other voluntary carbon offset programs have emerged. Some newly emerged carbon offset programs are Family Forest Carbon, National Capital Exchange (NCX), California CAP and Trade, CORE Carbon, Blue Source, Forest carbon works, and Green Trees (Maggard, Vandershaaf, 2022). They vary in attributes such as contract length, acreage size requirement, harvesting period, upfront cost, and annual payments.

The California CAP and Trade program was the first U.S. regulatory market that allowed landowners to sell forest-based carbon credits (Parajuli et al., 2019). The most comprehensive cap-and-trade program launched in 2012 represents real, verifiable, quantifiable, enforceable, permanent, and additional reductions or removals of GHC emissions to 1990 levels by 2020 (Parajuli et al., 2019). This program created a massive earning opportunity for the buyers and sellers of carbon credits (Burtraw et al., 2019). However, strict project development protocols and standards like long-term management plan (100 years), project initiation expenses, and third-party verification for each carbon project type created barriers to reaching out to all the landowners (Khanal et al. 2020). In 2008, $119 was traded on the voluntary market, and $704 million was traded on the regulated market (Hamilton et al., 2008). Despite the plenty of market opportunities and potential benefits of using forests to produce offsets, the voluntary markets have remained relatively small (Hamilton et al., 2008).

The recent revitalization of forest carbon programs has included the voluntary market, which allows individuals and companies to purchase carbon credits voluntarily to offset their carbon footprint or to support climate mitigation projects. It has created an opportunity for forest landowners, especially FFLs, to generate additional income from their forestland by participating in forest carbon programs and selling carbon credits. Projects such as American Carbon Registry's Improved Forest Management (IFM) and the Climate, Community, and Biodiversity Alliance's REDD+ have focused on developing methodologies to include more landowners and acres of forestland that have not been considered in the past (Pan et al., 2022). These projects aim to promote sustainable forest management practices while generating carbon credits and providing additional income for forest landowners.

This research focuses on assessing FFLs in the southern United States, particularly those who manage their forestland and harvest timber, familiarity with and interest in forest carbon programs. Further, we examine the likelihood that different factors and characteristics commonly associated with forest carbon programs influence their decision to participate or not. These results will help better understand what socioeconomic variables and ownership characteristics are correlated to FFLs willingness to participate in forest carbon programs and provide guidance for modifying forest carbon program methodology.

2.2 Methods

2.2.1 Study Area and Target Landowners

The survey was developed and aimed at understanding FFLs of southern United States who manage their forestland and harvest timber awareness of – and interest in forest carbon programs, attitudes toward their decision to participate, ownership objectives, and descriptive information. Target landowners were those who owned at least 10 acres of forestland from all thirteen southern United States (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, Virginia, and West Virginia).

2.2.2 Survey Instrument

This survey methodology followed Dillman's Tailored Design Method for online surveys and was developed using Qualtrics XM software (Tian et al., 2023). Tailor design is a scientific approach to conducting sample surveys focusing on reducing the four courses of survey error – coverage, sampling, nonresponse, and measurement (Lyberg et al., 1991). It involves developing a set of survey procedures, including the contact letters or emails to respondents, the questionnaire (De Leeuw et al., 1999), and its protocol approved by Auburn University's Institutional Review Board. Dillman's Tailored Design Method for online surveys involves an information letter, consent letter, survey questionnaire, and reminder email. The survey was implemented online and distributed through email as a method to increase the reach to our target audience and improve response numbers (Dillman et al., 2014).

2.2.3 Survey Distribution

The survey was distributed through email list by the Forest Landowners Association (FLA), Alabama Forest Owners Association (AFOA), Southern Region Extension Forestry

(SREF), and the Alabama Cooperative Extension System (ACES) – Forestry, Wildlife, and Natural Resource Team. As such, forwarded emails from the original distribution lists are unable to be known and accurate response rate to the questionnaire is unattainable. In May 2021, the first email distribution was sent to FFLs containing the information about the survey. A link was attached with a detailed consent letter for the participants to approve before they started filling out responses. This consent letter provided details about the research study, benefits of participation, risks, and discomforts associated, and compensation or costs for participating (which was none). Additional information about the study, the IRB protocol number and dates, and a statement that involvement in this study was entirely voluntary were all provided in the information letter. Approximately 10-14 days following the first email distribution, a follow-up reminder email was sent that contained the same information as the original email, with the addition of serving as a reminder notice. Approximately one month following the distribution of the first email, the survey was closed.

The survey was divided into four separate sections. The survey's first section assessed the FFLs forestland characteristics and ownership background. This section of the survey asks basic questions on how many acres of forestland they own, the majority of the forestland cover, describing their ownership, primary reasons for owning, and interests in generating revenue from their forestlands. The second section assessed participants knowledge of forest carbon programs, their interest levels towards participation, familiarity, interest in short and long-term programs, and factors influencing them to prevent participation. FFLs were provided brief information about forest carbon and carbon credits before being asked questions about their participation interests. It helps them clarify their understanding of what forest carbon programs are and helps in eliminating misunderstanding of what questions are asking for answers (Khanal et al., 2019).

The third section of the survey covers questions on the demographics of the respondents. This section included questions on FFLs age classification, gender, educational background, household's annual income, and describing their ethnicity and race. The final section addressed the additional comments or concerns that FFLs would like to share and about the follow-up interview about their experience with this survey.

2.2.4 Data analysis

The data collected from the survey was used to develop the descriptive statistics and part of the data was analyzed using R Studios to test for statistical significance and correlations among variables (RStudio Team, 2021). Incomplete responses from the participants were excluded from the analysis. Statistical analysis was focused on conducting a series of non-parametric tests to determine relationships among FFLs familiarity with and interest in participation of forest carbon programs and impact of several other factors on their attitudes towards the programs. As most of the responses in the survey were ordinal data type, Mann-Whitney U Rank Sum Test was used to test for statistical differences among groups. Kruskal-Wallis test was used for comparing two or more independent variables of equal or different sample size. Spearman’s Rank Correlation Test or Spearman’s Rho test was used to find significant correlations between FFLs familiarity with and interest in forest carbon programs and the factors preventing or likely impacting their decision to participate in a forest carbon program.

2.3 Results

Assessment of FFLs Characteristics, Forest Management Practices, and Income Generation

Overall, 262 responses were received, out of which 210 completed responses were received, resulting in a completion rate of 80.4%. Responses were received from all thirteen states, with the highest percentage (26%) from Georgia, and the lowest percentage (<1%) from Kentucky and West Virginia (Figure 1). Most of the respondents were white (89.3%), males (86.5%) over age 65 (65.9%), were well educated (90% with at least a college degree), with household income above $100,000 (58.1%).

Participants were grouped and classified based on the size of their forestland acreage with the highest percentage between 501 to 1000 acres (25%) and the lowest percentage between 51 to 100 acres (4.4%) (Figure 2). The overall average acreage owned by participants was 2092 acres. Participants were asked to select their primary reason for owning forestland from a list of options provided. The most cited reasons for owning forestland were timber production (33%), multiple reason (30%), land investment (9%), pass it on to heirs (8%), protection of natural resources (6%), part of a farm or ranch (4%), hunting recreation (3%), and enjoyment of beauty and scenery (2%) (Figure 3).

In terms of forest type, it was found that the majority owned by respondents were planted pine (57%), followed by mixed pine/hardwood (23%), natural hardwood (10%), and natural pine (7%) (Figure 4). Regarding the type of ownership, "family partnership, limited liability company (LLC), limited liability partnership (LLP)" accounted for the majority of the forestland (35%), followed by individuals (19%), joint with a spouse (17%), and family trust or estate (14%) (Figure 5).

When participants were asked about forest management activity, 96.9% of the respondents said they currently manage their forestland out of which 69.9% have a written management plan and 27.3% do not have a written management plan (Figure 6). The remaining

3.1% of respondents were neither managing nor had a written management plan (Figure 6). In terms of knowledge of – and involvement with cost-share programs, the majority (56.5%) of respondents are not involved in any kind of cost-share programs. Of those respondents, 45.1% had participated in cost-share programs in the past, and 54.9% had never participated (Figure 7). The remaining 43.5% reported that they were currently involved in cost – share programs (Figure 7). Of those involved with cost-share programs, the majority of respondents are involved in United States Department of Agriculture (USDA) natural resource conservation service programs (NRCS) (23.1%) like Environmental Quality Incentives Program (EQIP) (7.3%), Conservation Reserve Program (CRP) (5.9%) and Conservation Stewardship Program (CSP) (5.3%). The remaining were involved in state level programs like tree planting, site preparation, prescribed burning, weed control and wildlife management, quail restoration administered by the forestry commissions. When asked about the cost of owning and managing their forestland, 84.5% of respondents believed that the cost is about what they expect, 13.0% believed the cost is more than expected, and 2.5% believed that the cost is less than expected (Figure 8). Further, when asked about their plans for their forestland, 77.6% of respondents indicated that they plan to pass it on to heirs, 8.7% plan to sell, and 5.1% plan to bequeath (Figure 9).

A series of questions were asked to participants focused on income generation from their forestland. Currently, 76.6% of the respondents are generating income from their forestland (Figure 10). When participants were asked if they have interest in generating income from their forestland, the majority (92.1%) selected they did, 6.8% selected maybe, and 1.23% selected they did not (Figure 11). Further, participants were asked to choose all applicable sources of income from their forestland from a list of provided options. Overall, 75.7% of respondents chose some combination of multiple sources of income generation from their forestland. Of these, the top three multiple source combinations selected were timber sales along with hunting lease (31.3%), timber sales along with hunting lease and other types of leases (23.5%), and timber sales along with other non-timber sales (7.8%) (Figure 12). 24.3% of respondents chose a single source of income and the top three were timber sales (19.1%), hunting lease (3.5%), and non–timber forest products sales (1.7%) (Figure 12).

Assessment of Knowledge about and Participation in Forest Carbon Programs

Participants were asked about their familiarity with forest carbon programs. It was found that 90.2% of respondents had some familiarity with forest carbon programs, and 9.8% were not familiar (Figure 13). Of those with some familiarity, the majority of the respondents were moderately familiar (37%), followed by slightly familiar (26.6%), very familiar (17.5%), and extremely familiar (9.1%) (Figure 13). The remaining 9.8% of respondents were unfamiliar (Figure 13). In regard to participant interest in learning more about forest carbon programs, the majority of respondents (64.3%) indicated they are "extremely interested" or "very interested" (Figure 14). Of the remaining 35.7% of respondents, 25.2% were "moderately interested," 5.6% were "slightly interested," and 4.9% were "not at all interested" (Figure 14). Similarly, most respondents (63.6%) have enquired about or researched forest carbon programs within the last two years (Figure 15). Of the remaining respondents, 12.6% selected that they have inquired about or researched forest carbon programs, but it has been over two years since doing so, and 23.8% of respondents said they have never inquired about forest carbon programs (Figure 15).

Participants were asked to rank likelihood of factors preventing their participation in forest carbon programs. The top three factor with the most responses for extremely likely to influence their decision to prevent participation was the rate of return or amount of revenue generated (34.3%), and land use rights/limitations (29.4%), and upfront cost or any direct costs

(18.9%) (Figure 16). The top three factors that are extremely unlikely to influence respondents' decision in preventing participation were the upfront costs or any direct costs (35.6%), financial penalty for early withdrawal (25.2%) and rate of return or amount of revenue generated (17.5%) (Figure 16). The top three chosen factors, neither likely nor unlikely, were the length of contract commitment (31.5%), land use rights (23.1%), and financial penalty for early withdrawal (21.7%) (Figure 16).

Participants were then asked to select the type of forest carbon program they would most likely participate in if they decided to do so. Three options were provided to participants. The majority of respondents selected forest carbon programs that focus on maximizing carbon and paying for carbon gained by delaying/preventing timber harvest during the contract period (contract commitment range from 1 to 100+ years depending on the program) (76.9%), as opposed to forest carbon programs focused improved forest management by providing funding to assist with management cost (10-year to 20-year contract commitment) (16.8%) or afforestation programs that pay for carbon gained from newly planted land (afforestation) during the contract period (contract commitments of 40-years minimum focused on hardwoods) (6.3%) (Figure 17).

When assessing the willingness to participate in forest carbon programs based on dollar per acre value they would require, responses were variable with the majority of respondents (40%) selecting more than $30 per acre followed by a bell-shaped distribution of response spread across the remaining price range options peaking with 18.4% of responses selecting $11 to $15 per acre (Figure 18). Participants were then asked how likely they are interested in participating in a forest carbon program if eligible. It was found that the majority of the respondents (42.6%), were somewhat likely to participate in a forest carbon program, followed by extremely likely

(32.1%), neither likely nor unlikely (14.9%), extremely unlikely (5.6%), and somewhat unlikely (4.9%) (Figure 19).

Assessment of Forestland Impact from Natural Disasters and Influence on Participation in Forest Carbon Programs

Participants were asked if they had ever lost timber from their forestland due to a natural disaster (hurricane, tornado, severe storm, wildfire, drought) and if so, to what severity, if the possibility of occurrence influence their decision to participate in forest carbon credit programs, and how likely they would be to reforest their land if severe natural disaster did occur. In the first scenario, 65.7% of the respondents stated that they had lost timber due to natural disasters, while 34.3% had not (Figure 20). Among respondents who had lost timber, 50.0% had a minimal loss of timber, 40.3% a moderate loss of timber, and 9.7% a majority loss of timber. (Figure 20).

Participants were assessed on how being impacted by – or the potential of being impacted by a natural disaster would impact their decision to participate in a forest carbon program. The majority of the respondents chose might or might not (29.6%), followed by probably not (25.9%), definitely not (16.1%), probably yes (16.1%), and definitely yes (12.6%) (Figure 21). Further, participants were assessed on their decision to not reforest but rather change land use or sell their property if they encountered a significant loss of timber due to a natural disaster. The majority of the respondents were extremely unlikely (59.4%) to not reforest but rather change land use or sell their property (Figure 22).

On the contrary, when participants were asked if there was a forest carbon credit program that offered funds for reforestation costs to reforest following a natural disaster, how likely would they participate rather than change land use. Of the respondents, 28.6% selected it would be extremely likely they would participate, 39.8% selected somewhat likely, followed by 18.9% extremely likely, 8.4% somewhat unlikely, and 4.3% extremely unlikely (Figure 23).

Relationship among FFLs familiarity with and interest in forest carbon programs, their characteristics, and factors influencing/impacting their decision-making.

When observing the mean ranks produced by the Mann-Whitney U rank sum test, respondents that had a plan to harvest trees from their forestland in the future were more familiar with forest carbon programs ($p<0.0001$) (Table 1). Similarly, respondents that are members of a forestry association or local forestry planning committee ($p<0.0001$) and those who have inquired about forest carbon programs ($p<0.0001$) were more familiar with forest carbon programs (Table 2 & 3). Respondents that are member of a conservation organization ($p<0.0001$) and those who have inquired about the program ($p<0.0001$) were more likely to participate in the forest carbon programs in the future (Table 4 & 5). Respondents that generate income from their forestland were more familiar with the forest carbon programs than those who do not generate income ($p<0.001$) (Table 6). Respondents that currently manage their forestland owned significantly more forestland acres than those who do not manage their forestland ($p<0.001$) (Table 7).

When observing the mean ranks produced by Kruskal-Walli's test, respondents that are familiar with forest carbon programs significantly favored forest carbon programs that focus on maximizing carbon and pay for carbon gained by delaying/preventing timber harvest during the contract period (contract commitment range from 1-year to 100+ years depending on program) ($p = 0.0004$) (Table 8).

Using Spearman's Rho, three significant weak to moderate correlations were found between how familiar respondents are with forest carbon programs and factors likely influencing their decision to participate in such programs. The more familiar respondents are with carbon programs, the more likely they are to participate ($p = 0.0004$, $\rho = 0.295$) (Table 9). Further, respondents that are more familiar tend to view land use rights/limitations ($p = 0.0005$, $\rho = 0.286$) and amount of revenue they could earn by participating ($p = 0.03$, $\rho = 0.184$) as factors most likely to influence their decisions to participate (Table 9). The more familiar respondents are with forest carbon programs, the less likely the length of contract commitment tends to be a barrier for participation ($p = 0.02$, $\rho = -0.195$) (Table 9). However, without regard to familiarity, those respondents who selected they would likely participate in a carbon credit program if eligible also viewed length of contract ($p = 0.04$, $\rho = 0.174$) as more of an influence on their decision to participate as would land use rights/limitations ($p = 0.005$, $\rho = 0.236$) (Table 10). In terms of monetary expectations and participating in forest carbon programs, those respondents who would need a greater dollar per acre value to be willing to participate tend to be less likely to participate if eligible ($p = 0.0009$, $\rho = -0.276$) (Table 10).

Figures and Tables

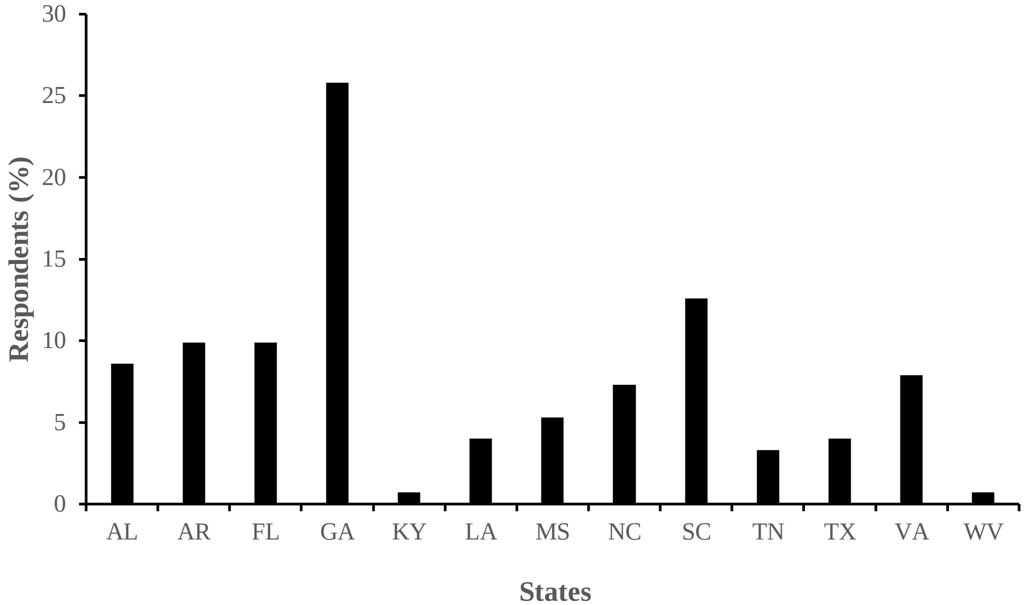

Figure 1: Percent respondents by state located in the distribution area of the southern United States (n = 162).

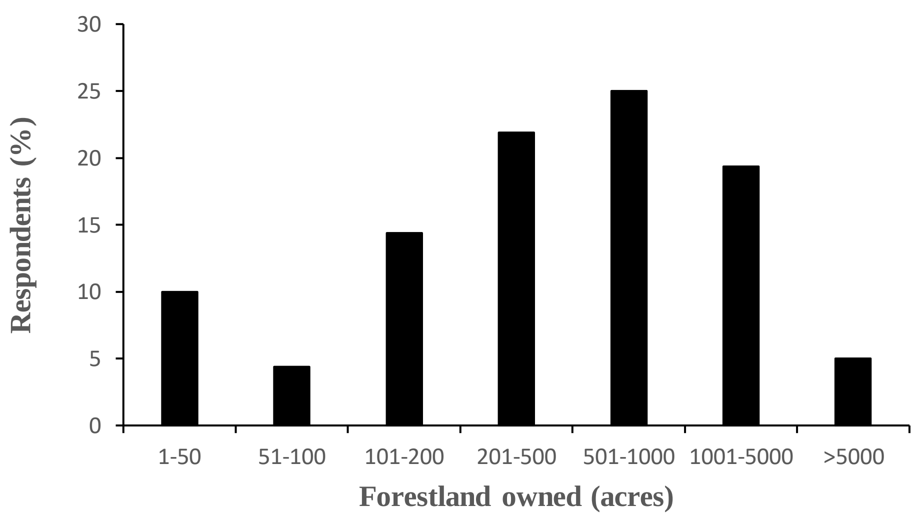

Figure 2: Classification of forestland acreage owned based on percent response from family forest landowners in the southern United States (n = 161).

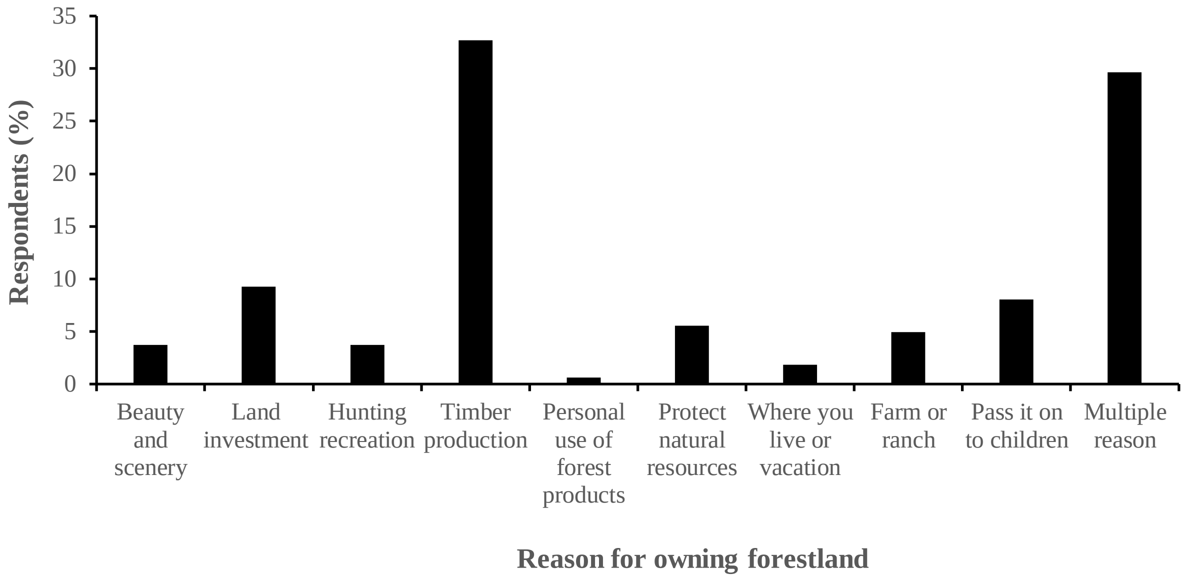

Figure 3: Primary reasons for owning forestland based on percent response from family forest landowners in the southern United States (n = 162).

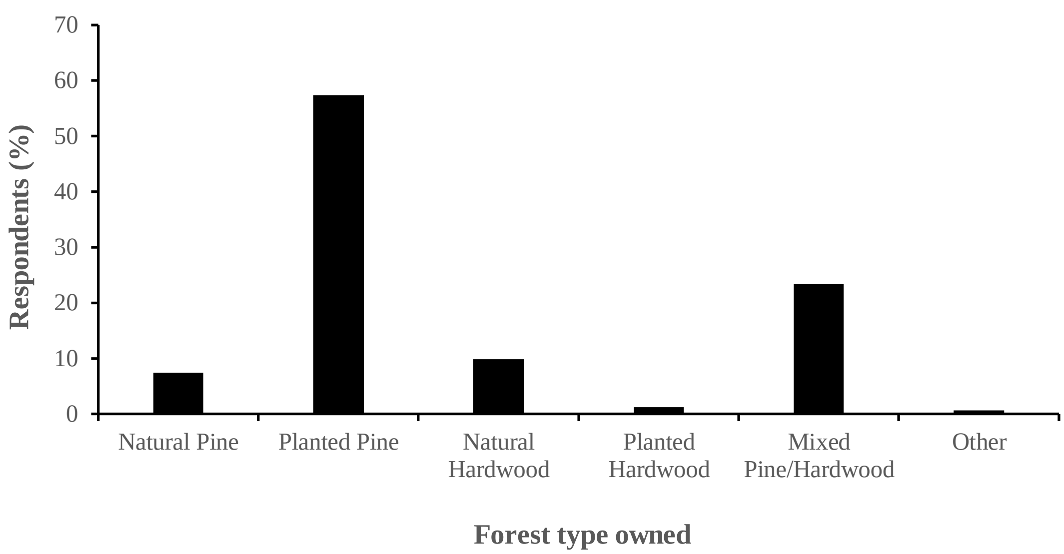

Figure 4: Forest type owned based on percent response from family forest landowners in the southern United States (n = 162).

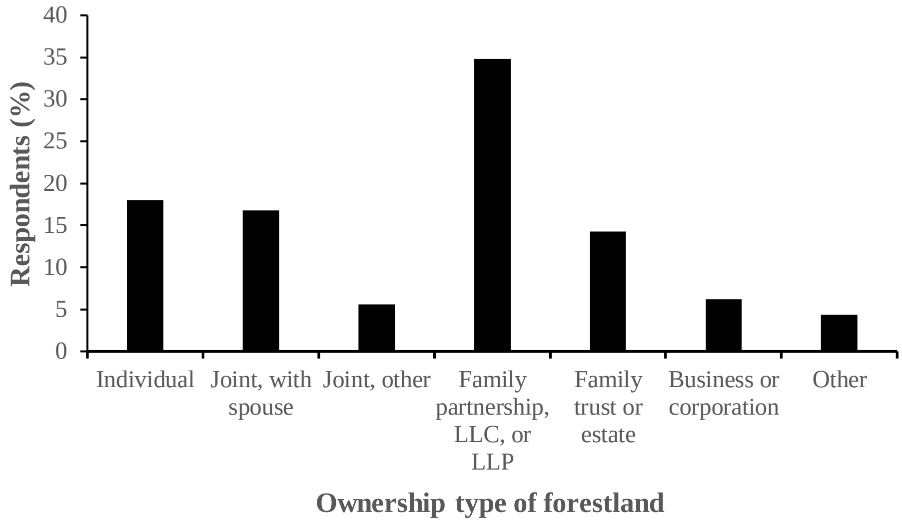

Figure 5: Ownership type of forestland based on percent response from family forest landowners in the southern United States (n = 162).

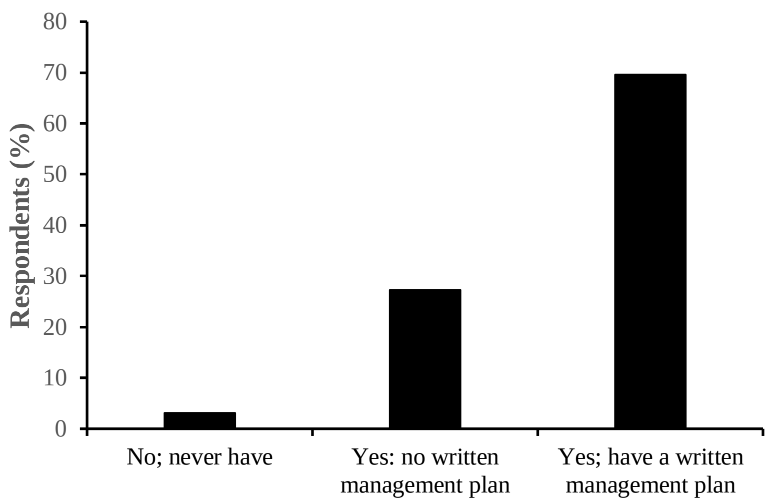

Figure 6: Proportion of family forest landowners in the southern United States that currently manage and have a written management plan, currently manage and do not have a written management plan, and do not manage and have never had written management plan based on percent response from survey participants (n = 161).

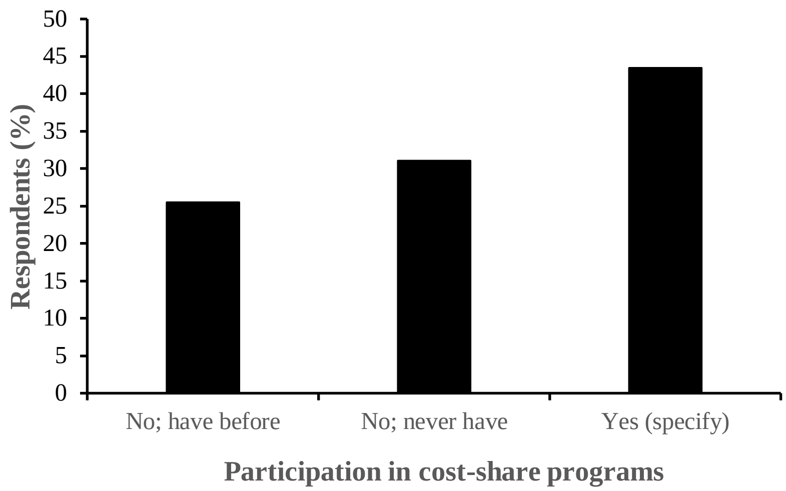

Figure 7: Proportion of family forest landowners in the southern United States that currently participate in a cost-share program, are not currently participating in a cost-share program and never have and are not participating in a cost-share program but have before based on percent response from survey participants (n = 161).

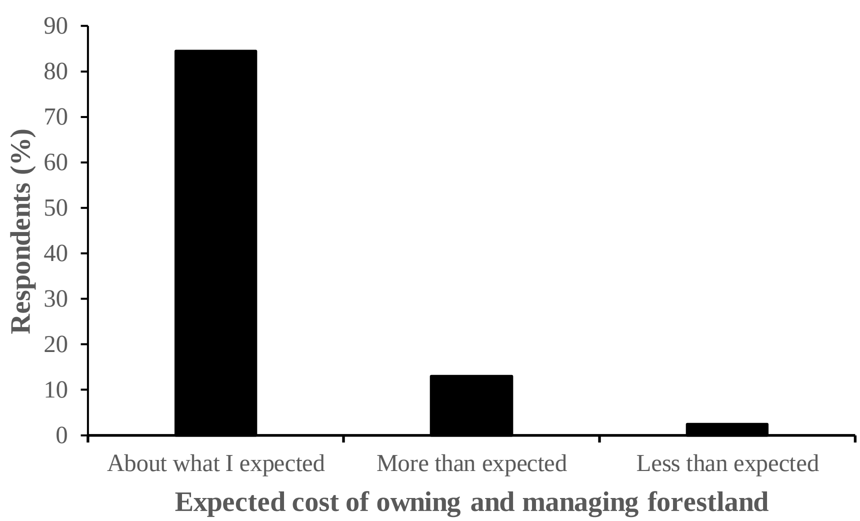

Figure 8: Proportion of family forest landowners in the southern United States that choose the cost of owning and managing their forestland is about what they expected, more than they expected, and less than they expected based on percent response from survey participants (n = 161).

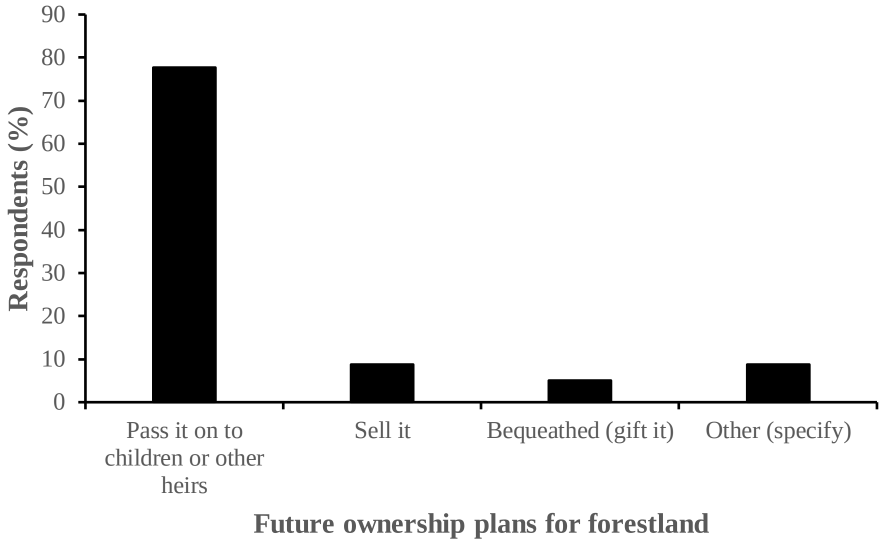

Figure 9: Future plans for ownership for forestland owned based on percent response of family forest landowners in the southern United States (n = 161).

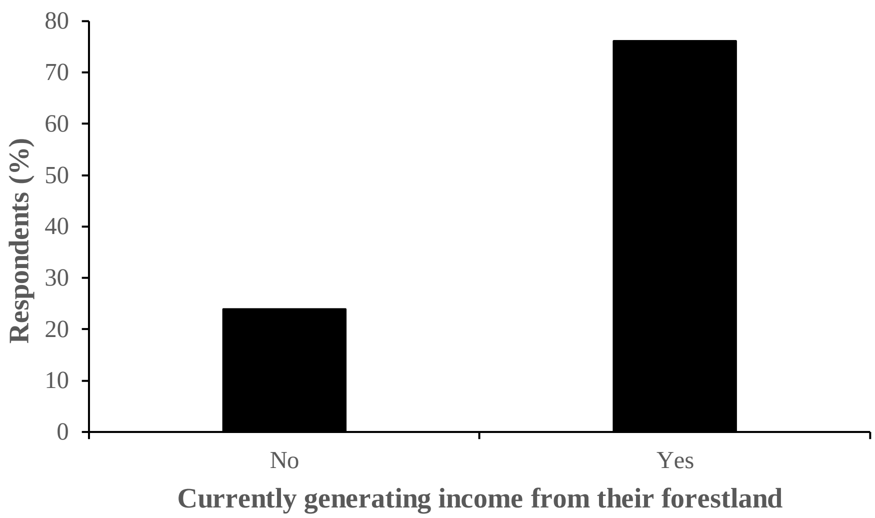

Figure 10: Proportion of family forest landowners in the southern United States that are currently generating income from their forestland and those who not currently generating income from their forestland based on percent response from survey participants (n = 162).

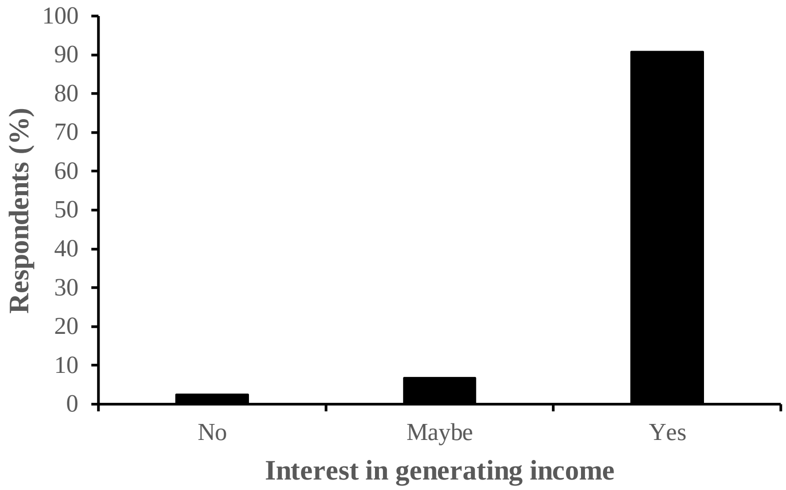

Figure 11: Proportion of family forest landowners in the southern United States that interested in generating income from their forestland, may or may not be interested in generating income from their forestland, and are not interested in generating income from their forestland based on percent response from survey participants (n = 162).

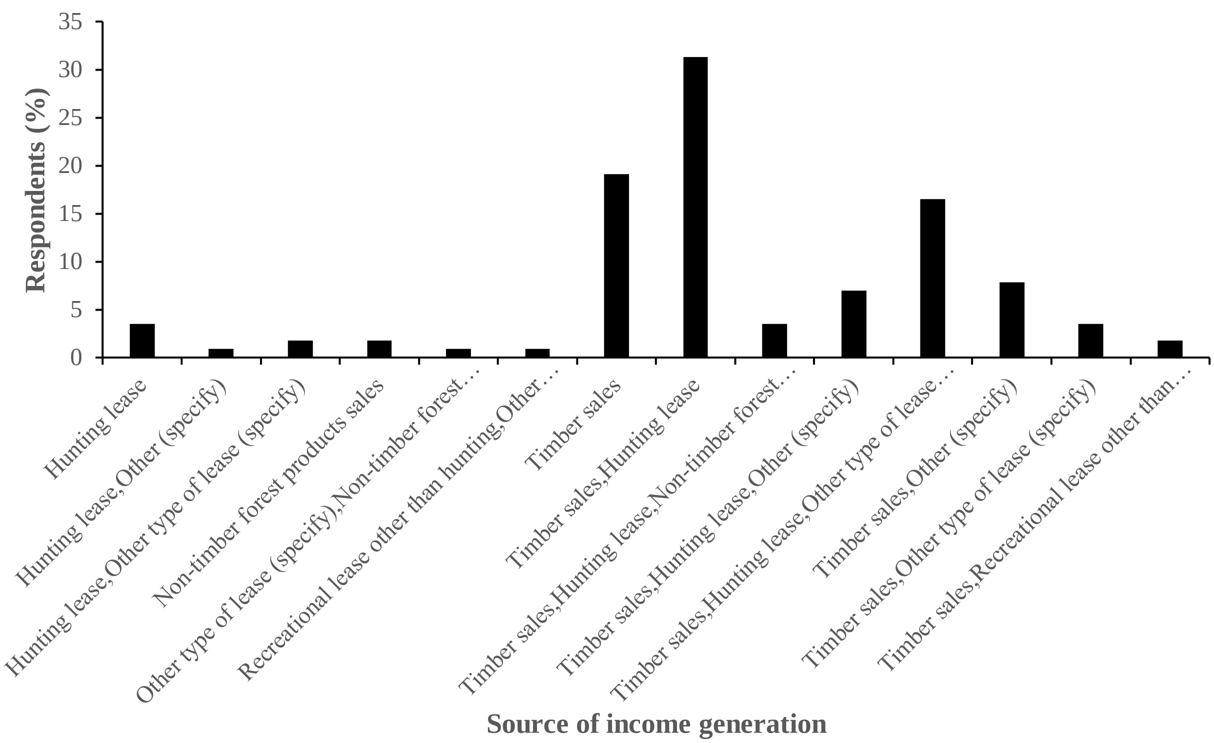

Figure 12: Source of income generation from forestland based on percent response of family forest landowners in the southern United States (n = 124).

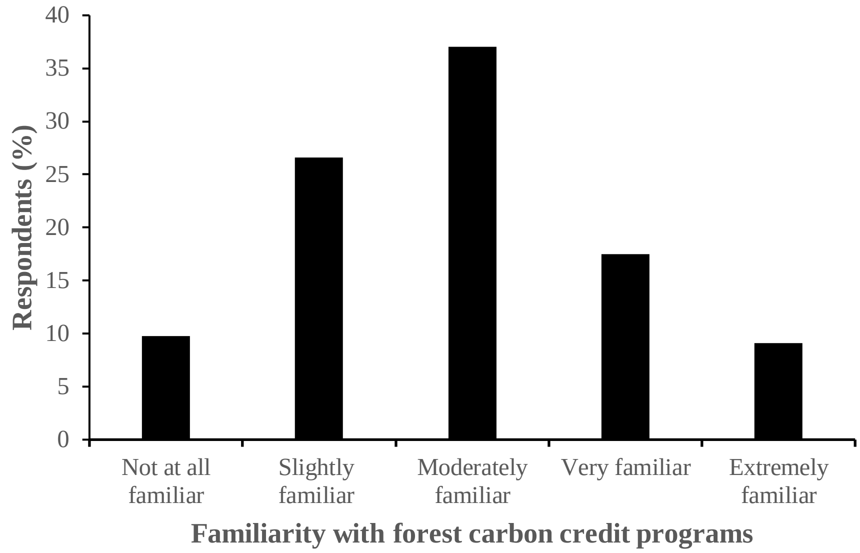

Figure 13: Level of familiarity with forest carbon credit programs based on percent response of family forest landowners in the southern United States (n = 143).

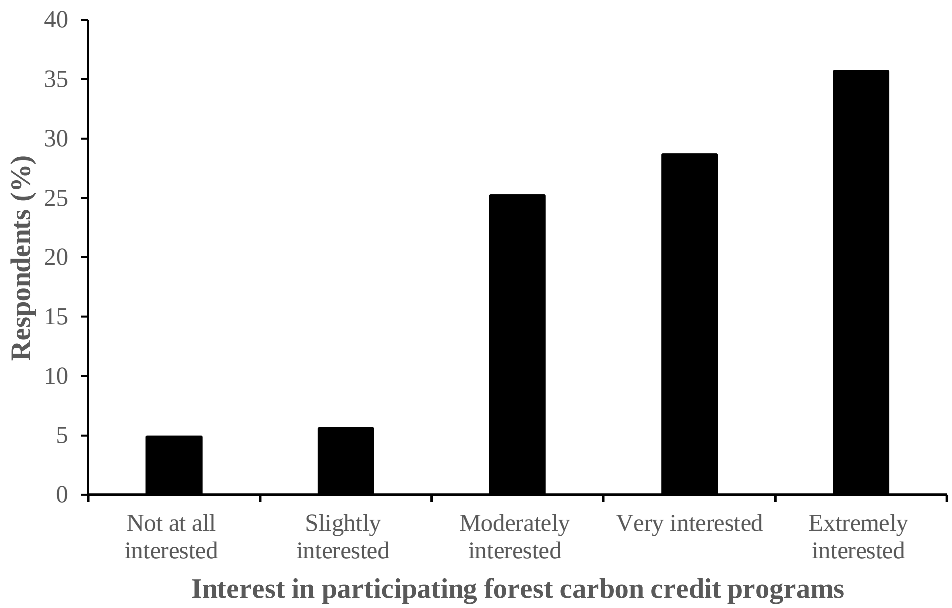

Figure 14: Interest in participating in forest carbon credit programs based on percent response by family forest landowners in the southern United States (n = 143).

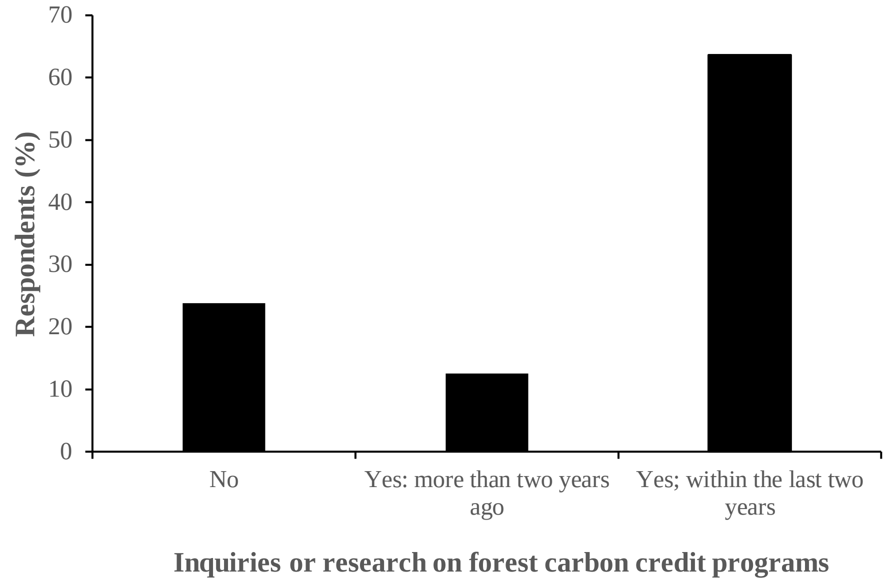

Figure 15: Classification of inquiry or research on carbon credit programs based on percent response by family forest landowners in the southern United States (n = 143).

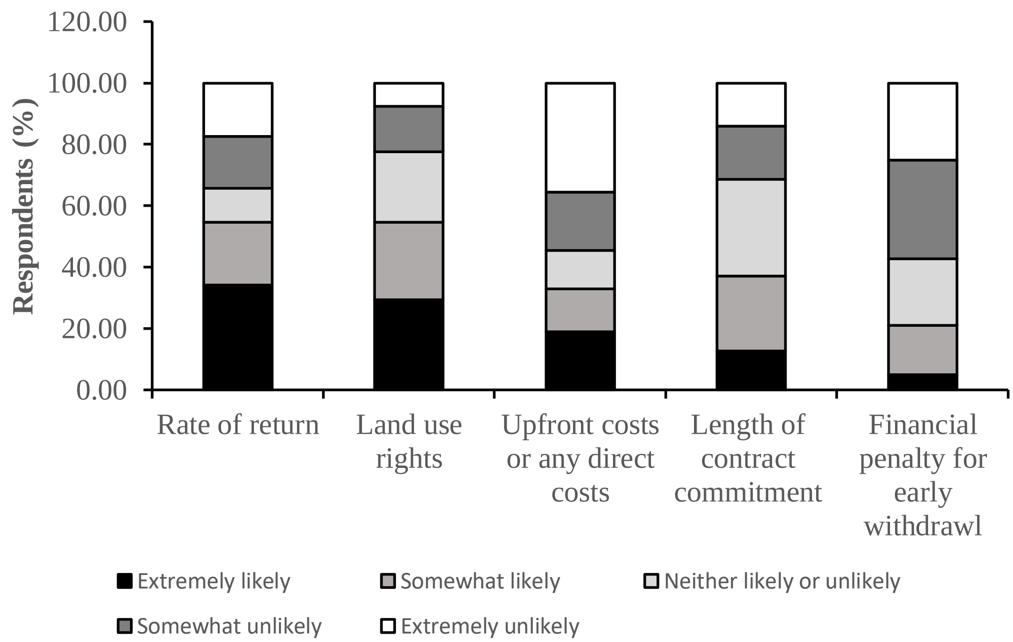

Figure 16: Likelihood of factors to prevent participation in forest carbon programs based on percent response of family forest landowners in the southern United States (n = 143).

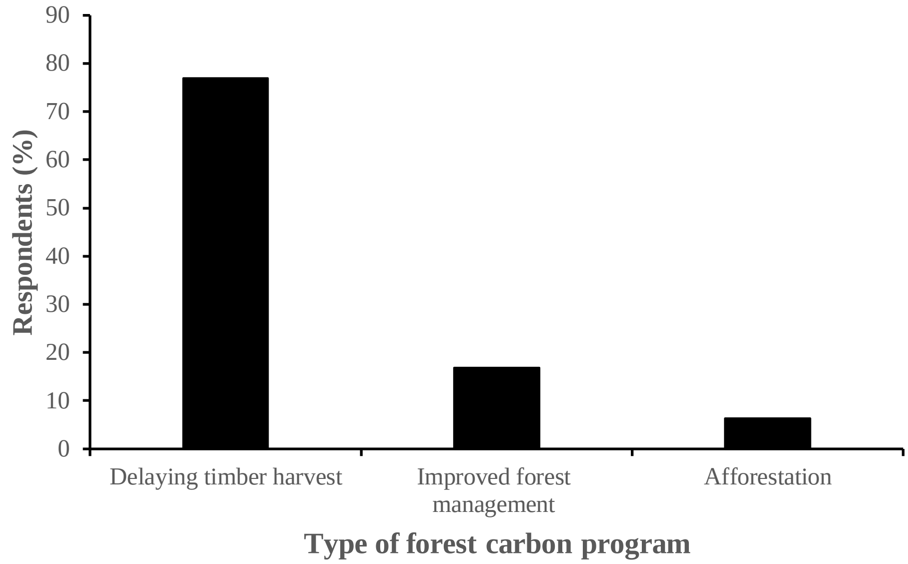

Figure 17: Proportion of family forest landowners that would be most likely to participate in any of the three different forest carbon programs based on percent response from survey participants (n = 143)

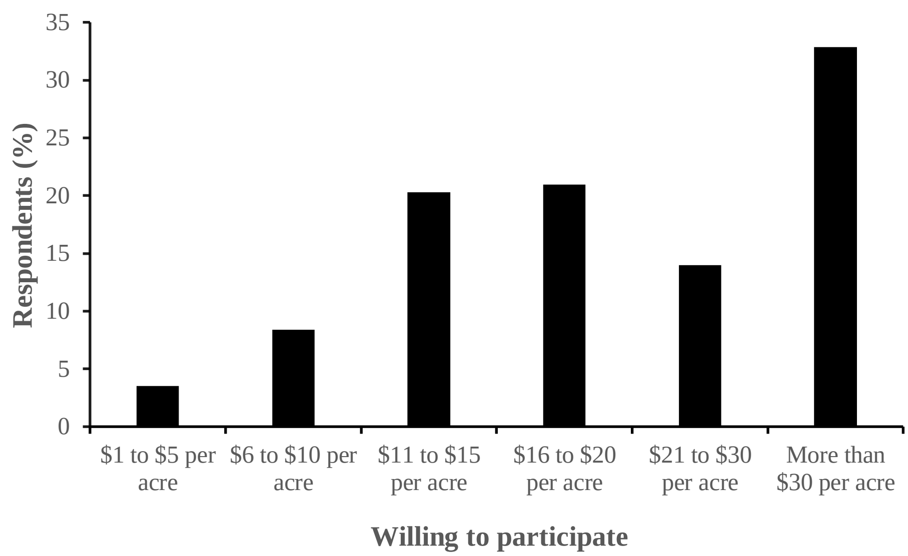

Figure 18: Price range per acre likely needed to be willing to participate in forest carbon credit programs if eligible based on percent response of family forest landowners in the southern United States (n = 143).

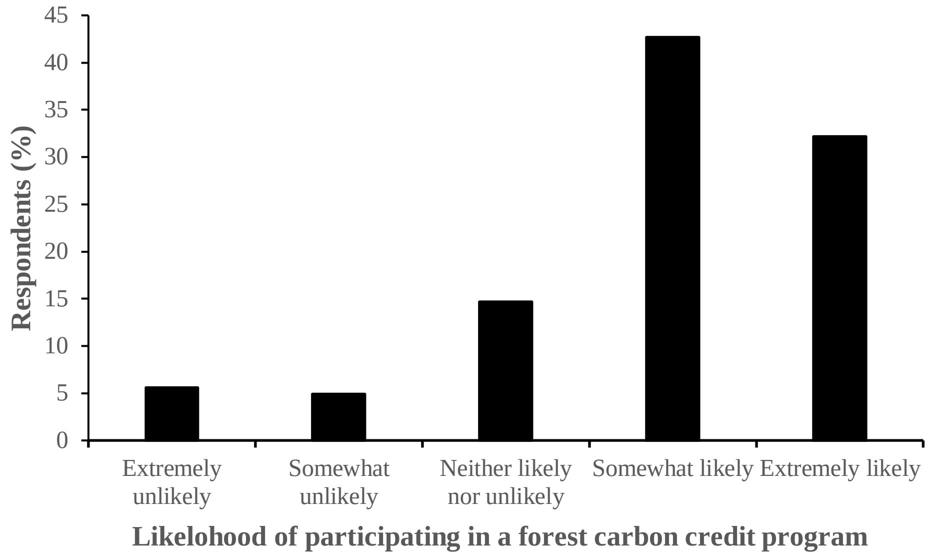

Figure 19: Likelihood of participating in a forest carbon credit program if eligible based on percent response of family forest landowners in the southern United States (n = 143).

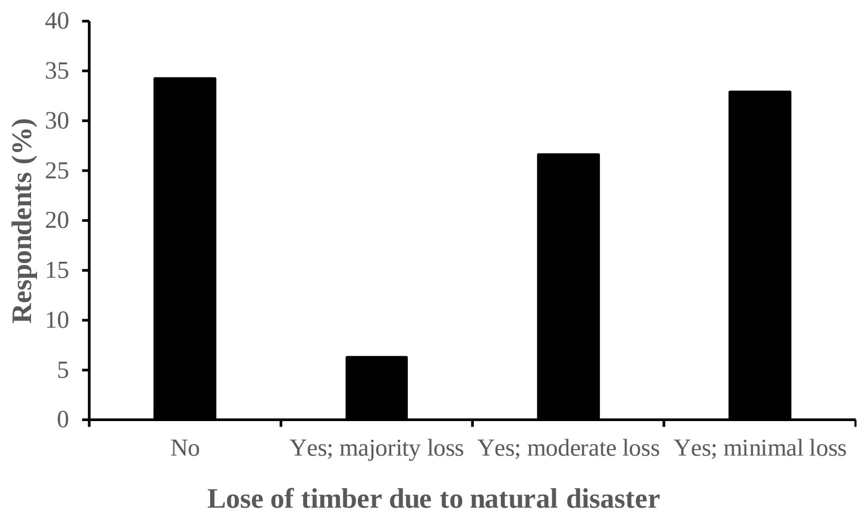

Figure 20: Loss of timber due to a natural disaster ranging from minimal loss, moderate loss, majority loss, or no loss of timber from owned forestland based on percent response of family forest landowners in the southern United States (n = 143).

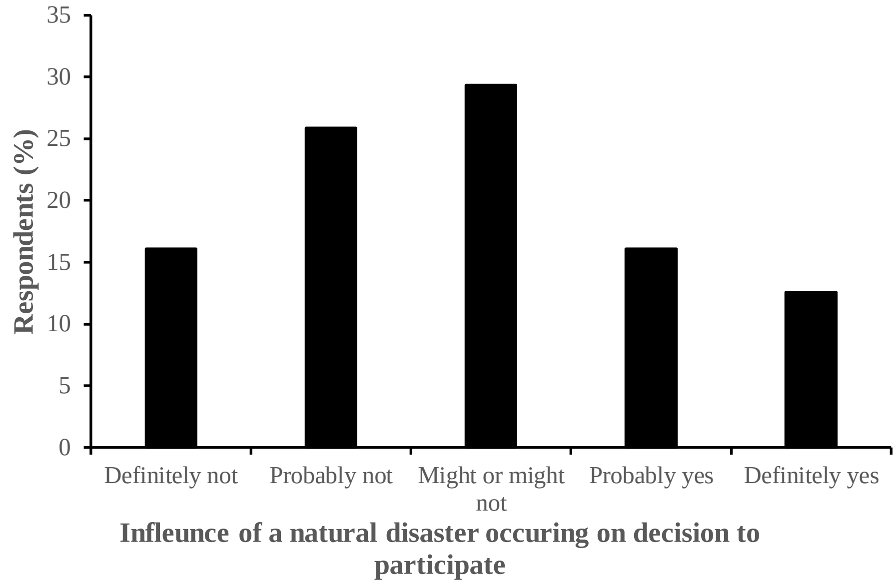

Figure 21: Likelihood of a timber a loss from a natural disaster occurring on the decision to participate in a forest carbon credit program if they would not get paid for carbon lost or would have to make a payment as a result based on percent response of family forest landowners in the southern United States (n = 143).

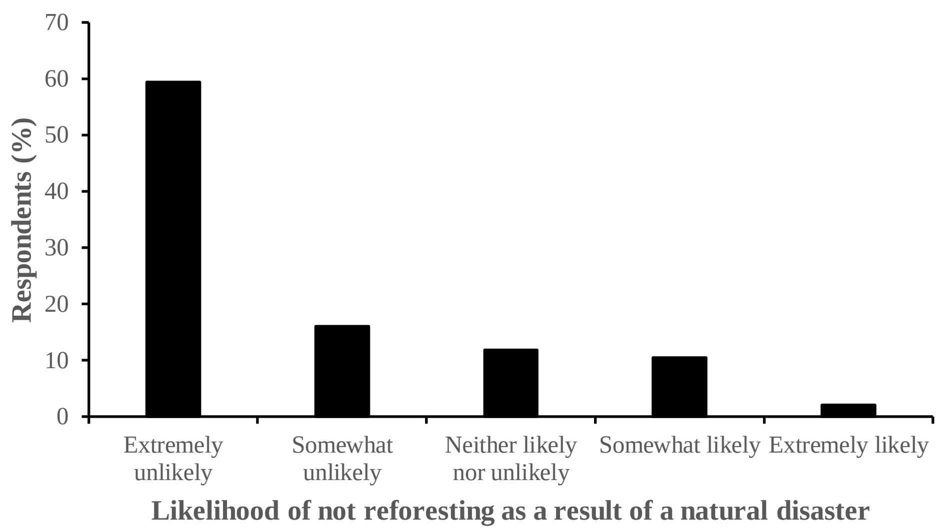

Figure 22: Likelihood of not reforesting but changing land use or selling the forestland if a significant loss of timber was encountered as a a result of natural disaster based on percent response of family forest landowners in the southern United States (n = 143).

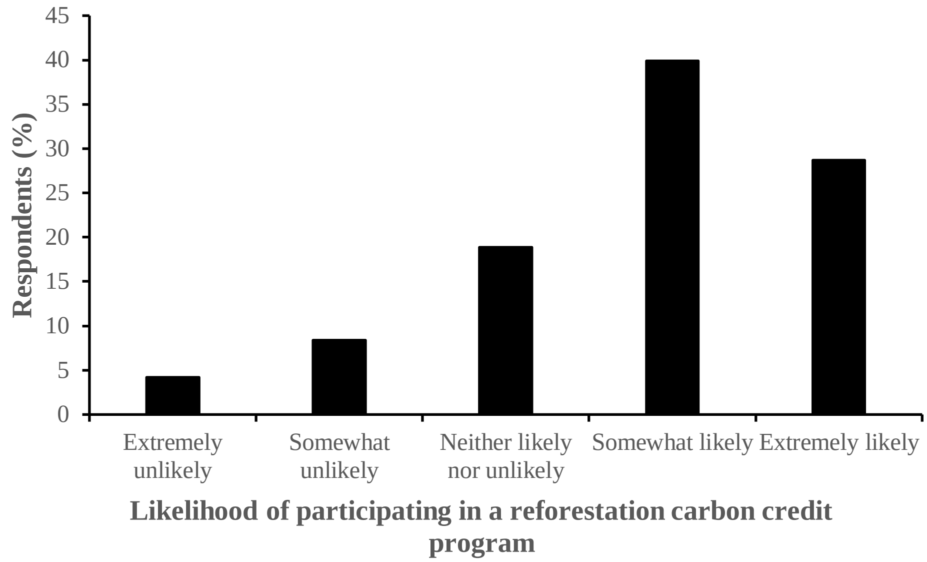

Figure 23: Likelihood of participating in a forest carbon credit program that pays for all or part of reforestation costs following a natural disaster as well as payments for carbon credits produced during the new rotation rather than change land use or sell forestland based on percent response of family forest landowners in the southern United States (n = 143).

Table 1: Mann-Whitney U test of differences in mean rankings between family forest landowners in the southern United States familiarity with forest carbon programs that are planning to harvest any trees from their forestland in the future.

Harvest	N	Mean rank	U	P
Have a plan	131	74.64		
Do not have a plan	12	43.20	440.5	0.000***
Total	143			
***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**				

Table 2: Mann-Whitney U test of differences in mean rankings between family forest landowners in the southern United States familiarity with forest carbon programs that are members of a forestry association or local forestry planning committee.

Member of a forestry association	N	Mean rank	U	P
Yes	109	78.37		
No	34	51.55	1158	0.000***
Total	143			
***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**				

Table 3: Mann-Whitney U test of differences in mean rankings between forest family landowners in the southern United States familiarity with forest carbon programs that have inquired about forest carbon programs.

Familiarity	N	Mean rank	U	P

Inquired	109	84.60		
Did not inquire	34	31.58	479	0.000***
Total	143			
***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**				

Table 4: Mann-Whitney U test of differences in mean rankings between family forest landowners in the southern United States interest in participating in a forest carbon program and that are members of a conservation organization.

Interest	N	Mean rank	U	P
Member	95	81.70		
Not a member	46	65.81	1692.5	0.000***
Total	141			
***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**				

Table 5: Mann-Whitney U test of differences in mean rankings between family forest landowners in the southern United States interest in participating in a forest carbon program and that have inquired about forest carbon program.

Interest	N	Mean rank	U	P
Inquired	109	76.47		
Did not inquire	34	53.77	1518.5	0.000***
Total	143			
***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**				

Table 6: Mann-Whitney U test of differences in mean rankings between family forest landowners in the southern United States familiarity with forest carbon programs and whether they generated income from their forestland or not.

Familiarity	N	Mean rank	U	P
Income	109	78.90		
No income	34	49.85	1100	0.00***
Total	143			
$*P \leq 0.05$, $**P \leq 0.01$, $*** P \leq 0.001$				

Table 7: Mann-Whitney U test for differences in mean rankings between family forest landowners in the southern United States forestland acreage ownership and whether they currently manage their forestland or not.

Acres owned	N	Mean rank	U	P
Currently manages	152	79.20		
Does not manage	3	17	45	0.00***
Total	155			
$*P \leq 0.05$, $**P \leq 0.01$, $*** P \leq 0.001$				

Table 8: Kruskal-Walli's test for differences in mean rankings between family forest landowners in the southern United States interest in participating in a forest carbon programs and that have shown interest to participate in three different types of forest carbon program.

Program type	N	Mean rank	Chi-square	P
Program 1	108	77.71		

Program 2	24	44.70	15.21	0.000***
Program 3	9	60.5		
Total	141			

***P ≤ 0.05, **P ≤ 0.01, *** P ≤ 0.001**

Table 9: Spearman Rho correlations of family forest landowners in the southern United States familiarity with and interest in forest carbon programs and the factors preventing them from participating in the program.

Comparison	**P**	**ρ**
Familiarity vs. Likelihood	0.0004	0.295
Familiarity vs. Land use rights/limitations	0.0005	0.286
Familiarity vs. Length of contract commitment	0.02	-0.195
Familiarity vs Amount of revenue they could earn	0.03	0.184

Table 10: Spearman Rho correlations of family forest landowners in the southern United States familiarity with and interest in forest carbon programs and the factors likely to impact their decision to participate in the program.

Comparison	**P**	**ρ**
Likelihood vs. Price per acre needed	0.0009	-0.276
Likelihood vs. Length of the contract commitment	0.04	0.174
Likelihood vs. Land use rights/Limitations	0.005	0.236

2.4 Discussion

Assessment of Family Forest Landowners Characteristics, Forest Management Practices, and Income Generation

The results of the survey provide insight into the characteristics, management practices, and income generation of FFLs in the southern United States. Many of the FFLs that participated in the survey were members associations, particularly, the Forest Landowner Association (FLA) and Alabama Forest Owners Association (AFOA). Overall, the study found that the majority of respondents were white, male, over 65 years of age, well-educated, and had a household income above $100,000. This demographic profile is consistent with previous studies on FFLs, which suggest that this group tends to be older, more affluent, and more educated than the general population (Butler and Leatherby, 2004; Kaetzel, 2011; Majumdar et al, 2009).

The study also found that the majority of FFLs owned between 501 to 1000 acres of forestland. This was larger than what has been reported in the literature previously on FFLs, where the majority of landowners reportedly held 10-50 acres (Butler et al., 2020).
The difference is likely driven by the source of distributing the survey. Both associations who assisted in distributing this survey have over 2,000 member who on average more engaged, own more forestland acres and are managing and harvesting timber. For example, FLA, which is a national organization, helps in advocating for the rights and interests of private forest landowners in the United States. While the objective of AFOA is to represent the interests of the forest owner and to keep its members up to date on all issues pertaining to forest ownership.

The primary reasons cited for owning forestland was timber production (Wear and Greis 2002; Zhang and Nagubadi 2005; Kaetzel et al, 2012; Singh, 2020) followed by multiple reasons

(Kaetzel et al, 2012; Singh et al., 2021), land investment, and passing it on to heirs. This indicates that the majority of FFLs who participated in our survey view their forestland as an economic asset rather than simply a recreational or conservation asset. This finding is consistent with previous research that suggests that FFLs are motivated by economic incentives when it comes to forest management (Miljand et al., 2021). This result is contrary to what was found by Butler and Leatheberry 2004, and Khanal et al., 2017 with recreational goals cited as primary reasons for owning forestland. Further, the fact that planted pine was the most common forest type owned by FFLs in our survey supports these findings in regard to timber production. It has also been documented from previous survey's that planted pine was one of the most common forest types owned by forest landowners surveyed (Godar Chhetri et al., 2022; Willis et al., 2019).

The majority of FFLs reported that they currently manage their forestland, with almost 70% having a management plan. These results are similar to findings by Singh (2020) where approximately 70% of respondents indicated they currently manage their forestland. Further, Khanal et al., (2020) found that FFLs in the southern United States having relatively larger tracts of land, actively managing forestland, and having a management plan are more likely to be members of forest owners association, which supports our findings as our survey was distributed through landowner association groups which commonly have members who are actively managing their forestland.

Regarding income generation from forestland, the study found that the majority of respondents were generating income from their forestland, and almost all respondents expressed interest in income generation. These findings are consistent with previous literatures on FFLs, in which majority generated income (Butler et al., 2016; Singh 2020). Timber sales were the most common source of income, followed by hunting leases and non-timber forest products sales. These results are in accordance with Kaetzel et al; (2012) and Singh (2020), where timber is the primary source of income generation, followed by hunting lease income. Previous studies mentioned that larger forestland tract, forest type and location influence income generation (Tran et al., 2020). Majority of the FFLs who own larger acreages are actively managing forestlands for timber production and are open to considering other revenue sources from their forestland (Tran et al., 2020). Since our survey found that majority of the FFLs actively managing forestlands, placed high importance on such subjects. This suggests that FFLs are actively seeking to generate revenue from their forestland and are exploring various income generation options.

The survey examined the knowledge and participation of FFLs in forest carbon programs and found that while the majority of respondents were familiar with forest carbon programs, only a small percentage were currently participating in such programs. These findings are consistent with previous research on forest landowner interest in selling forest carbon credits (Kilgore et al, 2008). Kilgore et al., (2008) in his findings reported that landowner's familiarity with the forest carbon programs is an important factor of their probability of participation.

Furthermore, the study found that the more familiar FFLs are with forest carbon programs, the more likely they are to participate. Familiarity with forest carbon programs was significantly associated with knowledge of land use rights/limitations and the length of contract commitment as potential barriers to participation. These findings align with studies on barriers to Massachusetts forest landowners' participation in forest carbon programs (Markowski-Lindsay et al, 2011). Further, those that are more familiar tend to view land use rights/limitations and amount of revenue they could earn by participating are likely to influence their decisions to participate the most. These results are in consistent with literature on Khanal et al., 2016. The more familiar they are with forest carbon programs, the less likely the length of contract commitment tends to be a barrier for participation. However, without regard to familiarity, those respondents who selected they would likely participate in a forest carbon program if eligible also viewed length of contract as more of an influence on their decision to participate as would land use rights/limitations. In terms of monetary expectations and participating in forest carbon programs, those respondents who would need a grater dollar per value to be willing to participate tend to be less likely to participate if eligible. Thus, FFLs may be hesitant to participate in forest carbon programs due to concerns about the impact on their land use rights and the long-term commitments required by the programs. This highlights the need to address these concerns and provide FFLs with clear information about the terms and conditions of the program. Another important finding of the study is that FFLs who were familiar with forest carbon programs significantly favored forest carbon programs that focus on maximizing carbon and pay for carbon gained by delaying/preventing timber harvest during the contract period, with contract commitments ranging from 1-year to 100+ years depending on the program. These findings are consistent with previous literatures (Kilgore et al., 2008; Diaz et al., 2009) indicating FFLs low interest in afforestation/reforestation projects. FFLs who are members of conservation programs also shown significant importance in participation (Floress et al., 2019).

FFLs interest in forest carbon programs was linked to the length of the contract commitment and the potential revenue generation. These results are in consistent with literature reported in previous research on forest landowners' interest in selling forest carbon credits in the Lake States (Miller et al., 2014). This suggests that FFLs are more likely to participate in forest carbon programs if offered financial incentives and short-term commitments. Thus, highlights the importance of designing forest carbon programs that provide attractive financial incentives and short-term commitments to encourage FFLs to participate. This suggests that while FFLs are aware of the potential benefits of forest carbon credits, more education and outreach are needed to increase participation in these programs.

2.5 Conclusion

The results of this study provide important insights into the factors that influence FFLs familiarity with and interest in forest carbon programs, as well as their participation in such programs. The findings suggest that outreach and education programs are needed to increase awareness of forest carbon programs among FFLs, and that financial incentives and short commitments are key factors in encouraging FFLs to participate in forest carbon programs. Knowledge and understanding of forest carbon programs have significant influence on willingness of FFLs to participate and barriers to participation. This highlights the importance of educating landowners on such programs. There is also an opportunity for landowners who own planted pine forest types and are actively managing with timber production objectives to participate in forest carbon programs if eligible as the interests from these landowners is apparent.

The study highlights the importance of designing forest carbon programs that address the concerns of FFLs and provide clear information about the terms and conditions of the programs. These findings can be used to inform the development of effective forest carbon programs that can help mitigate climate change and provide benefits to FFLs. Additionally, more research, refined methodology of carbon tracking, program methodology, education and outreach are necessary to increase FFLs who several hundred acres of forestland to participation in these forest carbon programs, despite their awareness of the potential benefits of forest carbon credits.

Chapter 3: Non – destructive method for predicting the carbon content in wood samples using Fourier-Transform Near-Infrared Spectroscopy (NIRS)

3.1 Introduction

Nowadays, forests are increasingly viewed by forest landowners, policy makers, and forest-based industries in the United States as a valuable source of renewable and sustainable natural resources for building materials, fibers, biofuels, and other renewable materials that can help mitigate climate change (Bergman et al., 2014). Forest-based industries and forest landowners have a plethora of reasons for managing their forestlands to produce wood products, including timber, wood composites, pulpwood/paper, firewood/ biofuel, in-land investments, and, more recently, emerging carbon market programs (Floress et al., 2019). They indicate that timber production is an important source of income generation (Hodges et al., 2019). As such, it is important to use proper tools to quantify and compare the benefits of these products.

The need to enhance biomass/timber production to generate additional revenue promotes forest landowners and industries to utilize cutting-edge forestry technologies for innovative applications. Near-infrared reflectance spectroscopy (NIRS) has emerged as a highly effective technique for analyzing the chemical properties of the analyzed samples. The technique has been widely reported to be non-invasive, rapid, cost-efficient, requires minimal sample preparation, and no addition of chemicals (Pasquini, 2018).

Given that the chemical properties of a sample are often closely linked to its physical and morphological characteristics, NIRS has shown great potential for estimating a wide range of properties. These may include, but are not limited to, moisture content, density, porosity, practical size, structural properties such as stiffness and elasticity. The ability to rapidly and accurately assess these properties using a single analytical technique makes NIRS an attractive option for a wide range of applications. For example, NIRS can be used to monitor the purity and quality of active ingredients of formulations utilized in the pharmaceutical industry (Razuc, 2019). The pulp and paper industry have also been using NIRS to monitor several properties during the fabrication process (Liang et al., 2020). In the forestry industry, the analytical technique can be utilized to study the chemical composition of wood, estimate moisture content and density, evaluate wood anatomical features and mechanical properties, and monitor chemical changes such as wood decay (Tsuchikawa & Kobori, 2015). However, little research has been reported regarding estimation of carbon content in the wood.

The applications of NIRS date back to the 1880s by Abney and Festing (Verena, 2017), but in the last two decades, NIRS has made remarkable progress for evaluation of agricultural products, foods, polymers, textiles, pharmaceuticals, petrochemicals, and wood products in the forestry sector (Ciurczak et al., 2021). In wood science and technology, Birkett and Gambino investigated NIRS to evaluate Kappa members in the pulp and paper industry (Yang et al., 2015). Since the review of the recent application of NIRS to wood science and technology, the methodology has been utilized in several research applications, and the activity of NIR in wood research has increased (Tsuchikawa, 2007; Tsuchikawa & Schwanninger, 2013; Tsuchikawa & Kobori, 2015). Previous studies reported that NIRS could be used to detect the physical, chemical, and anatomical properties of wood. NIR has been widely used to analyze the physical and chemical characteristics of wood in forest breeding programs. For example, Acquah et al. used NIRS to estimate basic density and mechanical properties of elite loblolly pine families (Acquah et al., 2018). Interestingly, wood species identification could also be possible using NIRS (Lazarescu et al., 2017; Hwang et al., 2016). Yang and Lu demonstrated the feasibility of using NIRS to identify wood species (Yang et al., 2015). NIRS has also been widely used in wood quality quantitative analysis. Schimleck et al. 1999 reviewed applications of NIRS as a rapid, inexpensive method for assessing the pulpwood quality of a Eucalyptus plantation (Eucalyptus globulus and Eucalyptus nitens) (Schimleck et al., 2000). Sandak et al. (2016) believe that rapid and reliable assessments are needed to identify the quality of the tree, timber, and wood products at all stages of production and processing. Hence, he built the NIR predictive model to assess the quality of trees, wood, and its derived products. So et al. reviewed applications of NIRS as an online monitoring tool for manufacturing process control in the solid wood and wood composites industries and tree improvement/ wood quality assessment. The applications of NIRS have not only been restricted to physical or chemical properties but have also been widely used in estimating anatomical properties. Leblon et al. (2013) proposed that it's significant to monitor wood moisture content and density to optimize the manufacturing processes in the current forest products industry, involving various procedures such as sorting, moisture content monitoring, pulp yield assessment, scaling, and grading of forest products. Recent publications indicate that NIRS can also estimate wood properties like density (Schimleck, 1999; Thygesen, 1994). Vidholdová et al. (2019) tested the effect of various heat treatment intensities on chemical changes of wood polymers in pine wood. All the results from the above research indicate that NIRS can be used as a non–invasive, rapid, and cost-efficient technique.

As mentioned in Chapter 1 of this thesis, FFLs can voluntarily participate in forest carbon programs taking advantage of the capacity of their forest to help reduce the CO_2 levels in the atmosphere and gain supplemental income from their forestland. Forests have great potential for mitigating climate change through appropriate conservation and management. For a forest landowner to actively enroll in forest carbon programs, the biomass on their forestland must be evaluated periodically. Still, there are limited reliable and easy methods of estimating biomass in the literature.

Carbon accounting requires a comprehensive estimate of biomass across all forestlands. Youkhana et al., (2017) used *Allometric models* for predicting aboveground biomass and carbon stock of tropical perennial C4 Grasses in Hawaii. Allometric models are based on relationships between biomass and morphological traits such as basal diameter, height, canopy diameter, and canopy volume (Martin et al., 2013; Cornet et al.,2015). Another traditional way to estimate biomass is using the guidelines provided by the Inter-Governmental Panel on Climate Change (IPCC), a scientific body established by the United Nations in 1988. According to IPCC, above-ground biomass can be estimated using allometric equations specific to the tree species or forest type and tree measurements such as diameter at breast height (DBH), tree height, and wood density. On the other hand, below-ground biomass is estimated using a root-to-shoot ration. The total carbon stored in each tree can be calculated based on the assumption that carbon makes up approximately 50% of the dry weight of woody tissues. (MacDicken, K. G. (1997). However, as will be demonstrated by the results presented in this thesis, the carbon content may vary significantly among different components. Furthermore, it has been established that distinct tree species exhibit varying carbon content values across various geographical locations and seasons (Zang et al., 2009; Yu et al., 2012). Some possible variations of these changes could include differences in environmental conditions such as temperature, humidity, and soil quality. Additionally, genetic factors and tree growth rates may also contribute to the observed differences. These finding have important implications for our understanding of carbon cycling and storage in forest ecosystems and highlight the need for further research to better estimate the carbon content and gain knowledge on the different patterns behind the variation.

Light Detection and Ranging (Lidar) remote sensing has emerged as a powerful tool for estimating the carbon content in trees (Stovall et al., 2017). Lidar uses laser pulses to accurately measure the height, diameter, and structure of individual trees and entire forests, depending on the platform (e.g., terrestrial, airborne, and spaceborne). Therefore, Lidar technologies can be used for carbon content estimation. Moreover, lidar data acquired from both aircraft and satellites may be used to derive information over large areas, providing several advantages over traditional field-based methods. For example, traditional methods are often labor-intensive, time-consuming, and less accurate in estimating tree volume. The information provided by Lidar is crucial for understanding the dynamics of forest ecosystems and developing effective forest management strategies.

Remotely sensed data are used for above and below-ground biomass estimation. These data can be especially useful in verifying ground measurements and observations (ground truth), classifying vegetation cover, and generating a vegetation-type map.

The chemical composition of wood samples is determined by Elemental analysis (Yargicoglu et al., 2015). An elemental analyzer is an instrument that determines the amount (typically a weight percent) of an element in a sample. The primary elements measured by this device are Carbon, Hydrogen, Nitrogen, and Sulphur. NIRS can also predict elemental composition in the sample; unlike Elemental analysis, it offers a practical alternative to the time–consuming chromatographic techniques and wet chemical methods.

Despite previous efforts, an accurate and simple way for measuring or estimating the carbon content in trees has yet to be developed. To bridge this research gap, we employed NIRS coupled with a chemometric model, based on Principal Components Regression (PCR+) analysis. Successful development of the chemometrics model for predicting carbon could make the life of landowners much easier in estimating carbon/biomass on their forestlands by themselves with the help of portable NIRS.

3.2 Methods

3.2.1 Study area

United States Department of Agriculture (USDA) Forest Service Research and Development implemented a nationwide study to collect tree data from various species. The study aims to develop nationally consistent volume, biomass, and carbon models for each species. The Forest Inventory and Analysis (FIA) program funded and coordinated the research. Tree data was collected from 8 states and 35 species and analyzed by private, university, federal, state, and non-governmental organizations. As part of the USDA project, we collected and analyzed 60 samples of Loblolly Pine (*Pinus Taeda*) species. Field data was collected from felled trees including stem, taper, tree height, and tree disk samples from multiple locations in each tree (Figure 24). Tree disk samples were processed to characterize various physical, chemical, and thermochemical properties by species.

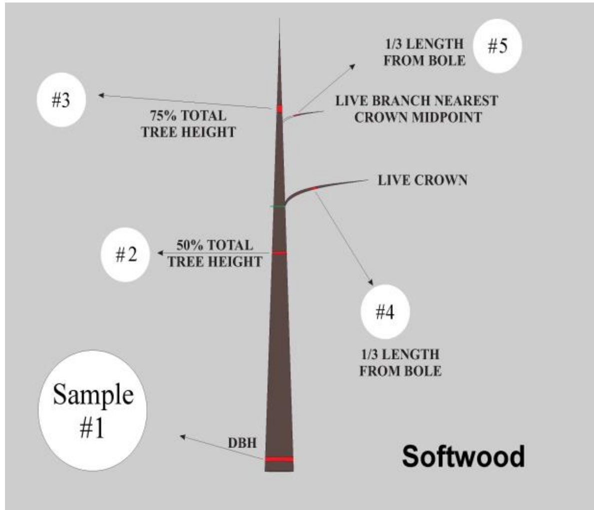

Figure 24: Sample collection scheme for softwood species.

3.2.2 Sample Preparation

Tree disk samples collected for the study were shipped to researchers at the Southern Research Station for processing. The samples from each tree were photographed and documented. The pith was removed, and the disks were cut into small portions and then ground using a hammer mill and a knife mill (Figure 25). Two particle sizes, 1 mm, and 4 mm were produced for the various laboratory analysis methods used to characterize the wood properties. A Thermo-Scientific Flash 2000 CHNS-O elemental analyzer was used to determine the carbon content of each sample. The remaining ground material from each sample was used to determine the carbon content using NIR chemometric model (Figure 25).

Figure 25: Picture of the Loblolly pine tree disk (on the left) and a ground sample of Loblolly pine species (on the right)

3.2.3 Carbon Content based on Chemical Analysis

Elemental analysis (C, H, and N) of pine samples were performed in a Flash 2000 Elemental analyzer (Thermo Fisher Scientific, Bremen, Germany) operating with the dynamic flash combustion of the samples. The aspartic acid weight used as a standard was 3.00-4.00 mg, and the weight of the unknown samples. All samples were weighed in aluminum tin capsules and dropped into the combustion reactor (left furnace) from the Thermo Scientific™ MAS Plus Autosampler. The samples were combusted in the reactor initially set at 950°C in oxygen and helium (carrier gas). The elemental gases were carried out into the gas chromatography column set at 75 °C and detected in a highly sensitive thermal conductivity detector (TCD) set at 1000 µV. The collected data were analyzed using Eager Xperience for flash elemental analyzers software (EA111X F/W Ver. 1.12, EA111x OCX Ver.01.02). All samples were analyzed, at least in triplicate and the results were reported as averaged values in percent by weight.

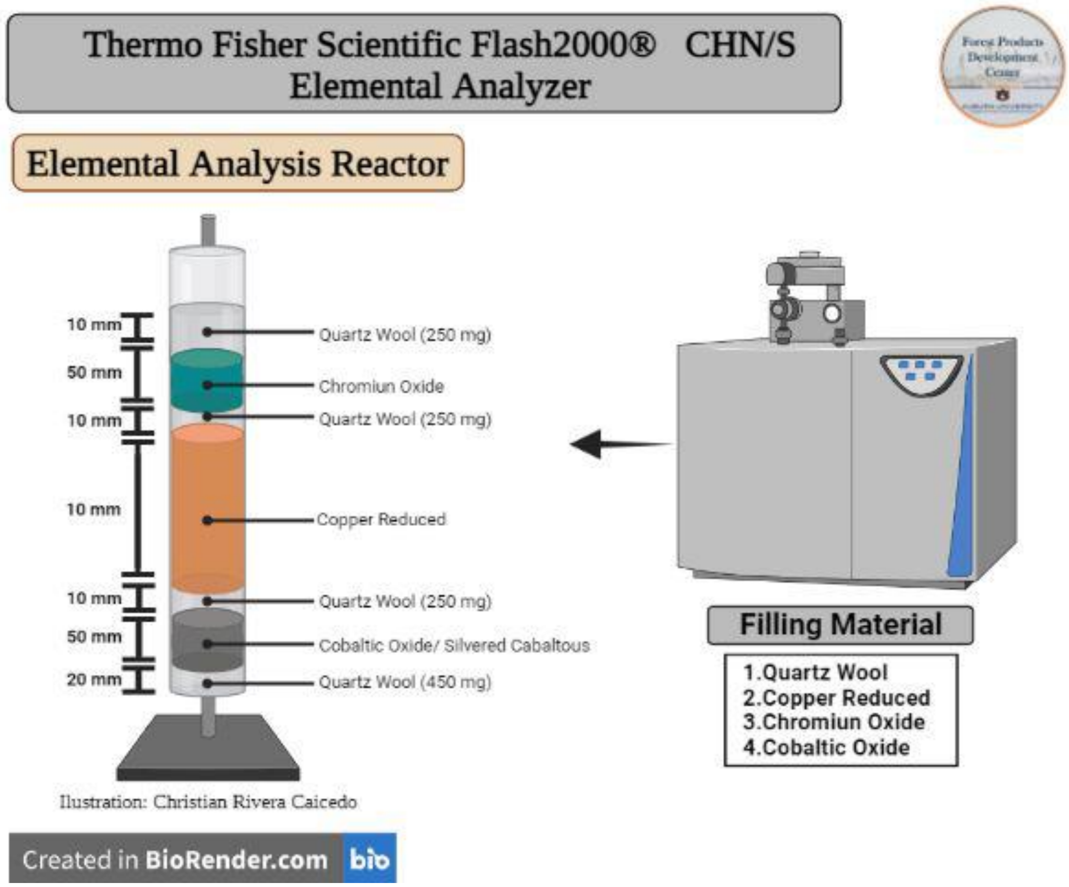

Figure 26: Illustration of the Elemental Analyzer and the configuration of the reactor

Spectra collection by NIR (Credits: Christian rivera caicedo)

The chemical composition of 60 Loblolly pine samples was analyzed using a Perkin Elmer Spectrum 400 FT-IR/FT-NIR Spectrophotometer (Llantrisan, UK). NIR region ranges between 10000-4000 cm^{-1}. The spectra were collected using an ATR accessory with ZnSe-Diamond crystal. The measurements were performed in the wavelength range from 4000-650 cm$^{-1,}$ with 4 cm^{-1} resolution and data interval of 1cm^{-1}. A total of 64 scans were collected for every measurement by using a rotatory NIR accessory. Subsequently, an evaluation of pine samples was carried out, in the specific area of 1800-1100 cm^{-1} with 2 cm^{-1} resolution and data interval of 1 cm^{-1} were collected 64 scans for every measurement.

Figure 27: Perkin Elmer Spectrum 400 FT-IR/FT-NIR Spectrophotometer (on the left) and Rotator (on the right)

3.2.4 Pre-Processing of Spectroscopic Data, Model Development, and Evaluation

NIR Spectroscopy is a valuable tool for analyzing the chemical and physical properties of materials. However, raw NIR spectra are often subject to various types of interference and noise, which can affect the accuracy and reliability of the analysis. To address these issues, pre-processing techniques are commonly applied to NIR spectra to remove systematic variation in the data, improve signal-to-noise ratio, and increase the accuracy and reliability of the resulting model before further analysis. The most widely used pre-processing techniques in NIR Spectroscopy are Multiplicative Scatter Correlation (MSC), Inverse MSC, Extended MSC (EMSC), 1D, 2D, Baseline correction, Extended Inverse MSC, de-trending, Standard Normal Variate (SNV), OSC, and normalization. In our study, baseline correction pre-processing method was used to eliminate baseline and background interference, increase spectral resolution, separate overlapping peaks, and adjust the spectral offset by aligning the data to the minimum point in the data. It is crucial to note that only some preprocessing methods are appropriate for some models. The optimal pre-processing method for a particular model depends on the specific characteristics of the data and the goals of the model.

The study involves building a chemometrics model to predict the carbon in tree species. Chemometrics is an interdisciplinary field that applies mathematical and statistical methods to chemical data in order to extract useful information and insights. It involves using techniques such as multivariate analysis, experimental design, pattern recognition, and calibration to analyze chemical data and solve chemical problems. Chemometrics has applications in various fields, including analytical chemistry, biochemistry, environmental chemistry, and materials science. It is an essential tool for interpreting complex chemical data and has contributed significantly to developing new analytical methods.

In this study, we used Principal Component Analysis (PCA), one of the most common methods used in chemometrics to deal with a large amount of near-infrared spectral information, commonly used in Vis/NIR spectral analysis. The PCA model helps associate the independent variable (Specified Carbon) with the dependent carbon (Estimated Carbon) and the data was split into a calibration set and a validation set using the 2:1 SPXY algorithm. We then performed Principal Component Regression (PCR+) and Partial Least Square (PLS) regression analysis to model the data, optimizing the number of latent variables with a five-fold cross-validation procedure. We set the maximum number of principal components to 10 and tested the model for each number of components from 1 to 10. We chose the optimal number of components based on the lowest root mean square error of cross-validation (RMSECV). Finally, we re-calibrated the model with the optimal number of components and validated it, calculating the R2 and RMSE values.

We used PerkinElmer Spectrum IR Quant software version: 10.6.2.1159 to obtain the results. Spectrum Quant is a quantitative software system used to determine the quantities of components in a mixture by analyzing its TR spectrum. This is done by using different algorithms based on the nature of the sample being analyzed.

3.3 Results

Chemical composition Analysis

In the present study, we evaluated the potential use of NIRS to predict the carbon content of tree species. As mentioned earlier, we performed elemental analysis using ThermoFisher 2000-Flash elemental analyzer.

The elemental composition obtained for each sample is presented in Table 12.

Table 11: Elemental composition and standard deviation of 60 Loblolly pine samples measured using ThermoFisher 2000-Flash elemental analyzer.

Sample ID	Disk group ID	C		N		H	
		(%)	(σ)	(%)	(σ)	(%)	(σ)
131OK104621202	2	48.54	0.61	1.44	0.01	6.24	0.07
131OK104621302	2	48.42	0.42	1.69	0.04	6.03	0.12
131OK1047170302	2	48.64	0.23	0.49	0.05	6.43	0.14
131OK104717602	2	48.79	0.61	0.46	0.04	6.41	0.06
131OK105511102	2	47.31	0.03	1.52	0.05	6.30	0.28
131OK105511202	2	48.00	0.03	1.54	0.04	6.32	0.02
131OK20263402	2	48.68	0.44	0.76	0.08	6.40	0.06
131OK20263602	2	49.10	0.22	0.75	0.03	6.38	0.12
131OK203410502	2	46.83	0.48	1.73	0.06	6.22	0.54
131OK20501302	2	46.08	0.42	1.72	0.09	6.21	0.05
131OK20501402	2	46.12	0.19	1.69	0.05	6.13	0.03
131OK20526102	2	47.08	0.32	1.72	0.04	6.12	0.12
131OK20526202	2	46.67	0.48	1.49	0.13	6.09	0.11
131OK20526302	2	46.61	0.59	1.49	0.14	6.18	0.09
131OK20526702	2	47.04	0.39	1.55	0.09	6.18	0.04
131OK20526802	2	45.78	0.31	1.43	0.08	6.03	0.02
131OK20526902	2	46.62	0.25	1.48	0.09	6.09	0.03
131OK20541102	2	46.93	0.55	1.43	0.07	6.05	0.08
131OK20541202	2	46.49	1.87	1.52	0.07	6.19	0.17
131OK20541302	2	46.44	0.21	1.55	0.07	5.30	1.48
131OK20541402	2	46.92	0.44	1.58	0.13	6.08	0.02
131OK20541502	2	46.60	0.36	1.52	0.08	6.10	0.06
131OK20559402	2	47.17	0.23	1.51	0.06	6.08	0.07
131OK20559502	2	46.62	0.10	1.50	0.04	6.12	0.06
131OK20559602	2	47.85	2.80	0.62	0.04	6.11	0.42
131OK20559802	2	47.38	0.06	0.60	0.00	6.01	0.08
131OK20559902	2	48.14	0.23	0.84	0.02	6.19	0.08
131OK20622102	2	47.39	0.08	0.81	0.02	6.14	0.03
131OK20622202	2	48.34	0.27	0.87	0.01	6.11	0.14
131OK20622302	2	47.62	0.31	0.87	0.02	6.05	0.12
131OK20622502	2	47.47	0.20	0.87	0.03	6.09	0.04
131OK104621204	4	46.75	1.13	1.46	0.16	6.27	0.20
131OK104621304	4	47.86	2.41	1.58	0.05	6.46	0.37
131OK104621604	4	46.72	0.35	1.61	0.08	6.26	0.09
131OK104717104	4	46.06	0.51	1.42	0.10	6.21	0.06
131OK104717204	4	46.30	0.51	1.46	0.04	6.25	0.06
131OK104717304	4	45.98	0.58	1.47	0.13	6.18	0.13
131OK203410404	4	50.53	0.37	-0.92	0.10	6.61	0.14
131OK20501104	4	47.21	0.46	1.55	0.12	6.18	0.04
131OK104621206	6	46.38	0.08	1.42	0.05	6.30	0.04
131OK104621306	6	45.62	0.45	1.47	0.08	6.15	0.08
131OK104621406	6	46.72	0.13	0.80	0.02	6.18	0.03
131OK104717606	6	47.00	0.15	0.75	0.02	6.24	0.03
131OK20263206	6	48.91	0.59	0.80	0.03	6.41	0.04
131OK20263406	6	48.78	0.44	0.80	0.03	6.36	0.20

131OK20263606	6	49.22	0.20	0.67	0.01	6.20	0.06
131OK20541206	6	50.68	0.53	1.50	0.14	6.73	0.12
131OK20559806	6	48.04	0.11	0.70	0.07	6.21	0.04
131OK104621208	8	46.69	0.41	1.43	0.06	6.31	0.00
131OK104621308	8	46.15	0.20	1.48	0.05	6.14	0.11
131OK104717208	8	46.11	0.27	1.55	0.08	6.23	0.02
131OK104717608	8	46.76	0.36	1.63	0.10	6.08	0.04
131OK20501308	8	46.72	0.13	0.76	0.00	6.20	0.03
131OK104621210	10	46.70	0.28	1.53	0.07	6.33	0.03
131OK104621310	10	46.32	0.51	1.51	0.10	6.23	0.03
131OK104621610	10	45.82	0.44	1.52	0.06	6.15	0.11
131OK104717110	10	45.88	0.68	1.49	0.18	6.24	0.08
131OK104717210	10	46.41	0.36	1.59	0.08	6.29	0.05
131OK20526112	12	48.40	0.42	0.66	0.04	6.35	0.06
131OK20755112	12	48.57	0.17	0.63	0.02	6.27	0.03

NIRS measurements were collected for each sample and performed a multivariate analysis using Quant Software to develop a chemometric model and predict the carbon content of the unknown samples.

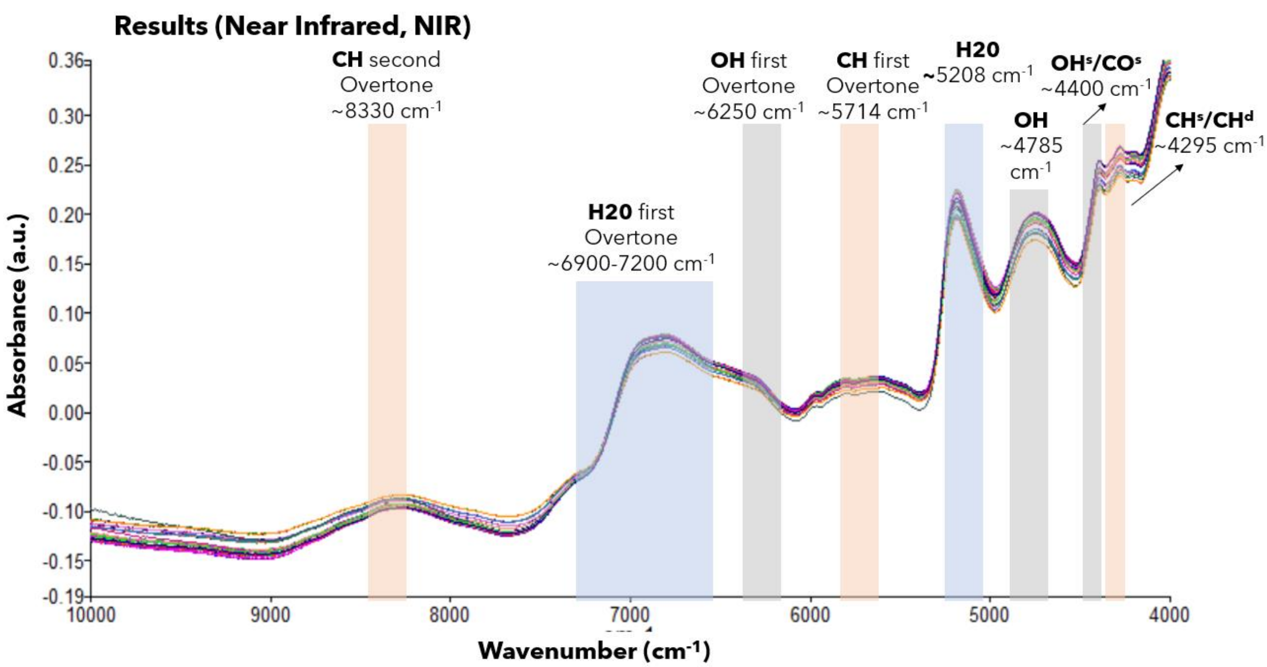

Figure 28: The raw Near-Infrared Spectroscopy of Loblolly Pine samples utilized as standards for developing the chemometric model.

The spectra presented in Figure 26 show the typical absorption NIR bands expected for woody biomass, with peaks at six different wavelengths: 8330 cm^{-1}, 6900 to 7200 cm^{-1}, 5714 cm^{-1}, 5208 cm^{-1}, 4785 cm^{-1}, and 4295 cm^{-1}. These bands are attributed to the vibration of chemical bonds from specific chemical compounds in the wood sample. Further analysis and interpretation of the spectral data provided us with more insights into the composition of the tree species being studied.

The first absorption peak observed at 8330 cm^{-1} is attributed to the second overtone of C-H stretching vibration. The second peak between 6990 – 7200 cm^{-1} is attributed to different vibrational bonds. At 7057 cm^{-1} wavelengths, the first overtone of C-H stretching and C-H bending vibration is observed, associated with C-H aromatic. At 7073 cm^{-1} and 7092 cm^{-1}, the first overtone of O-H stretching vibration is observed. These bonds help in the formation of water and the development of bulk water, depending on the water content in microcrystalline cellulose. The third peak at 5714 cm^{-1} is attributed to the first overtone C-H stretching vibration bond where CH2 groups are found. The fourth peak at 5208 cm^{-1} is attributed to an O-H asymmetric stretching bond with O-H deformation vibration of H2O. The fifth peak at 4785 cm^{-1} is attributed to O-H and C-H deformation vibration and O-H stretching vibrational bond. The last peak at 4295 cm^{-1} corresponds to the C-H stretching and deformation vibration.

Chemometric Model

As mentioned, a chemometric model was developed using carbon content data (%) obtained from EA and NIRS spectra. We have developed our model based on PCR+ using PerkinElmer Spectrum IR Quant software. The number of principal components (PCs) utilized for the model was set at 11. Figure 29 shows the major graph obtained after calibration of our chemometric model.

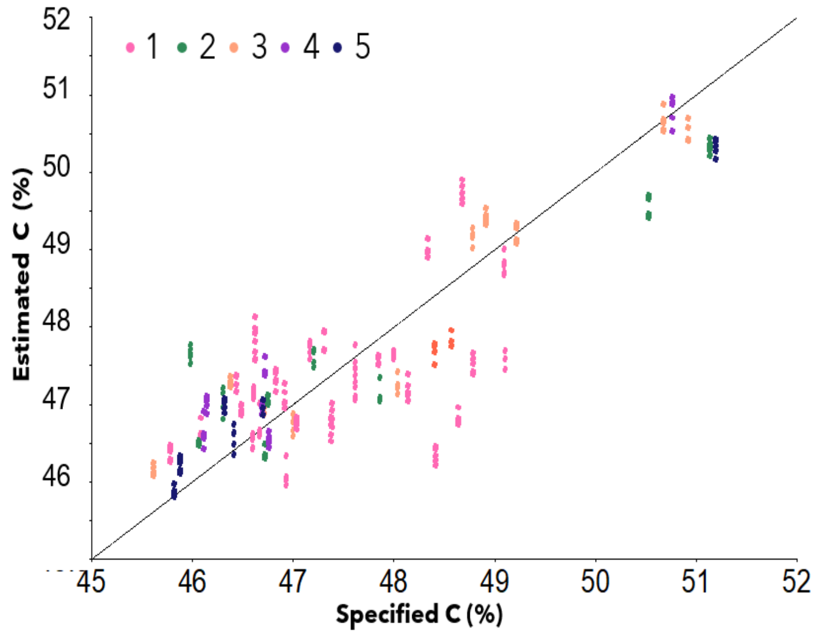

Figure 29: Estimated C(%) versus the specified C(%) color-coded by group number.

Figure 29 shows the Estimated C(%), obtained with the chemometric model, versus the Specified C(%) of each standard corresponding to the carbon content obtained from EA. The data for different group of samples collected as disk1, disk2, disk3, disk 4 and disk 5 are shown in pink, green, orange, purple and blue, respectively. The plot was obtained after calibration of the model using baseline offset as pre-processing method, and represent the main plot obtained by the chemometric model.

PCR+ Algorithm

The technique attempts to establish a linear relationship, one for each component or property of interest, between the spectra of a set of calibration standards, and the corresponding property values determined by independent means (e.g., experimentally). These relationships can be used for the subsequent prediction of unknown samples.

In PCR+, the spectra are again modelled by one set of factors, and each property is modelled by relating the concentration values to those factors. PCR+, in the PCA stage, only seeks to account for variations in the spectral data and then, in the Multiple Linear Regression (MLR) stage, correlates this with the property data.

For PCR+, the factors are dropped from the regression starting with the least significant factor (smallest t-value), until only one factor remains, calculating the statistics at each iteration. The percentage significance level to a minimum SEP result is taken as giving the best model (whether using SEP estimates or SEPs generated from validation).

For PCR+ the average spectral variance is given by the sum of the error eigenvalues.

$$\text{FSR} = \frac{(\text{u} - \hat{\text{u}})^{\text{T}}.\ (\text{u} - \hat{\text{u}})\ \text{ns}}{\text{resudial spectral variance of calibration spectra}}$$

Which for

$$\text{PCR+} = \sum_{\text{i}=\text{n}_{\text{f}-1}}^{\text{n}_\text{x}} \lambda_\text{i}$$

where:

u is the eigen vector of an unknown spectrum.

û is the eigen vector of a spectrum produced from the factors up to the cutoff point.

With eigen vectors linearly independent and orthonormal vectors.

Our model was calculated using 11 PCs, and the main parameters of the resulting PCR+ model are shown in Table 13.

Table 12. Chemometric model for Carbon prediction main parameters, using principal components regression (PCR).

Property	Value
Number of PCs	11
% Variance	72.63
Standard Error of Prediction (SEP)	0.7874
Cross Validation SEP	0.791
Mean Property Value	47.57

The properties and values of each parameter in Table 13 are clearly explained below.

R^2 or Coefficient of Determination

The R^2 is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variable (s) in a regression model. It is expressed as a percentage and ranges from 0% to 100%. The coefficient of determination listed as R-squared for the full model gives the proportion of variability of the property that is described by the model, and is calculated as

$$R^2 = 1 - \frac{residual\ property\ variance}{total\ property\ variance} = 1 - \frac{RSS}{SYY} = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y})^2}$$

The R^2 value can be interpreted as the proportion of the total variation in the dependent variable that is explained by the regression model. For example, if the R^2 value is 0.80 (or 80%), this means that 80% of the variation in the dependent variable is explained by the independent variable(s) in the model, while the remaining 20% is due to the other factors or random error. R^2 is often used as a goodness-of fit measure for regression models, and higher values of R^2 generally indicate a better fit. However, it is important to note that a high R^2 value does not necessarily mean that model is a good predictor of future outcomes, as there may be other factors that are not captured by the model.

The Standard Error Estimate (SEE)

SEE is a measure of the accuracy of the predictions made by a regression model. It is also known as the Root Mean Squared Error (RMSE) or the Residual Standard Error (RSE). The SEE represents the average distance between the observed values of the dependent variable and the predicted values from the regression model.

The SEE is calculated by taking the square root of the sum of the squared residuals (i.e., the difference between the observed values and the predicted values) divided by the degrees of freedom. The degrees of freedom are equal to the number of observations minus the number of independent variables in the model.

$$SEE = \left(\frac{residual\ variance}{number\ of\ degrees\ of\ freedom}\right)^{\frac{1}{2}}$$

$$= \left(\frac{RSS}{n_{s-}n_{f-1}}\right)^{\frac{1}{2}}$$

The SEE is expressed in the same units as the dependent variable, and it is used to assess the goodness-of-fit of the regression model. Lower values of SEE indicate a better fit between the model and the observed data, while higher values indicate a poorer fit. The SEE can also be used to estimate the range of values within which future observations are likely to fall with a certain degree of confidence. Specifically, it can be used to construct prediction intervals, which represent the range of values within which future observations are expected to fall with a certain level of confidence (e.g., 95%). The width of the prediction interval depends on the SEE, the number of observations, and the level of confidence desired. The value should not be confused with Standard Error of Prediction (SEP). The SEP estimate, which is the magnitude of the error expected when independent samples are predicted using the model, is calculated using the

$$SEP = \sqrt{\frac{\Sigma e_i^2}{n}}$$

where $e_i^2 = (y_t - y_i)^2$

Where equation denotes the predicted property value for the equation standard when it was dropped from the multilinear regression.

Principal Components

Principal components (PCs) are used to reduce the dimensionality of complex data sets while retaining the maximum amount of information. Each principal component is a linear combination of the original variables, with the first principal component explaining the most variation in the data, the second principal component explaining the second most variation, and so on. According to the results, there were 11 principal components used to develop the model as shown in Figure 30 and Figure 31.

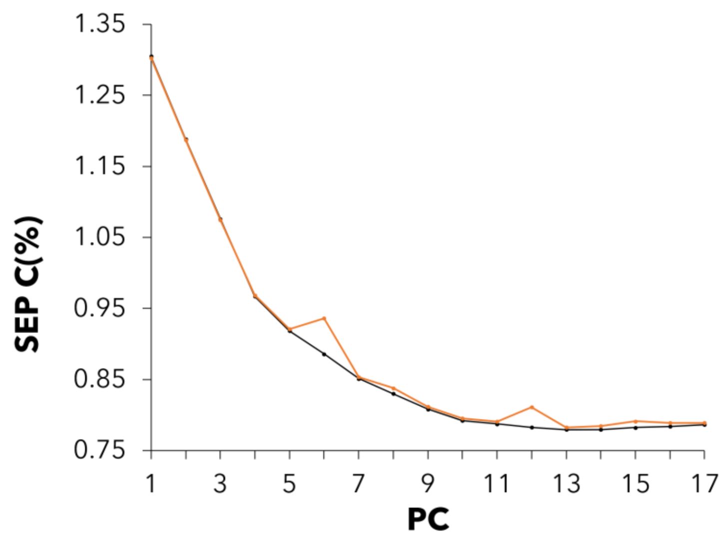

Figure 30: Effect of the PC on the SEP and the cross-validation SEP represented in black and orange colors, respectively. PC, principal component; SEP, standard error of prediction.

In Figure 30 the first principal component (PC1) explains the largest amount of variability in the data, followed by PC2, PC3, and so on.

In Figure 30 the orange curve indicated the Cross Validation, which enables to performance of an approximation of an independent validation using only the data in the calibration set. This is done by removing one or more standards from the calibration, then predicting that standard against the calibration, and repeating until each standard or group of standards has been left out once.

Cross-validation

Cross-validation is a technique used to evaluate the performance of a statistical or machine learning model. It involves dividing the dataset into multiple subsets or "folds," where each fold is used to train the model and the remaining folds are used to test the model's performance.

The basic idea behind cross-validation is to simulate how well the model will perform on new, unseen data by using only a portion of the data to train the model and the remaining data to evaluate the model's performance. By repeating this process with different subsets of the data, we can obtain a more reliable estimate of the model's performance than by simply evaluating it on a single test set.

There are several types of cross validation techniques, including k-fold cross-validation, leave-one-out cross validation, and stratified cross-validation. K-fold cross-validation is the most commonly used technique, where data is divided into k equal-sized folds, and the model is trained and tested k times, with each fold being used once as the test set and the remaining k-1 folds being used as the training set.

The main advantage of cross-validation is that provides a more reliable estimate of the model's performance than simply evaluation it on a single test set. It also helps to prevent overfitting, as the model is evaluated on multiple tests sets rather than just one. However, cross-validation can be computationally expensive, especially for larger datasets or complex models.

F Test of Significane

The F-value can be viewed as a measure of the signial-to-noise in the model. In order to evaluate the performance of the model and determine whether the property variance accounted for by models is significantly better than the residual variance. In other words, the test shows whether an individual PC is of a similar significane compared to the higher-numbered PC pooled together. Therefore, a low value shows that the PC is significantly different from the susequent PCs and is likely to be caused by real variation in the spctral data, rather than noise. For the calculation of the F-test of significance, the software uses

$$F = \frac{\sum_{i-1}^{\mathrm{n_s}} (y_i - \mathrm{y})^2 \ (n_s - n_f - 1)}{\sum_{i-1}^{\mathrm{n_s}} (y_i - y_j)^2 \ (n_f - 1)}$$

where n_f is the number of significant factors in the model. Note that each sum square has been corrected for the degrees of freedom.

The % significane value, 100(1- α), for the F-term can be found using F $(\alpha; n_f -1, n_s - n_f -1)$ = *F-value*, in statistical tables. A poor regression will give a low (<3) value for F. The F-value can be viewed as a measure of the signal-to-noise in the model.

A suggested F-test would be F $(a; (n_v - n_f) / 2, (n_v - n_f)(n_s - n_f - 1) / 2)$, but because n_v is usually very large, then for a = 0.95 the F-value would always be close to 1. As an approximate, an F-*test of F* $(a; 1, (n_s - n_f - 1))$ could be used.

The results of the F-test of significance are shown in Figure 31. As evidenced from the plot, the F-test value for 11 PCs is very low, and the value rapidly increase after PC number 12, indicating that PC values above 13 might be generated by artifacts (noise) rather real chemical differences.

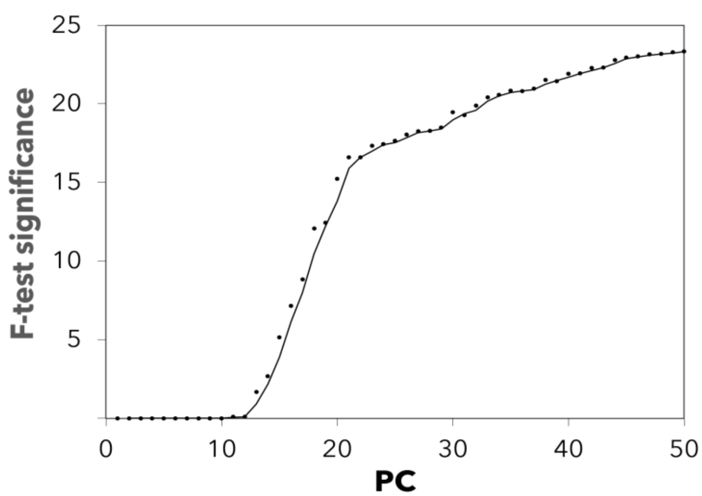

Figure 31: No. of PCs used against F-test significance.

Residual percentage:

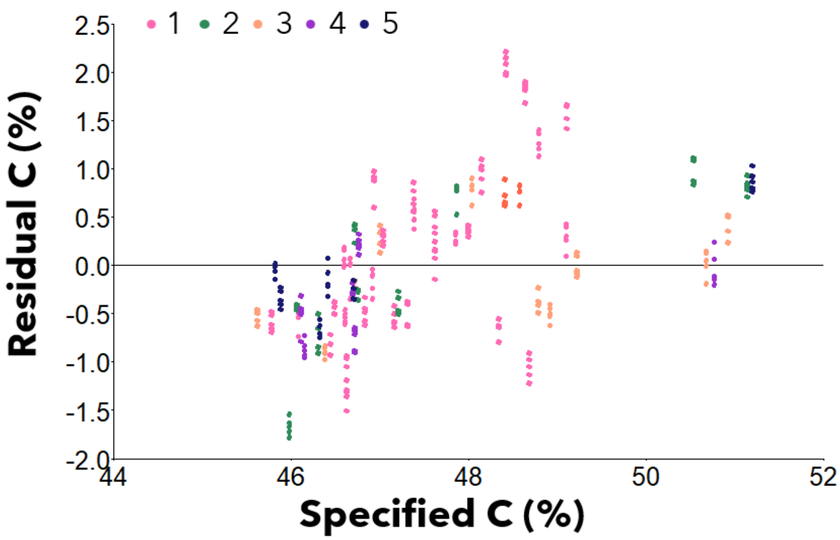

Figure 32. Residual C (%) versus the specified C (%) color-coded by group number.

Figure 32 shows a non-random distribution of the residuals about the zero point of the y-axis. Positive residual values indicate the model overestimated the real carbon content in the corresponding samples.

3.4 Discussion

The bands shown in Figure 28 are typically observed in biomass samples due to the presence of carbohydrates, hemicellulose, and lignin, which agree with reported data in the literature (Xu et al., 2020). The identification of the main bands is essential for various applications, including the ability to predict carbon content using a non-destructive technique.

However, as Figure 28 illustrates, there are minimal differences between the 300 spectra of the 60 Loblolly pine tree samples, which highlights the limitations of relying solely on NIRS for accurately estimating carbon content. The advantages of using a chemometric model to address these limitations are shown below.

The elemental composition observed for each sample is the typical composition of softwood samples also. The standard deviation of the carbon content values obtained by elemental analysis was lower than 1 percent in all the analyzed samples, showing the accuracy of the elemental analysis, which was used as a primary method in developing our chemometric model.

For the calibration of our chemometric model we have set the number of factors (i.e., PCs) equal to 11, and performed pre-processing adjusting the baseline offset for each spectrum. By reducing the number of variables, PCR+ can help to simplify the analysis and improve the interpretability of the results. PCR+ also helped to visualize high-dimensional data in a lower-dimensional space, such as scatter plot, making it easier to identify the patterns and relationships in the data. However, it is important to note that even a low number of PCs might be challenging to interpret, as they are often linear combinations of multiple original variables and may not have a direct physical or intuitive meaning. Therefore, we calibrated our model with 11 PCs to minimize the error of prediction. A higher number of PCs does not provide lower SEP and reduced the quality of our model as the F-test value rapidly increased after PC number 13. Based on the parameters shown in Table 12, it is possible to predict the carbon content of an unknown sample with an error below 1 percent using our chemometric model. The residual values in Figure 32 exhibit a structured distribution around the zero y-axis. The slightly structured distribution indicates a minor issue in our model which could be attributed to several factors. For instance, the samples from group 1 and group 2 are clearly overestimated by the model, whereas the predicted carbon content for samples in other groups is underestimated. In other words, the variability within the samples collected from different parts of the trees appears to play a significant role in the differences observed between the specified carbon content from EA and the calculated carbon content value from the calibration. Moreover, factors such as tree age, environmental conditions, or seasonal effects, which were not considered in our study, may contribute to a complex relationship between the specified carbon content for the standard samples and their NIR spectra. This complexity might not be captured accurately by the chemometric model, leading to systematic errors in the model prediction. However, indicators describing the quality of the model, including R-squared of 73%, F-test <3, and SEE of 78%, and cross-validation SEE, demonstrate the wood quality of our model for predicting the carbon content of wood samples. Nevertheless, further research is necessary to understand the complex relationship between the tree characteristics, such as tree species, age, location, and environmental factors and carbon content.

3.5 Conclusion

In conclusion, we have demonstrated the potential of NIRS coupled with a chemometric model for the prediction of the carbon content from different parts of the tree. The research described in this thesis will help to improve the quality of the future chemometric models, which will enable the prediction of carbon content in woody biomass with high accuracy.

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Appendix A

Dr. Adam O. Maggard
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(NOTE: DO NOT AGREE TO PARTICIPATE UNLESS AN IRB APPROVAL STAMP WITH CURRENT DATES HAS BEEN APPLIED TO THIS DOCUMENT.)

INFORMATION LETTER
For a Research Study entitled
"Assessment of supplemental income generation by family forest landowners in Alabama"

Dear Sir or Madam,

You are invited to participate in a research study to obtain information on forest landowner awareness and interests in carbon credit programs that provide a revenue source to landowners. The study is being conducted by Dr. Adam O. Maggard, Alabama Cooperative Extension System Specialist, in the Auburn University School of Forestry and Wildlife Sciences, and Suharsha Baskarla, MS student in School of Forestry and Wildlife Sciences at Auburn University, and in cooperation with the Forest Landowner Association. You are invited to participate because you are a family forestland owner and are age 19 or older.

What will be involved if you participate? If you decide to participate in this research study, you will be asked to fill out the following online questionnaire reporting your knowledge and interests in carbon credit programs and information regarding current forest management practices on your forestland. Your total time commitment will be approximately 15-20 minutes depending on the availability of your information.

Are there any risks or discomforts? The risks and discomforts associated with participating in this study are minimal but may include taking an extended period of time to complete the survey. Risks are not anticipated.

Are there any benefits to yourself or others? The information collected will be made available for landowners and resource professionals through national extension websites, professional publications, presentations, and a thesis. The readily available information will be used to assist family forest landowners with educational opportunities, revenue opportunities from their forestland, and forest management and planning to enhance the health and resiliency of their forests. This will benefit landowners and resource professionals by better understanding opportunities for carbon credit programs, and design, methods, and implementation of such programs available to landowners. I cannot promise you any or all of the benefits described will be received.

Will you receive compensation for participating? No, there is no compensation for completing this survey.

Are there any costs? If you decide to participate, there are no costs to you except time expended to complete the survey.

If you change your mind about participating you can withdraw at any time during the study. Your participation is completely voluntary. If you choose to withdraw, your data can be deleted as long as it is identifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the School of Forestry and Wildlife Sciences, or the Alabama Cooperative Extension System.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide will never connected your name to your responses once it is returned. The data will be anonymous. We ask that you do not write your name or other information associated with your or your business on the questionnaire. Any information obtained in connection with this study will not be connected to the participant at any time during the data collection or storage.

If you have any questions about this study please contact Dr. Adam Maggard by phone at (334)-844-2401 or by email at adm0074@auburn.edu.

If you have any questions about your rights as a research participant you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone at (334)-844-5966 or email at hsubjec@auburn.edu or IRBChair@auburn.edu.

Sincerely,

Dr. Adam O. Maggard
Forestry Extension Specialist
Alabama Cooperative Extension System
School of Forestry and Wildlife Sciences
Auburn University

○ Yes

○ No

Please provide an answer to all questions. Only answer questions based on forestland you own.

The primary decision-maker for your forestland should answer this survey.

If you have questions, additional comments, or concerns, please include them in the space provided in the final question of this survey.

General Questions about your forestland and ownership in Alabama

A defined by the U.S. Forest Service, forestland is land that has a minimum stocking level of 10% of forest trees and is at least 1 acre in size and 120 feet wide in crown width. This includes land where trees were removed and will be planted or grow naturally again. Forestland does not include orchards, nurseries, Christmas tree farms, or land that is mowed as part of a lawn/yard.

How many total acres of forestland do you currently own?

List the ***state*** and ***county*** where you own forestland?

How long have you owned your forestland?

○ Less than 5 years
○ 6 to 15 years
○ 16 to 30 years
○ More than 30 years

How close do you live to the forestland you own? ***(If own more than one forested property, answer the question for the one closest to where you live)***

- ○ On the property
- ○ Less than 10 miles
- ○ 10 - 100 miles
- ○ More than 100 miles

Which of the following best represents the ***majority*** of your forestland?

- ○ Natural pine (specify species)
- ○ Planted pine (specify species)
- ○ Natural hardwoods
- ○ Planted hardwoods (specify species)
- ○ Mixed pine/hardwood
- ○ Other (specify)

Which of the following best describes your ownership of forestland?

- ○ Individual
- ○ Joint, with spouse
- ○ Joint, other
- ○ Family partnership, LLC, or LLP
- ○ Family trust or estate
- ○ Business or corporation
- ○ Other (specify)

Which of the following options below **best** represents the primary reason for owning your forestland? ***(Only select one)***

- ○ Enjoyment of beauty and scenery
- ○ Land investment

○ Hunting recreation

○ Recreation other than hunting (wildlife viewing, hiking, biking, horseback riding, ATV/UTVs riding, etc...)

○ Production and harvest of timber

○ Production and harvest of Non-timber forest products (plants, fungi, other floral material such as seeds, bark, leaves)

○ Personal use of forest products (timber and/or timber forest products)

○ To protect or improve natural resources (water, wildlife, wildlife habitat, trees, biological diversity)

○ Where you live or vacation

○ Part of a farm or ranch

○ For privacy

○ To pass it on to my children or other heirs

○ Multiple reasons (specify) __________

○ Other (specify) __________

Select "Yes" or "No" for the following questions as they relate to you and your forestland.

	Yes	No
Has timber been harvested from your forestland since you have owned it?	○	○
Have you hired a consulting forester in the past 10 years?	○	○
Have you sold timber from your forestland in the past 10 years?	○	○
Do you plan to harvest any trees from your forestland in the future?	○	○
Is any of your forestland under a conservation easement?	○	○
Are you a member of a forestry association or local forestry planning committee or similar? ***(If yes, specify which below)*** __________	○	○

	Yes	No
Are you a member of a conservation organization? ***(If yes, specify which below)***	○	○

Are you interested in generating revenue from your forestland?

- ○ No
- ○ Maybe
- ○ Yes

Do you currently generate revenue from your forestland?

- ○ No
- ○ Yes

How do you generate revenue from your forestland? ***(Select all that apply)***

- ☐ Timber sales
- ☐ Hunting lease
- ☐ Recreational lease other than hunting
- ☐ Other type of lease (specify)
- ☐ Non-timber forest products sales
- ☐ Other (specify)

If you do not generate revenue from your forestland, what is the reason(s)? ***(Select all that apply)***

- ☐ Not interested
- ☐ Not sure how to do so
- ☐ Do not have the time
- ☐ Potential resource needs other than time (monetary, assistance, labor, etc...)
- ☐ Lack of market for product(s)

- [ ] Other (specify)
- [ ] **I do** generate revenue from my forestland

Do you currently manage your forestland for any purpose? **(*Examples can include but are not limited to: timber, non-timber forest products, wildlife habitat, recreation*)**

- ○ No; never have
- ○ No; have before
- ○ Yes; have a written management plan
- ○ Yes: no written management plan

Do you currently participate in any cost-share programs on your forestland? ***(cost-share programs are forestry incentive programs that support tree planting, management planning, improvement of forest management practices, and improvement and protection of forest and wildlife resources)***

- ○ No; never have
- ○ No; have before
- ○ Yes (specify)

Is the ***cost*** of owning and managing your forestland:

- ○ Less than expected
- ○ About what I expected
- ○ More than expected

Which best represents your future ownership plan for your forestland?

- ○ Pass it on to children or other heirs
- ○ Sell it
- ○ Bequeathed (gift it)
- ○ Other (specify)

Questions related to carbon credit programs

This section focuses on voluntary carbon credit programs offered to forest landowners. Carbon credit programs, also known as carbon offset programs, can provide an additional source of revenue from your forestland if you manage your forest to increase carbon sequestration. Below is additional information about forest carbon and carbon credits. Please read this information before proceeding.

Information about forest carbon and carbon credits:
Trees take in carbon from the atmosphere as they grow and store in their leaves, main stem, branches, and roots. When this occurs, carbon dioxide is removed from the atmosphere.

Carbon credits are credits provided based on the additional amount of increased carbon stored in the trees on your forestland due to a specific management activity or action. Carbon programs are markets where these credits can be sold to businesses or corporations that produce carbon dioxide during their operations and want to offset the amount of carbon dioxide they are releasing into the atmosphere as a result. They can use purchased carbon credits to reduce (offset) their net carbon dioxide emissions.

How familiar are you with carbon credit program for forest landowners?

- ○ Not familiar at all
- ○ Slightly familiar
- ○ Moderately familiar
- ○ Very familiar
- ○ Extremely familiar

Have you ever inquired about or researched information on forest carbon credit programs?

- ○ No
- ○ Yes; within the last two years
- ○ Yes: more than two years ago

What is your interest level towards participation in carbon credit programs?

- ○ Not at all interested
- ○ Slightly interested
- ○ Moderately interested
- ○ Very interested
- ○ Extremely interested

Rank the following factors based on their likely influence of preventing your participation into a forest carbon credit program. ***1 = most important influence/biggest decision factor/most concern; 5 = least important influence factor/least concernn***

	1	2	3	4	5
Rate of return or amount of revenue it would generate	○	○	○	○	○
Land use rights/limitations	○	○	○	○	○
Length of contract commitment	○	○	○	○	○
Financial penalty amount for early withdrawal or breach of contract	○	○	○	○	○
Upfront costs or any direct costs (if applicable)	○	○	○	○	○

For each statement below, select how likely it is to impact your decision to participate in a forest carbon credit program.

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely
Acreage size requirements (min or max)	○	○	○	○	○
Length of contract commitment	○	○	○	○	○
Restrictions on tree harvesting	○	○	○	○	○
Restrictions of land use	○	○	○	○	○
Amount monetary costs to you as a result of participating	○	○	○	○	○
Amount of revenue you could earn as a result of participating	○	○	○	○	○

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely
Frequency & timing of revenue payments	O	O	O	O	O
Must create or adhere to a management plan as a result of participating	O	O	O	O	O

Assuming you are going to participate in a forest carbon credit program, which of the following would you be most likely to participate in if your forestland was eligible for all of them?

- O Carbon credit programs that focus on maximizing carbon and pay for carbon gained by delaying/preventing timber harvest during the contract period (contract commitments range from 1-year to 100+ years depending on program)
- O Carbon credit programs focused on improving forest health and value by providing funding to assist management costs consultations, advice, and creation of a management plan (currently, 10-year or 20-year contract commitments depending on program), but do not pay the landowner for the actual carbon stored on their land.
- O Carbon credit programs focused on afforestation/reforestation by restoring tree cover to non-forested land and pay for carbon gained during the contract period but may or may not pay for part or all of the reforestation costs (currently, contract commitments of 40-years minimum and focused on hardwoods)

Have you ever lost timber from your forestland due to a natural disaster ***(hurricane, tornado, severe storm, wildfire, drought, etc...)?***

- O No
- O Yes; majority loss
- O Yes; moderate loss
- O Yes; minimal loss

Does the possibility of your forestland being impacted by a natural disaster influence your decision to participate in forest carbon credit programs ***(Assuming you won't get paid for the carbon or may have to return any payments already received if still under contract)?***

- O Definitely not
- O Probably not
- O Might or might not

- Probably yes
- Definitely yes

If you did encounter a significant loss of timber on your forestland due to a natural disaster, how likely would it be that you would not reforest but rather change land use or sell?

- Extremely unlikely
- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Extremely likely

If you were eligible for a reforestation carbon credit program that paid some or all of your reforestation costs plus at least a percentage of lost revenue from timber loss due to a natural disaster through carbon credits sold from your forestland over the course of the new rotation, how likely would you participate in the program rather than change land use or sell?

- Extremely unlikely
- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Extremely likely

Knowing that carbon credit programs can have restrictions on tree harvesting and land use, and can range in contract commitments from as short as 1-year to 40 or more years. Which of the following would likely best represent the price range you would need to be willing to participate?

- $1 to $5 per acre
- $6 to $10 per acre
- $11 to $15 per acre
- $16 to $20 per acre
- $21 to $30 per acre
- More than $30 per acre

How likely are you to participate in a carbon credit program if eligible?

- ○ Extremely unlikely
- ○ Somewhat unlikely
- ○ Neither likely nor unlikely
- ○ Somewhat likely
- ○ Extremely likely

Would you be interested in learning more about forest carbon credit programs?

- ○ No
- ○ Maybe
- ○ Yes

Questions about you

Please answer the following questions about yourself. Completion of this section is the end of the survey.

Which best describes your age class?

- ○ Under 25
- ○ 25 to 34
- ○ 35 to 44
- ○ 45 to 54
- ○ 55 to 64
- ○ 65 or older
- ○ Prefer not to say

What is you gender?

- ○ Male
- ○ Female

○ Non-binary / third gender
○ Prefer not to say

What is the highest level of education completed?

○ Less than high school
○ High school graduate or GED
○ Some college
○ Associates or technical degree
○ Bachelor's degree
○ Master's degree
○ Professional degree
○ Doctorate degree
○ Prefer not to say

Which best represents your household's annual income?

○ Less than $25,000
○ $25,000 to $49,999
○ $50,000 to 74,999
○ $75,000 to $99,999
○ $100,000 to $149,999
○ $150.000 to $200,000
○ More than $200,000
○ Prefer not to say

Which best describes your Ethnicity?

○ Hispanic, Latino, or Spanish Origin
○ Non-Hispanic, Latino, or Spanish Origin

Which of the following best describes your Race?

○ White

- ○ Black or African American
- ○ American Indian or Alaska Native
- ○ Asian
- ○ Native Hawaiian or Other Pacific Islander
- ○ Other
- ○ More than one race
- ○ Prefer not to say

Would you be willing to participate in a follow up interview about your experience with this survey?

- ○ No
- ○ Yes (please list preferred contact info) ______

If you have any additional comments or concerns you would like to share about the survey, please do so in the space provided below.

______

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Appendix B

EMAIL TO BE USED FOR DISTRIBUTING THE SURVEY

Dear Sir or Madam,

You are invited to participate in a research study to obtain information on forest landowner awareness and interests in carbon credit programs that provide a revenue source to landowners. The study is being conducted by Dr. Adam O. Maggard, Alabama Cooperative Extension System Specialist, in the Auburn University School of Forestry and Wildlife Sciences, and Suharsha Baskarla, MS student in School of Forestry and Wildlife Sciences at Auburn University, and in cooperation with the Forest Landowner Association. You are invited to participate because you are a family forestland owner and are age 19 or older.

Questionnaire Information: Trees take in carbon from the atmosphere as they grow and store in their leaves, main stem, branches, and roots. When this occurs, carbon dioxide is removed from the atmosphere. Carbon credits are credits provided based on the additional amount of increased carbon stored in the trees on your forestland due to a specific management activity or action. Carbon programs are markets where these credits can be sold to businesses or corporations that produce carbon dioxide during their operations and want to offset the amount of carbon dioxide they are releasing into the atmosphere as a result. They can use purchased carbon credits to reduce (offset) their net carbon dioxide emissions. The objective of this survey is better understand forest landowners' awareness, perceptions, and willingness to participate in such programs.

The information collected will be made available for landowners and resource professionals through national extension websites, professional publications, presentations, and a thesis. The readily available information will be used to assist family forest landowners with educational opportunities, revenue opportunities from their forestland, and forest management and planning to enhance the health and resiliency of their forests. This will benefit landowners and resource professionals by better understanding opportunities for carbon credit programs, and design, methods, and implementation of such programs available to landowners. I cannot promise you any or all of the benefits described will be received.

Accessing The Questionnaire: If you decide to participate in this research study, you are asked to fill out the questionnaire using an on-line survey format available at the following link: https://auburn.qualtrics.com/jfe/form/SV_7QdV2dv1hEKsBUO.

You can right-click and select "open hyperlink" or copy and paste the link into your web browser. Your total time commitment will be approximately 15-20 minutes depending on the availability of your information. If you do not manage or own any forestland, please disregard this notice.

Contact Information:

If you have any questions, please contact Adam Maggard, Ph. D., Alabama Cooperative Extension Specialist and Assistant Professor, School of Wildlife Sciences, Auburn University, by email: adam0074@auburn.edu or by phone: 334.844.2401

Appendix C

Dr. Adam O. Maggard
Forestry Extension Specialist
3301 School of Forestry and Wildlife Sciences
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(NOTE: DO NOT AGREE TO PARTICIPATE UNLESS AN IRB APPROVAL STAMP WITH CURRENT DATES HAS BEEN APPLIED TO THIS DOCUMENT.)

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What will be involved if you participate? If you decide to participate in this research study, you will be asked to fill out the following online questionnaire reporting your knowledge and interests in carbon credit programs and information regarding current forest management practices on your forestland. Your total time commitment will be approximately 15-20 minutes depending on the availability of your information.

Are there any risks or discomforts? The risks and discomforts associated with participating in this study are minimal but may include taking an extended period of time to complete the survey. Risks are not anticipated.

Are there any benefits to yourself or others? The information collected will be made available for landowners and resource professionals through national extension websites, professional publications, presentations, and a thesis. The readily available information will be used to assist family forest landowners with educational opportunities, revenue opportunities from their forestland, and forest management and planning to enhance the health and resiliency of their forests. This will benefit landowners and resource professionals by better understanding opportunities for carbon credit programs, and design, methods, and implementation of such programs available to landowners. I cannot promise you any or all of the benefits described will be received.

Will you receive compensation for participating? No, there is no compensation for completing this survey.

Are there any costs? If you decide to participate, there are no costs to you except time expended to complete the survey.

If you change your mind about participating you can withdraw at any time during the study. Your participation is completely voluntary. If you choose to withdraw, your data can be deleted as long as it is identifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the School of Forestry and Wildlife Sciences, or the Alabama Cooperative Extension System.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide will never connected your name to your responses once it is returned. The data will be anonymous. We ask that you do not write your name or other information associated with your or your business on the questionnaire. Any information obtained in connection with this study will not be connected to the participant at any time during the data collection or storage.

If you have any questions about this study please contact Dr. Adam Maggard by phone at (334)-844-2401 or by email at adm0074@auburn.edu.

If you have any questions about your rights as a research participant you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone at (334)-844-5966 or email at hsubjec@auburn.edu or IRBChair@auburn.edu.

Sincerely,

Dr. Adam O. Maggard
Forestry Extension Specialist
Alabama Cooperative Extension System
School of Forestry and Wildlife Sciences
Auburn University

Appendix D

Dear IRB:

Thank you for reviewing protocol titled "Beyond the timberline: Assessment of carbon markets as a revenue source for family forest landowners and their willingness to participate". We have addressed all comments for the revision. In response to the IRB's comments the following changes have been made:

- For the EXEMPT application:
  - Updated today's date
  - Included the principle investigator in item 1C and answered all of item 1Cs questions
  - In item 4B, we added "A family forest landowner is defined as forest landowners who own forestland in terms of single person ownership, family ownership, partnership, estate, or trusts". And added "Family forest landowners contacts are provided from the Alabama Extension – Forestry, Wildlife, and Natural Resources Team contacts, which Dr. Maggard is an Extension Specialist with the School of Forestry and Wildlife Sciences and the Alabama Cooperative Extension System and has available for his Extension work. Further, the survey will be distributed to family forest landowners who are members of the Forest Landowners Association and Alabama Forest Owners Association".
  - For item 6, we added "meaning no identifiable information will be associated with participants and their responses to the questions"
  - For item 8, we added "The researcher will not collect any identifying data or report information about individuals in any research report. No identifying information will be extracted from the survey. Identification of the research participants will not be recorded at any time during or after the data collection and no identifying information will be recorded that will link data to any individual participant".
  - For item10, we added a list of attachments included in this submission stating "*Attachment include: Email notification to participate in the survey, Information letter, and the survey itself*".
  - Principle investigated signed and updated the date for the revision.
- For the information letter and email recruitment text:
  - Title was added to recruitment email.
  - Clarified student procedures are online in the recruitment email.
  - For questions 12 and 13 provided by IRB reviewer, the information letter includes Risks and we added "Risks are not anticipated" to that paragraph. We already state that compensation or costs is not available to participants in the information letter. Please review again. IRB contact information is already included in the information letter, please review again.

We believe we have made all required and necessary changed and updates to this protocol. We appreciate the comments and guidance. Within this document you will find one complete copy of our revised request, highlighting any and all changes and including all documents as well as one completed revised copy without highlighted changes.

Sincerely,

Adam O. Maggard

AUBURN UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM (HRPP)

EXEMPT REVIEW APPLICATION

For assistance, contact: **The Office of Research Compliance (ORC)**
Phone: **334-844-5966** E-Mail: **IRBAdmin@auburn.edu** Web Address: **http://www.auburn.edu/research/vpr/ohs**
Submit completed form and supporting materials as one PDF through the IRB Submission Page
Hand written forms are not accepted. Where links are found hold down the control button (Ctrl) then click the link..

1. Project Identification **Today's Date: December 16, 2021**

Anticipated start date of the project: January 12, 2021 Anticipated duration of project: 2 Years

a. **Project Title: Assessment of carbon markets as a revenue source for family forest landowners and their willingness to participate.**

b. **Principal Investigator (PI): Adam Maggard** Degree(s): PhD, MS, BS
Rank/Title: Assistant Professor Department/School: School of Forestry and Wildlife Sciences
Role/responsibilities in this project: **Survey design/creation, distribution, and analysis**
Preferred Phone Number: **334-844-2401** AU Email: adm0074@auburn.edu

Faculty Advisor Principal Investigator (if applicable): Click or tap here to enter text.
Rank/Title: Choose Rank/Title Department/School: Choose Department/School
Role/responsibilities in this project: Click or tap here to enter text.
Preferred Phone Number: Click or tap here to enter text. AU Email: Click or tap here to enter text.

Department Head: Daowei Zhang Department/School: School of Forestry and Wildlife Sciences
Preferred Phone Number: **334-844-1067** AU Email: ZHANGD1@auburn.edu
Role/responsibilities in this project: NA

c. **Project Key Personnel** – Identify all key personnel who will be involved with the conduct of the research and describe their role in the project. Role may include design, recruitment, consent process, data collection, data analysis, and reporting. (To determine key personnel, see decision tree). *Exempt determinations are made by individual institutions; reliance on other institutions for exempt determination is not feasible. Non-AU personnel conducting exempt research activities must obtain approval from the IRB at their home institution.*

Key personnel are required to maintain human subjects training through CITI. Only for EXEMPT level research is documentation of completed CITI training NO LONGER REQUIRED to be included in the submission packet. NOTE however, **the IRB will perform random audits of CITI training records to confirm** reported training courses and expiration dates. Course title and expiration dates are shown on training certificates.

Name: Suharsha Baskarla Degree(s): **MS**
Rank/Title: Graduate Student Department/School: School of Forestry and Wildlife Sciences
Role/responsibilities in this project: **Assist with design, distribution, and analysis of survey and results. This work is part of written thesis for MS degree.**

- AU affiliated? ☒ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☒ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☒ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised Exempt Application form.
- If YES, choose course(s) the researcher has completed: Human Sciences Basic Course 5/17/2024

Choose a course Expiration Date

Name: Adam Maggard Degree(s): **PhD, MS, BS**

Rank/Title: Assistant Professor/Extension Specialist Department/School: School of Forestry and Wildlife Sciences

Role/responsibilities in this project: Lead PI, will lead and participate in steps of the project from survey creation, distribution, and analysis.

- AU affiliated? ☒ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☒ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☒ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised EXEMPT application form.
- If YES, choose course(s) the researcher has completed: Human Sciences Basic Course 1/16/2023
  Choose a course Expiration Date

Name: Click or tap here to enter text. Degree(s): Click or tap here to enter text.

Rank/Title: Choose Rank/Title Department/School: Choose Department/School

Role/responsibilities in this project: Click or tap here to enter text.

- AU affiliated? ☐ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☐ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☐ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised EXEMPT application form.
- If YES, choose course(s) the researcher has completed: Choose a course Expiration Date
  Choose a course Expiration Date

d. Funding Source – Is this project funded by the investigator(s)? Yes ☒ No ☐

Is this project funded by AU? Yes ☐ No ☒ If YES, identify source Click or tap here to enter text.

Is this project funded by an external sponsor? Yes ☐ No ☒ If YES, provide name of sponsor, type of sponsor (governmental, non-profit, corporate, other), and an identification number for the award.

Name: Click or tap here to enter text. Type: Click or tap here to enter text. Grant #: Click or tap here to enter text.

e. List other AU IRB-approved research projects and/or IRB approvals from other institutions that are associated with this project. Describe the association between this project and the listed project(s):
Click or tap here to enter text.

2. Project Summary

a. Does the study *TARGET* any special populations? Answer YES or NO to all.

Minors (under 18 years of age)	Yes ☐ No ☒
Auburn University Students	Yes ☐ No ☒
Pregnant women, fetuses, or any products of conception	Yes ☐ No ☒
Prisoners or wards (unless incidental, not allowed for Exempt research)	Yes ☐ No ☒

Temporarily or permanently impaired Yes ☐ No ☒

b. Does the research pose more than minimal risk to participants? Yes ☐ No ☒

If YES, to question 2.b, then the research activity is NOT eligible for EXEMPT review. Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research is not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or test. 42 CFR 46.102(i)

c. Does the study involve any of the following? *If YES to any of the questions in item 2.c, then the research activity is NOT eligible for EXEMPT review.*

Procedures subject to FDA regulations (drugs, devices, etc.) Yes ☐ No ☒

Use of school records of identifiable students or information from instructors about specific students. Yes ☐ No ☒

Protected health or medical information when there is a direct or indirect link which could identify the participant. Yes ☐ No ☒

Collection of sensitive aspects of the participant's own behavior, such as illegal conduct, drug use, sexual behavior or alcohol use. Yes ☐ No ☒

d. **Does the study include deception? Requires limited review by the IRB*** Yes ☐ No ☒

3. MARK the category or categories below that describe the proposed research. Note the IRB Reviewer will make the final determination of the eligible category or categories.

☐ **1.** Research conducted in established or commonly accepted educational settings, involving normal educational practices. The research is not likely to adversely impact students' opportunity to learn or assessment of educators providing instruction. 104(d)(1)

☒ **2.** Research only includes interactions involving educational tests, surveys, interviews, public observation if at least ONE of the following criteria. (The research includes data collection only; may include visual or auditory recording; may NOT include intervention and only includes interactions). **Mark the applicable sub-category below (I, ii, or iii). 104(d)(2)**

☒ **(i)** Recorded information cannot readily identify the participant (directly or indirectly/ linked);

OR

- surveys and interviews: no children;
- educational tests or observation of public behavior: can only include children when investigators do not participate in activities being observed.

☐ **(ii)** Any disclosures of responses outside would not reasonably place participant at risk; **OR**

☐ **(iii)** Information is recorded with identifiers or code linked to identifiers and IRB conducts limited review; no children. **Requires limited review by the IRB.** *

☐ **3.** Research involving Benign Behavioral Interventions (BBI)** through verbal, written responses including data entry or audiovisual recording from adult subjects who prospectively agree and ONE of the following criteria is met. (This research does not include children and does not include medical interventions. Research cannot have deception unless the participant prospectively agrees that they will be unaware of or misled regarding the nature and purpose of the research) **Mark the applicable sub-category below (A, B, or C).** 104(d)(3)(i)

☐ **(A)** Recorded information cannot readily identify the subject (directly or indirectly/ linked); **OR**

☐ **(B)** Any disclosure of responses outside of the research would not reasonably place subject at risk; **OR**

☐ **(C)** Information is recorded with identifies and cannot have deception unless participants prospectively agree. **Requires limited review by the IRB. ***

☐ **4.** Secondary research for which consent is not required: use of identifiable information or identifiable bio-specimen that have been or will be collected for some other 'primary' or 'initial' activity, if one of the following criteria is met. Allows retrospective and prospective secondary use. **Mark the applicable sub-category below (i, ii, iii, or iv).** 104 (d)(4)

☐ **(i)** Bio-specimens or information are publicly available;

☐ **(ii)** Information recorded so subject cannot readily be identified, directly or indirectly/linked investigator does not contact subjects and will not re-identify the subjects; **OR**

☐ **(iii)** Collection and analysis involving investigators use of identifiable health information when us is regulated by HIPAA "health care operations" or "research" or "public health activities and purposes" (does not include bio-specimens (only PHI and requires federal guidance on how to apply); **OR**

☐ **(iv)** Research information collected by or on behalf of federal government using government generated or collected information obtained for non-research activities.

☐ **5.** Research and demonstration projects which are supported by a federal agency/department AND designed to study and which are designed to study, evaluate, or otherwise examine: (i)public benefit or service programs; (ii) procedures for obtaining benefits or services under those programs; (iii) possible changes in or alternatives to those programs or procedures; or (iv) possible changes in methods or levels of payment for benefits or service under those programs. (must be posted on a federal web site). 104.5(d)(5) (must be posted on a federal web site)

☐ **6.** Taste and food quality evaluation and consumer acceptance studies, (i) if wholesome foods without additives and consumed or (ii) if a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture. The research does not involve prisoners as participants. 104(d)(6)

**Limited IRB review – the IRB Chair or designated IRB reviewer reviews the protocol to ensure adequate provisions are in place to protect privacy and confidentiality.*

***Category 3 – Benign Behavioral Interventions (BBI) must be brief in duration, painless/harmless, not physically invasive, not likely to have a significant adverse lasting impact on participants, and it is unlikely participants will find the interventions offensive or embarrassing.*

**** Exemption categories 7 and 8 require broad consent. The AU IRB has determined the regulatory requirements for legally effective broad consent are not feasible within the current institutional infrastructure. EXEMPT categories 7 and 8 will not be implemented at this time.*

4. Describe the proposed research including who does what, when, where, how, and for how long, etc.

a. Purpose

The purpose of this research is to assess the awareness and willingness to participate forest carbon credit markets by family forest landowners in the Southeast, United States. This project focusses on family forest landowners' interest in carbon sequestration and newly emerging various carbon markets/ voluntary carbon credit programs. Furthermore, the research seeks to determine how emerging carbon markets could help landowners to generate supplemental income for their livelihood. Carbon markets/ voluntary carbon credit programs offered to landowners can provide an additional source of revenue from their forestland if they manage to increase carbon sequestration. Carbon credits are credits provided based on the additional amount of increased carbon stored in the trees on the forestland due to specific management activity or action.

b. Participant population, including the number of participants and the rationale for determining number of participants to recruit and enroll.

Participant population includes family forest landowners of a minimum of approximately 2000 count. Participants are selected from email contacts based on their criteria of being a family forest landowner. A family forest landowner is defined as forest landowners who own forestland in terms of single person ownership, family ownership, partnership, estate, or trusts. The reason for selecting family forest landowners as targeted population for our research is because they form the majority of the forest landowners in the Southeast and historically, such market opportunities have not been available to this group of forest owners. Reaching a sufficient sample size of at least 2,000 with expectation of a 20-25% response rate is our target. And provide sufficient data for our project goals. We hope to reach and receive more than this, but we believe based on commonly published response rates for similar type survey work with similar target audiences, and family forest landowner email contacts available to us for this project, our sufficient sample size target is possible. Family forest landowners contacts are provided from the Alabama Extension – Forestry, Wildlife, and Natural Resources Team contacts, which Dr. Maggard is an Extension Specialist with the School of Forestry and Wildlife Sciences and the Alabama Cooperative Extension System and has available for his Extension work. Further, the survey will be distributed to family forest landowners who are members of the Forest Landowners Association and Alabama Forest Owners Association.

c. Recruitment process. Address whether recruitment includes communications/interactions between study staff and potential participants either in person or online. *Submit a copy of all recruitment materials.*

Survey would be completely conducted through online mailing. No direct contact or interface with participants will occur. The survey is designed using Qualtrics and all information will be provided via email and through the Survey link created in the Qualtrics survey platform.

d. Consent process including how information is presented to participants, etc.

A detailed consent letter is attached with the survey before participants get started to fill out the questionnaire. If they decide to participate in this research study, they will be asked to fill out the questionnaire reporting their knowledge and interests in carbon credit programs and information regarding current forest management practices on their forestland. This consent letter provides details on their wiliness to participate in research study, benefits of participation, risks and discomforts associated, and compensations or costs for participating.

e. Research procedures and methodology

This survey methodology will follow Dillman's Tailored Design Method for online survey's and is implemented through online mailing (E-mail). Family forest landowners contacts are provided from the Alabama Extension – Forestry, Wildlife, and Natural Resources Team contacts, which Dr. Maggard is an Extension Specialist with the School of Forestry and Wildlife Sciences and the Alabama Cooperative Extension System and has available for his Extension work. Further, the survey will be distributed to family forest landowners who are members of the Forest Landowners Association and Alabama Forest Owners Association. Contacts will be sent an email that contains information about the survey and the survey link. Once they open the link, a detailed consent letter is attached with the survey before participants get started to fill out the questionnaire. If they decide to participate in this research study, they will be asked to fill out the questionnaire reporting their knowledge and interests in carbon credit programs and information regarding current forest management practices on their forestland. This consent letter provides details on their wiliness to participate in research study, benefits of participation, risks and discomforts associated, and compensations or costs for participating (which is none). The questionnaire was developed using Qualtrics XM software. Approximately 10-14 days following the first email distribution, a follow-up reminder email will be sent that contains the same information as the original email with the addition of serving as a reminder notice. Approximately, 1-month following the distribution of the first email the survey will close.

f. Anticipated time per study exercise/activity and total time if participants complete all study activities.
Anticipated time per study activity would take approximately 15 – 20 minutes depending on the availability of the information that family forest landowners' have.

g. Location of the research activities.
Southeast region-wide, through online survey.

h. Costs to and compensation for participants? If participants will be compensated describe the amount, type, and process to distribute.
There is no compensation offered for participation in this survey. There is no monetary cost to participate.

i. Non-AU locations, site, institutions. *Submit a copy of agreements/IRB approvals.*
N/A

j. Additional relevant information.
N/A

5. Waivers
Check applicable waivers and describe how the project meets the criteria for the waiver.

☐ Waiver of Consent (Including existing de-identified data)

☒ Waiver of Documentation of Consent (Use of Information Letter, rather than consent form requiring signatures)

☒ Waiver of Parental Permission (in Alabama, 18 years-old may be considered adults for research purposes)

a. Provide the rationale for the waiver request.
We will provide an information letter and a mandatory selection to either participate or not participate before providing access to the survey questions. No persons under 18-years of age will be targeted or contacted for this project.

6. Describe the process to select participants/data/specimens. If applicable, include gender, race, and ethnicity of the participant population.

The source of all data for this research will be closed case records, meaning no identifiable information will be associated with participants and their responses to the questions, of adult family forest landowners of regardless of their gender, race, ethnicity or education levels. The only selection criteria is that they contacts fall under the category of family forest landowner which is defined as forest landowners who own forestland in terms of single person ownership, family ownership, partnership, estate, or trusts. Landowners not in this category are not selected as potential participants. Source of data will be through email contacts.

7. Describe why none of the research procedures would cause a participant either physical or psychological discomfort or be perceived as discomfort above and beyond what the person would

experience in daily life (minimal risk).

We are only asking participants about their awareness, knowledge, willingness to consider, and willingness to learn about, managing forest, generating income from forest, carbon sequestration, carbon markets, and questions about what could attract or exclude their willingness to participate in such markets if available. No personal information, records, financial, or health related information will be asked or collected. We are simply assessing this category of landowner to better understand would could or could not be impactful to the establishment, success, and longevity of such markets and to gather information that can help researchers and educators better understand how such programs need to be designed to assist with improving such opportunities.

8. Describe the provisions to maintain confidentiality of data, including collection, transmission, and storage. Identify platforms used to collect and store study data. *For EXEMPT research, the AU IRB recommends AU BOX or using an AU issued and encrypted device. If a data collection form will be used, submit a copy.*

The researcher will not collect any identifying data or report information about individuals in any research report. No identifying information will be extracted from the survey. Identification of the research participants will not be recorded at any time during or after the data collection and no identifying information will be recorded that will link data to any individual participant. The researcher will utilize a numerical coding system so that no one can connect data collected. Following the completion of the data collection and analysis, the data sheet will be sorted in a locked cabinet in the office of researcher's faculty professor for a period, after which time it will be destroyed. The researcher will analyze the extracted data using ANNOVA using standard statistical tests. She will produce a paper for her MS thesis, and provide a summary of the findings and assessment to the family forest landowners.

a. If applicable, submit a copy of the data management plan or data use agreement.

9. Describe the provisions included in the research to protect the privacy interests of participants (e.g., others will not overhear conversations with potential participants, individuals will not be publicly identified or embarrassed).

To protect the privacy and the data provided by the participants, we ask them not to disclose their names on the survey. The data will be anonymous. We ask them not to write their name or any other information associated with their business on the questionnaire. Any information obtained in connection with this study will not be connected to the participant at any time during the data collection or storage.

10. Additional Information and/or attachments.

In the space below, provide any additional information you believe may help the IRB review of the proposed research. If attachments are included, list the attachments below. Attachments may include recruitment materials, consent documents, site permissions, IRB approvals from other institutions, data use agreements, data collection form, CITI training documentation, etc.

Attachment include: Email notification to participate in the survey, Information letter, and the survey itself.

Required Signatures *(If a student PI is identified in item 1.a, the EXEMPT application must be re-signed and updated at every revision by the student PI and faculty advisor. The signature of the department head is required only on the initial submission of the EXEMPT application, regardless of PI. Staff and faculty PI submissions require the PI signature on all version, the department head signature on the original submission)*

Signature of Principal Investigator: ____________ **Date:** 12/16/2021

Signature of Faculty Advisor (If applicable): ____________ **Date:** ____________

Signature of Dept. Head: ____________ **Date:** ____________

Version Date: **12/16/2021**