AN EXPLORATION OF THE ECONOMIC AND ENVIRONMENTAL TRADEOFFS ACROSS FORESTS, WATER QUALITY, AND SOLAR POWER GENERATION IN GEORGIA, UNITED STATES

by

CATHERINE ELLIS COOPER

(Under the Direction of Puneet Dwivedi)

ABSTRACT

A need exists to understand the financial viability of solar power generation in Georgia and its potential for deforestation. Additionally, market-based avenues for improving water quality should be considered, such as forest certification programs focusing on forestry best management practices. An economic and environmental comparison of South Georgia loblolly pine and solar power generation of similar acreage was completed. Solar power was identified as more profitable at a larger scale (1 MW), indicating that there exists a potential for small-acreage landowners to convert their forestlands into solar farms. Following, a multi-watershed exploration of the impact of the Sustainable Forestry Initiative's Fiber Sourcing Standard (SFI-FSS) on water quality (through suspended sediment concentration, SSC) in Georgia was performed. Based on developed regression-based models, a positive relationship was identified between SFI-FSS wood basket cover and water quality, indicating an increase in SSC and discharge occurs with an increase in SFI-FSS certified wood baskets.

INDEX WORDS: Family Forestlands, Renewable Energy, Forest Management, Certification

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by

Catherine Ellis Cooper

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Catherine Ellis Cooper

Major Professor:	Puneet Dwivedi
Committee:	Gary L. Hawkins C. Rhett Jackson

Electronic Version Approved:

Ron Walcott
Dean of the Graduate School
The University of Georgia
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DEDICATION

I dedicate this thesis to my family.

To my parents, Anne and Rick, and my sister Cassie for their never-ending support throughout my professional and educational journey.

To my cats, Platinum and Palladium, for always being ready to give a supportive purr and reminding me to take a break every now and then.

To my husband, Nick, for loving and encouraging me in all that I do and hope to achieve.

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Introduction

1.1 Georgia's Forests

Georgia is home to the largest acreage of forestlands in the Southeast at 24.6 million acres[1], comprising over 65% of Georgia's land area. Of that, 24 million acres are classified as timberlands[1], or "land that is commercially available with no timber harvesting restrictions."[2] As such, the wood products sector is vital to the economy of Georgia, the largest roundwood producer in the United States[2], by contributing over $41 billion to the state's economy and providing over 143,000 jobs in 2021[3]. Forestry, particularly pine silviculture, is the foundation of Georgia's forestry sector. Georgia's most common timberland species is loblolly pine (Pinus taeda), which is utilized by numerous paper, pulp, and dimensional lumber mills located throughout the state[1].

As is the trend in the larger Southeast region, the majority (55%) of Georgia's forestlands are owned by individuals or families[2]. Most of these holdings are small, with 54% of individual and family landowners holding less than 100 acres of land[4]. And while the timber industry itself is profitable, timber prices paid to growers have stagnated in recent years[5]. This price stagnation may incentivize Georgia forestland owners, particularly those family forest landowners, to seek alternative sources of income from their land.

1.2 Forests Under Threat

As the region with some of the fastest growing population in the nation[6], Southern forests are under a multitude of threats. Georgia is no exception to this trend, with the population increasing by 10.6% between 2010 and 2020, with the majority of that population concentrated in urban areas[7]. Urbanization has been identified as the most significant factor for the conversion of forestland to non-forest land use in Georgia, with 1.7 million acres of forests lost between 1982 and 2012, mainly due to urbanization[8]. Urban development's threat to forests is only expected to continue, as a loss of 1.9 million acres of forestland is projected to occur between 2000 and 2050[9].

As the impacts of climate change worsen and become more visible, the calls to shift from fossil fuels to renewable energy sources have grown. While progress on the transition remains slow, as evidenced by the 2022 United Nations Conference of the Parties' (COP27) omission of the phasing out of fossil fuels in the final COP27 agreement[10], approximately 26% of global electricity generation was provided by renewable energy sources in 2018[11]. Domestically, the Biden-Harris Administration's Inflation Reduction Act (IRA) increased incentives for clean energies. Some of those incentives have been directed at photovoltaic or solar energy generation, providing tax credits and accelerated depreciation for installing solar panels. No greenhouse gas emissions are emitted during solar energy generation, making them a preferred alternative to coal, oil, and natural gas energy production in the fight against climate change. While the full lifecycle emissions of solar cells and solar energy production were beyond the scope of this research, it should be noted that the material mining, production, transportation, and disposal of solar cells are all opportunities for emissions generation[12].

The major threat to forests from renewable energy, particularly solar energy, arises due to the large land requirements of solar arrays. Previous studies have estimated that a 1 megawatt (MW) solar array would require between 3 and 7.5 acres of land[13]. Variations in land requirements may be due to the type of equipment used (fixed versus tracking solar arrays), latitude (in which lower latitudes receive greater sun exposure), and climate of the area (warmer climates reduce the efficiency of solar panels)[13, 14]. In Georgia, the Georgia Power Company (GPC, the largest utility provider in the state) was required by the state's Public Service Commission to procure an additional 2,210 MW of solar energy by 2022[15]. Between 6,600 and 16,500 acres of land would have been needed to meet this need through ground-mounted solar arrays. Therefore, to meet our ever-growing energy needs through solar power generation, a large amount of land would be needed and likely converted from its current use to solar arrays. In a forested state such as Georgia, this is likely to generate increased competition for land between renewable energy production and roundwood production.

1.3 Forests & Water Quality

The relationship between forests and water has been well-established in the literature. While decreased forest cover resulted in an increased volume of water within a catchment (resulting in increased water yield)[16, 17], various studies have shown that the same loss in forest cover resulted in reduced water quality, as summarized in Table 1.1. These studies have identified the impacts of land use change and conversion away from forests on water quality. Research regarding timber management practices on water quality has been mixed, with Lebo and Herrmann (1998) finding insignificant changes in water quality due to silvicultural practices[18], while Grace III, Skaggs, and Chescheir (2006) identified considerable changes in water quality due to thinning[19].

Table 1.1: Summary of existing literature regarding the impact of forest cover on turbidity and total suspended solids (TSS) concentrations.

Study	**Study Area**	**Time Period**	**Major Findings**
Riekerk (1983)[20]	Florida, United States	1978-1980	Harvest of poorly drained flatwoods resulted in increased suspended sediments, though absolute values remained low relative to upland forests
Lebo and Herrmann (1998) [18]	North Carolina, United States	1986-1994	Loblolly pine silviculture operation activities resulted in increased water flow and negligible change in TSS
Bradshaw et al. (2005)[21]	Georgia, United States	2003-2004	Forested streams resulted in decreased sediment yields as compared to agricultural and suburban streams
Grace III et al. (2006)[19]	North Carolina, United States	2000-2002	Thinning in drained loblolly pine resulted in increased TSS
Tu (2011)[22]	North Georgia, United States	1974-2005	Higher percentage of urban land resulted in elevated water pollutants
Singh and Mishra (2014) [23]	Western Ghats, India	1998-2010	A 1% decrease in forest cover resulted in 8.41% and 4.17% increase in turbidity and TSS, respectively
Hovenga et al. (2016)[24]	Florida, United States	2000-2100	Simulated land use land cover change indicated higher sediment loads in urban and agricultural areas compared to forested areas
Erdoğan et al. (2018)[25]	Istanbul, Turkey	2005-2015	18% broadleaf timber thinning resulted in increase in turbidity and suspended sediment concentration
Piffer et al. (2021)[26]	Brazil	2000-2014	Forest land cover resulted in lower turbidity concentrations

The relationship between forests and water quality does not only have implications for the larger ecosystem but for the region's drinking water supply. In the Southern United States, 58% of the population relies upon surface water withdrawals to meet their daily domestic needs[27]. This is especially true of Georgia's urban centers in the northern portion of the state, which are expected to continue growing in the region, while the Lower Coastal Plain region relies predominately on groundwater for domestic water needs. As forests can provide the valuable ecosystem service of water filtration without charge, a decrease in water quality from a loss of forest cover could have implications for water treatment costs. Table 1.2 illustrates previous work quantifying the monetary impact of reduced water quality, with studies broadly identifying an inverse relationship between forestland cover and water treatment costs (i.e., as forest cover decreases, treatment costs increase).

Table 1.2: Summary of existing literature pertaining to the impact of water quality on water treatment costs.

Study	**Study Area**	**Time Period**	**Major Findings**
Holmes (1988) [28]	United States	1986	1% increase in turbidity resulted in 0.07% increase in treatment costs per million gallons (MG)
Dearmont et al. (1998) [29]	Texas, United States	1988-1991	1% decrease in turbidity resulted in 0.27% reduction in treatment costs per MG
Ernst et al. (2004) [30]	United States	2002	A 1% increase in forest cover resulted in 2% decrease in treatment and chemical costs per MG
Heberling et al. (2015) [31]	Ohio, United States	2007-2011	1% decrease in turbidity resulted in 0.02% decrease in treatment costs immediately and additional 0.01% over future days per 1,000 gallons
Price et al. (2017) [32]	Canada	2011	1% increase in turbidity resulted in 0.099% increase in treatment costs per 1,000 cubic meters

In addition to the presence of forests, proper forest management has been found to have a positive influence on water quality. Best management practices (BMPs) are those that "protect and improve the physical, chemical, and biological integrity of the nation's waters."[33] Examples of BMPs have been included in Table 1.3. BMPs were instituted by state forestry agencies following the passage of the Clean Water Act to reduce nonpoint source pollution into waterways from managed timber tracts[34]. The practices vary from properly locating skid trails and access roads to maintaining buffers and streamside management zones along waterways, with the overall goal of controlling or reducing soil erosion and stream sedimentation[33]. The use of BMPs in the Southeast Coastal Plain region was found to reduce sediment delivery to waterways by 95% from clearcut stands[35], illustrating the impact of proper forest management.

Table 1.3: Examples of forestry BMPs across various categories[33].

Streamside Management Zone (SMZ)	**Roads**
Limit stream crossings	Schedule construction for favorable weather
Determine appropriate SMZ width based on stream type	Follow contour of land for roads as much as possible
Locate log decks, staging areas, and skid trails out of SMZ	Minimize number, length, and width of access roads
Site Preparation	**Timber Harvesting**
Cleanup or contain all pesticide spills immediately	Minimize soil disturbance
Hand plant on >21% slopes with severely erosive soils	Maintain stream bank integrity

While state forestry agencies publish and encourage BMPs, forest certification programs around the world emphasize their implementation for certification requirements. Forest certification is a market-based mechanism with third-party verification used to promote sustainable forest management practices[36, 37]. One such program is the Sustainable Forestry Initiative (SFI), which operates in the United States and Canada. Unlike other certification programs, SFI's Fiber Sourcing Standard (FSS) certification program certifies wood processing mills while allowing them to source from certified and non-certified timberlands[38]. This is especially important for Georgia's small-acreage individual and family forest landowners, for whom forest management certification is prohibitively expensive[38].

1.4 Study Objectives

As the transition to renewable energy and solar power generation heats up, and the economics of small-scale solar farms encourage Georgia's small-acreage timberland owners to convert their timberlands to solar arrays as an alternative source of income, the economic and environmental tradeoffs of the two land uses should be considered to ascertain deforestation potential in the state. In this context, we compare the economic and environmental performances of loblolly pine stands and solar farms at a common scale in South Georgia. However, as greater pressure is placed on the state's forestlands from development and the renewable energy transition, alternative avenues to improving water quality other than forest cover should be explored, such as forest certification programs, with their emphasis on BMPs. To do so, we explore how changes in

SFI-FSS certified mill wood baskets impact suspended sediment concentrations in watersheds throughout Georgia.

Chapter 2

An Economic and Environmental Comparison of Loblolly Pine and Solar Power in South Georgia

2.1 Solar Power in Georgia

As the transition to renewable energy has increased throughout the United States and the globe, solar power generation in Georgia has accelerated in recent years. Georgia moved from 22nd in the nation in solar power generation to 9th between 2017 and 2018 and to 5th in 2021[39, 40]. As of the first half of 2022, 4,299 MW of solar power systems had been installed in the state (Figure 2.1), the majority of which was utility-scale[40]. Solar capacity is expected to continue rising, as the Georgia Public Service Commission approved GPC's 2022 Integrated Resource Plan to add an additional 2,300 MW of renewable energy resources to the grid by 2024, the majority of which will be from solar energy generation[41].

Interest in solar power generation has led to several solar programs and opportunities in the state. Community Solar Programs with GPC and local Electric Membership Corporations (EMC) allows customers to purchase monthly subscriptions to solar power[15, 42]. Solar power can also be sold to utilities in various ways, with utility customers selling excess solar generation from behind-the-meter systems or larger generators (250 kilowatts (kW) and 80 MW) selling all energy generation to the utility company at pre-determined rates through

Power Purchase Agreements (PPAs)[43, 44]. GPC's Distributed Customer-Connected Solar Program allows up to 50 MW of solar power generation to be connected from non-utility-scale customers. The program allows smaller-scale solar systems, between 1 kW and 3 MW, to sell 100% of generated electricity to GPC through PPAs[44]. In addition to generating solar energy, property owners can lease their land for solar energy development, per interviews with Ben Oberman of Green Power EMC[45] and Candler Boyd of Coastal Solar Power[46].

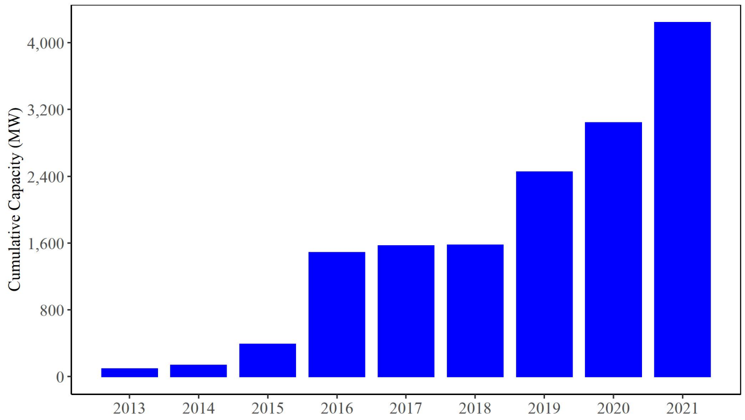


Figure 2.1: Cumulative utility solar installations in Georgia.[40]

Previous studies have identified various benefits of solar energy, including emission reduction potential in comparison to fossil fuel sources, energy independence, and low operation costs. Limitations for solar energy include high start-up costs, intermittency, resource requirements[47], and large land requirements, as previously discussed. Research has identified the financial viability of behind-the-meter solar systems, in which some or all of the generated energy is utilized by the generator[48, 49]. Woodson[48] compared the financial and environmental benefits of longleaf pine and behind-the-meter solar energy in Florida, concluding solar energy was a financially viable option. In addition, Farangi et al.[49] studied the economic potential of solar energy with a government-backed payment system, identifying a five-year payback period for the solar system costs.

The economics of small-scale solar farms encourage small-acreage timberland owners to convert their timberlands to solar arrays as an alternative source of income. This could lead to a loss of a significant percentage of Georgia timberlands, in addition to projected loss from urbanization[50]. As such, an understanding of the economic and environmental tradeoffs between forestry and solar power generation in Georgia is essential for ascertaining deforestation potential, especially in the context of those family forest landowners who own small acreage (<100 acres) across Georgia. This is especially true as there is practically no literature and research on this issue. In this context, this study compares the economic performances of loblolly pine stands and solar farms so that the generated information could feed into ongoing policy deliberations on promoting conservation and renewable energy generation at the state level and beyond.

2.2 Methods

2.2.1 Economic Analysis

The economic potential of the two land uses was compared using net present value (NPV) and land expectation value (LEV). NPV is a commonly used standard in forest valuation[51] which utilizes cash flow from revenues and costs and discounts them back to the present day[52], expressed as:

$$NPV = \sum_{0}^{t} PV_{Cash\,inflows\,\&\,outflows} \tag{2.1}$$

$$PV = \frac{Future\,Value}{(1+r)^t - 1} \tag{2.2}$$

where PV is the present value of individual cash inflows and outflows in year t with the discount rate, r. LEV, another commonly used standard in forest valuation, calculates bare land value with the assumption that the current land use will continue in perpetuity[53]. LEV is expressed as:

$$LEV = \frac{NFV}{(1+r)^t - 1} \tag{2.3}$$

$$NFV = PV \times (1+r)^t \tag{2.4}$$

where NFV is the net future value of one timber rotation or 25 years of a PPA, PV is the same as defined in Equation 2.2, and r and t are the same as previously defined[53, 54]. While NPV estimates the discounted value of one timber rotation or one PPA, LEV estimates the discounted value of all timber rotations or all PPAs by estimating the bare value of the land with the assumption that the current land use will continue in perpetuity, i.e., new trees will continue to be planted following the final harvest or that new solar panels will be installed following the completion of the PPA[53]. Cash inflows and outflows are held constant for the analyses.

2.2.2 Roundwood Availability

Roundwood growth and carbon stocks were modeled using version 1.32 of the Growth, Yield, and Carbon Balance Model for Planted Loblolly Pine[55], which utilizes allometric and biometric equations to simulate above and below ground tree growth and estimate carbon stocks. Three timber products (sawtimber, chip-and-saw (CNS), and pulpwood) were modeled at three site indices (60 ft, 70 ft, and 80 ft), differentiated by diameter-at-breast height and the top diameter of the stem (outside bark)[54]. All started with a planting density of 567 seedlings/acre and initial fertilization at Year 2. One round of thinning and additional fertilization was performed (Table 2.1). Timber growth was modeled to a Stand Age of 25 years to make a direct comparison to the assumed 25-year life of the solar arrays. Two discount rates (6% and 8%) were used to evaluate the economic performance of loblolly pine plantations. Inflows and outflows, along with their associated prices, are reported in Table 2.2.

Table 2.1: Inputs for Growth, Yield, and Carbon Balance Model for three loblolly pine simulations. Numbers indicate stand age. Initial fertilization consisted of 125 lbs/acre of Diammonium Phosphate (DAP) and secondary fertilization consisted of 125 lbs DAP and 385 lbs/acre of Urea[56]. Thinning age and intensity was determined when the total thinned biomass weight was at least 28 tons/acre.

	Site Index (ft)		
	60	**70**	**80**
Site Preparation	0	0	0
Weed Control	1	1	1
Initial Fertilization	2	2	2
Secondary Fertilization	19	16	14
Thinning Intensity (%)	33	33	33
Thinning Age	19	16	14

Table 2.2: Parameters and prices used in estimating cash flows. Timber stumpage prices are based on South Georgia average prices from 2019-2021 and all others are based on 2020-2021 pricing[57–61].

Parameter	**Price**	**Type of Cash Flow**
Mechanical Site Preparation	$131.44/acre(ac)	Outflow
Chemical Site Preparation	$82.34/ac	Outflow
Hand Planting	$78.29/ac	Outflow
Seedling Purchase	$75/1000 seedlings	Outflow
Herbaceous Weed Control	$53.80/ac	Outflow
Initial Fertilization	$65.00/ac	Outflow
Secondary Fertilization	$278.00/ac	Outflow
Management Costs	$5.00/ac/year(yr)	Outflow
Tax	$5.00/ac/yr	Outflow
Hunting Lease	$11.74/ac/yr	Inflow
Sawtimber Stumpage Price	$28.00/ton	Inflow
Chip-N-Saw Stumpage Price	$21.89/ton	Inflow
Pulpwood Stumpage Price	$14.17/ton	Inflow

Atmospheric Carbon Reduction Potential

To demonstrate the atmospheric carbon reduction potential of the timber stands, carbon sequestration was modeled using the Gonzales-Benecke et al.[55] model. It was operationally defined as the in-situ carbon stock minus silviculture emissions from fertilization, harvesting, and transportation. Ex-situ carbon from harvested wood products was not included in carbon stock estimates because the sequestered carbon in harvested wood products is already accounted for in in-situ estimates prior to removal and the types of potential harvested wood products can vary depending on available mills in the vicinity. For modeling carbon sequestration, default model parameters were used.

2.2.3 Solar Power

Various models have been created to estimate energy generation and installation costs of renewable energy projects, including the National Renewable Energy Laboratory's (NREL) System Advisor Model (SAM) and PVWatts Calculator. SAM allows users to simulate projects using generic inputs or detailed equipment parameters along with financial inputs, utilizing hourly typical meteorological data from NREL's National Solar Radiation Database (NSRD) to determine irradiance. PVWatts Calculator, a simplified system developed by NREL, estimates energy production in a single year, utilizing NREL's NSRD for irradiance and estimated system size[62]. Inputs are limited in PVWatts Calculator, and no detailed cost inputs or outputs are included. In addition to SAM and PVWatts Calculator, NREL publishes solar installation cost estimates for various solar arrays, ranging from residential roof-mounted systems to utility-sized arrays, utilizing national average values[63]. To better compare Georgia-based timber and solar investments, Georgia-based solar installers Radiance Solar and Coastal Solar Power were consulted regarding the solar energy industry in Georgia and solar installation costs. Detailed installation costs and energy generation estimates were provided by Radiance Solar, a prominent solar installer based in Atlanta, Georgia, who performs installations throughout the Southeast, specializing in commercial and utility solar arrays[64, 65]. By basing costs off a local installer rather than NREL's national average, the cost estimate should resemble quotes Georgia landowners would receive.

Installation costs and energy generation were identified for a 350 kW system occupying approximately one acre of land and a 1 MW system occupying approximately five acres. These smaller system sizes, representing mid-range sized systems eligible for revenue through GPC's Distributed Customer-Connected Solar Program[44], allow for approximate scaling of investment estimates for interested small-acreage landowners. The land area required for the solar systems does not scale linearly (linear scaling based on one acre for the 350 kW system would result in a 1.75 MW system occupying five acres of land). The one and five acres of land include both direct (the panels and equipment themselves) and indirect (buffer needed to reduce shading on array) land use. While the larger 1 MW array has more panels and greater direct land use than the 350 kW array, the indirect land use does not scale linearly, resulting in lower per Watt land use for the 1 MW array. Both systems were ground-mounted, fixed-tilt systems located in Waycross, Georgia. The price per Watt estimate for the 350 kW system was $1.31 per Watt (W) and $1.20/W for the 1 MW system, lower than the national average cost estimates produced by NREL, $1.97/W for 200 kW and $1.59/W for 1 MW[63]. A breakdown of solar installation costs, along with a comparison to NREL's 1 MW estimate, is reported in Table 2.3. Radiance Solar prices for equipment and labor were based on 2022 pricing. We used a discount rate of 8% for selected solar systems.

The Federal Investment Tax Credit (ITC) and federal bonus depreciation were included in the estimate. The ITC is a tax credit that covers up to 30% of the cost of a solar system, including equipment and installation costs, increased from 26% by the 2022 Inflation Reduction Act[66]. Current federal bonus depreciation rules allow taxpayers to claim a 100% bonus depreciation for solar systems placed in service by December 31, 2022, with bonus depreciation reducing by 20% each year for those systems placed in service after 2022[67]. In addition, accelerated depreciation (known as the Modified Accelerated Cost-Recovery

Table 2.3: Solar installation cost breakdown, with all costs in \$/Watt. Radiance Solar estimates based on solar system oriented with an azimuth of 180°, the irradiance of 5.57 kWh/m2/day, a degradation factor of 0.4%, and an inverter efficiency of 95%[62, 64]. NREL estimates based on pre-2021 pricing and solar power system with a degradation factor of 0.7% and inverter efficiency of 98%; no details available regarding the azimuth or irradiance used in the NREL estimates[63]. (BOS = balance of system; EPC = engineering, procurement, and construction; PII = permitting, inspection, and interconnection)

	Radiance Solar		**NREL**
	350 kW	**1 MW**	**1 MW**
Module	0.49*	0.46	0.41
Inverter	0.04	0.03	0.07
Structural BOS	0.19	0.19	0.11
Electrical BOS	0.04	0.06	0.18
Install Labor& Equipment	0.2551	0.1956	0.14
EPC/Developer Overhead	0.0238	0.0375	0.43
PII	0.055	0.055	0.04
Sales Tax	0	0	0.05
Contingency	0.015	0.015	0.04
EPC/Developer Profit	0.205	0.156	0.12
Total	1.31	1.20	1.59

*note all costs in \$/W

System, MARCS) can also be applied to reduce solar system costs[67]. To both illustrate the benefit of depreciation and simplify the model, we utilized the one-time 100% bonus depreciation method, taken in Year 1 of system use. When the ITC is used with bonus depreciation, the depreciation basis equals 100% of the total installation cost minus half of the ITC[67]. Therefore, 85% (100% - 30%/2) of the total installation costs were eligible for federal depreciation, using a 22% tax rate (based on the median income in Georgia from 2015-2019)[68]. Taxes were not calculated as part of this estimate, as each individual's tax basis will vary widely. As such, depreciation, typically used to reduce the tax base and thus the amount of tax owed, was considered a source of revenue or available funds, consistent with depreciation being considered a noncash expense. Per example quotes from Radiance Solar and Coastal Solar Power, this practice is used for illustrating potential tax benefits for clients without needing to identify their tax status. No grants or other forms of aid were included in the analysis.

In addition, an annual maintenance plan was included. It was estimated using Radiance Solar's basic maintenance plan starting at \$1,500/year for the 350 kW system and $3,000/year for the 1 MW system, with an annual 2.5% expense increase. Maintenance costs cover basic cleaning and upkeep of the panels. Unexpected maintenance costs, such as broken or damaged equipment, were not included. Inverter replacement is typically required partway through the life of the system. As such, all inverters were replaced in Year 12.

Solar power profit from the electricity sold to the grid was based on the GPC's 25-year PPA, with a 2021 beginning payout rate of 3.195 cents (¢)/kilowatt-hour (kWh)[44]. As previously discussed, PPAs are part of GPC's Distributed Customer-Connected Generation program, which allows customers to sell 100% of the solar energy from systems ranging from 1 kW to 3 MW located on or adjacent to the customer's property[44].

To mimic the harvesting of the loblolly pine stands, we include the removal of the solar panels at the end of the 25th year of use in our analysis. Removing all components of a solar array (panels, racking, pilings) at the end of the PPA to then immediately replace them is not a practical solution in the majority of cases. In addition, the panels themselves, constituting the largest portion of the solar array installation costs (Table 2.3), are the major component that would require replacement, as the racking and pilings would only require periodic repair (assuming replacement solar panels are fully compatible with the remaining equipment). As such, we remove and recycle the solar panels to set the solar array land to a reasonable starting point in which new panels can be installed to begin anew. The solar panel recycling industry is in its infancy, and much of the information regarding processes and costs is considered proprietary and anecdotal[69]. We utilize a $20/module recycling cost, based on the range of $10-$45/module for the recycling process[69–71], and 75% of installation labor costs for panel removal labor costs[72]. We do not include transportation costs because those will vary greatly depending on the location of the recycler and fuel prices. Energy generation, costs, and revenues were estimated for the year of installation and 25 years of use, the typical guaranteed life of solar panels.

Carbon Emissions Reduction Potential

The carbon emissions reduction potential of the solar arrays was identified as emissions averted by displacing electricity generated using natural gas, the primary energy source for electricity in Georgia. To estimate the averted emissions from solar power generation, the CO_2 emission rate of natural gas-fired electricity generation was used, 900 pounds/megawatt-hour[73]. This estimate does not include emissions generated during the mining of materials, production, or transportation of the solar panels. A lifecycle assessment of solar panels was beyond the scope of this analysis.

2.3 Results

For the loblolly pine stands, a higher site index resulted in increased roundwood availability over 25 years (Figure 2.2). At Stand Age (SA) 25, biomass availability for SI80 was 48% and 22% higher than SI60 and SI70, respectively. At thinning, pulpwood decreased significantly by 34% (SI60) and 33% (SI70 & SI80). CNS growth increased significantly after thinning, comprising 46-60% of total roundwood availability at SA25 for all three site indices. Annual sawtimber growth rate reached a peak five years after thinning, with a maximum annual growth of 5.32 tons/acre at SA23 for SI60 (SI70: 7.4 tons/acre at SA20; SI80: 10.1 tons/acre at SA18), after which sawtimber growth slowed for all three site indices.

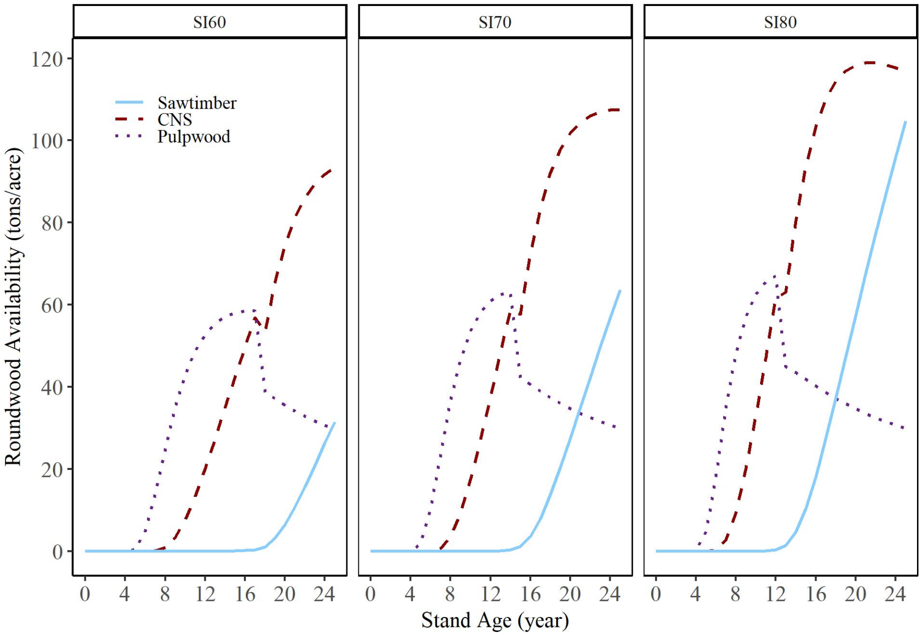


Figure 2.2: Biomass availability over 25 years for the three site indices (SI60, SI70, SI80) for an acre of loblolly pine stand in South Georgia.

NPV and LEV were higher over 25 years and increased at a faster rate for higher site indices (Figure 2.3) due to the greater availability of CNS and sawtimber. All three site indices followed roughly the same pattern and generated the same NPV or LEV until about SA4, after which they began to diverge. A positive NPV and LEV, i.e., a profit, was reached by SA10 for SI60, SA9 for SI70, and SA8 for SI80. Differences in the two discounted cash flow methods emerge for the maximum point of NPV and LEV (Figure 2.3). The maximum NPV for SI60 (at one-acre) was $412 in SA24, while the maximum LEV was $555 in SA23. The differences in both dollar amount and timing occur due to the number of rotations considered by each method. NPV considers only one timber rotation, whereas LEV considers profits made over multiple timber rotations, which results in both an increase in the amount of profit and a shorter rotation period (by one year) for maximum profit. This same pattern is seen for the five-acre stand and for both SI70 and SI80, in which LEV is greater than NPV, and the maximum is reached earlier. Following the peak, NPV and LEV decreased for the timber stands to SA25, which was used as the direct comparison to solar power generation. As shown in Figure 2.4, maximum LEV was reached earlier in the timber rotation with an 8% discount rate, but with a reduced profit. For SI60 (at one-acre), maximum LEV occurred prior to thinning in SA16 at $195, with maximum LEV after thinning reaching only $147 in SA22. The maximum LEV for SI70 was $500 in SA19 and for SI80 was $907 in SA17.

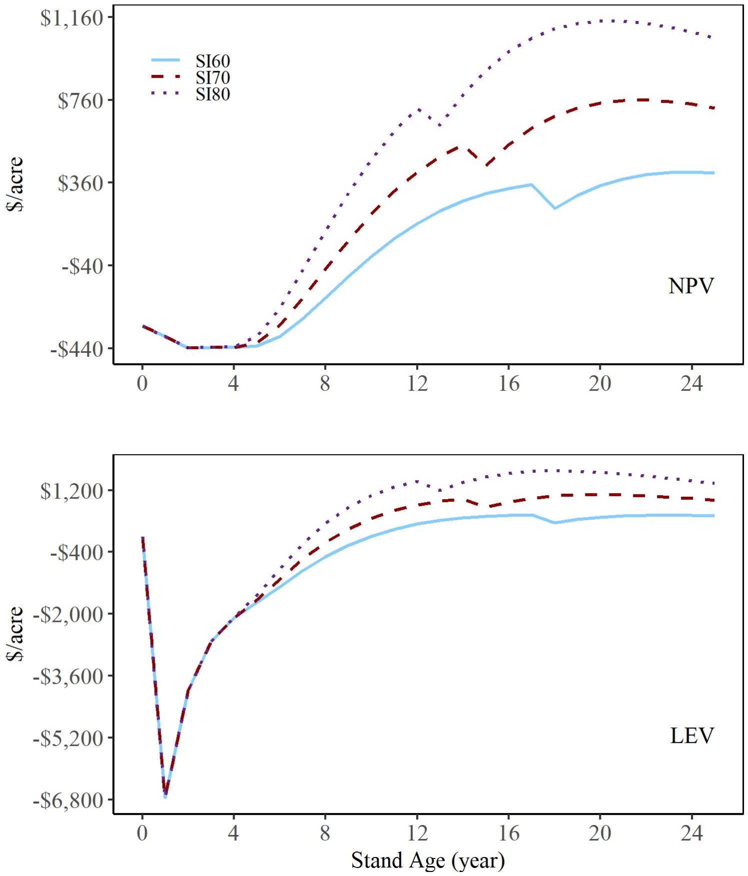


Figure 2.3: NPV and LEV (at 6% discount rate) over 25 years for the three site indices at a given stand age.

Annual electricity conversion for the 350 kW and 1 MW solar power systems is illustrated in Figure 2.5. Solar power generation declined over the 25 years following the annual degradation factor of 0.4%, with a 25-year rate of

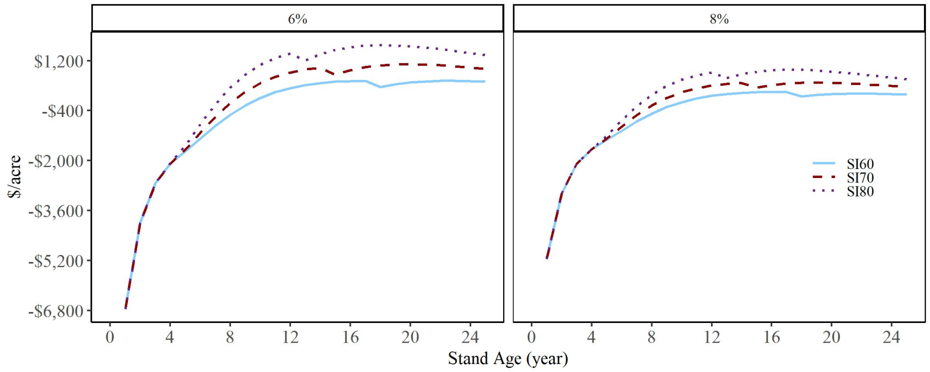


Figure 2.4: LEV at 6% and 8% discount rates over 25 years for the three site indices at a given stand age.

decline of 9.17% for both systems. The 1 MW solar power system had a higher amount of total lost solar conversion each year than the 350 kW system due to its higher conversion capacity. Figure 2.6 shows cumulative costs, revenues, and NPV over the 25-year timeframe for both solar systems. The 350 kW system was unable to generate a positive NPV within the 25-year timeframe. The 1 MW system, on the other hand, generated a positive NPV in Year 23 and remained positive through Year 25. Following the initial influx of revenue generated by the ITC and Year 1 federal bonus depreciation (100%), the annual revenue rate of change for both solar power systems steadily declined over the 25 years as annual electricity generation declined. However, the decline was lessened by the rate increase built into the 25-year PPA. A slight increase in costs occurred in Year 12 due to the replacement of the inverters and in Year 25 due to solar panel recycling.

A comparison of the Year 25 NPV and LEV for the timber stands and the two solar arrays is included in Figure 2.7. As previously discussed, all three timber stands generated a positive profit within the 25-year timeframe, and this is reflected in the positive Year 25 NPVs and LEVs. The modest profits generated at the one-acre scale by the timber stands performed better than the 350 kW solar system, which remained negative by the last year. In comparison, the story is flipped for the five-acre scale, where the 1 MW solar array generated a significantly greater profit within the 25-year timeframe than any timber stands. However, the timber stands generated a profit earlier (SA8-10) than the solar array (Year 23).

Annual carbon stored on loblolly pine stands was significantly lower than the annual avoided carbon emissions from solar energy use (Figure 2.8). For the loblolly pine stands, annual carbon is based on the accumulated biomass of the past year, not the total biomass of the tree at any one time. In comparison,

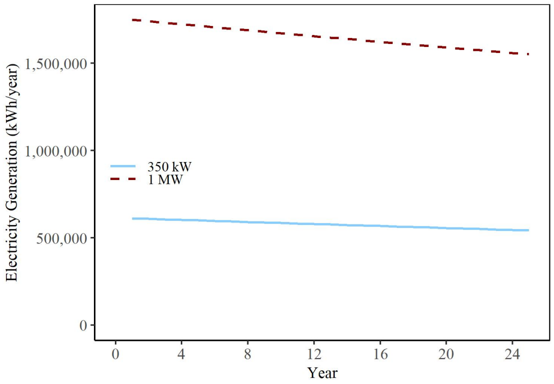


Figure 2.5: Annual electricity conversion for 350 kW and 1 MW solar systems. Electricity conversion decreases due to solar panel degradation over time. Note, scales differ between 350 kW and 1 MW.

emissions averted by solar power are independent year to year as CO_2-generating natural gas use is replaced. For loblolly pine stands, carbon stored was higher for increased site indices, with the maximum net annual amount for the one-acre stands at 15.6 short tons CO_2 at SA8 for SI60, 19.6 short tons CO_2 at SA8 for SI70, and 24.3 short tons CO2 at SA7 for SI80. Thinning caused a significant drop in stored carbon, which rebounded to only just above pre-thinning levels before resuming a decline, the result of decreased growth rates (Figure 2.2). The overall rate of decline of stored carbon from peak to SA25 for the loblolly pine stands was 59% for SI60, 62% for SI70, and 64% for SI80. Carbon emissions averted by the solar arrays followed the same pattern as electricity generation (Figure 2.5). Cumulative carbon stored over 25 years for SI80 was 351 short tons CO_2 for one acre and 1,753 short tons CO_2 over five acres, the highest for the timber stands. In comparison, cumulative avoided carbon emissions by solar power over the 25 years were 6,493 short tons of CO_2 and 18,550 short tons of CO_2 for the 350 kW and 1 MW systems, respectively. However, as previously mentioned, the analysis does not include embodied emissions which may be generated during the material mining, manufacturing, transportation, and disposal stages of the solar arrays life cycle, all of which constitute potential additional sources of emissions. The environmental benefit of reduced atmospheric CO_2 during electricity generation adds to the economic benefit of solar power compared to loblolly pine stands in South Georgia.

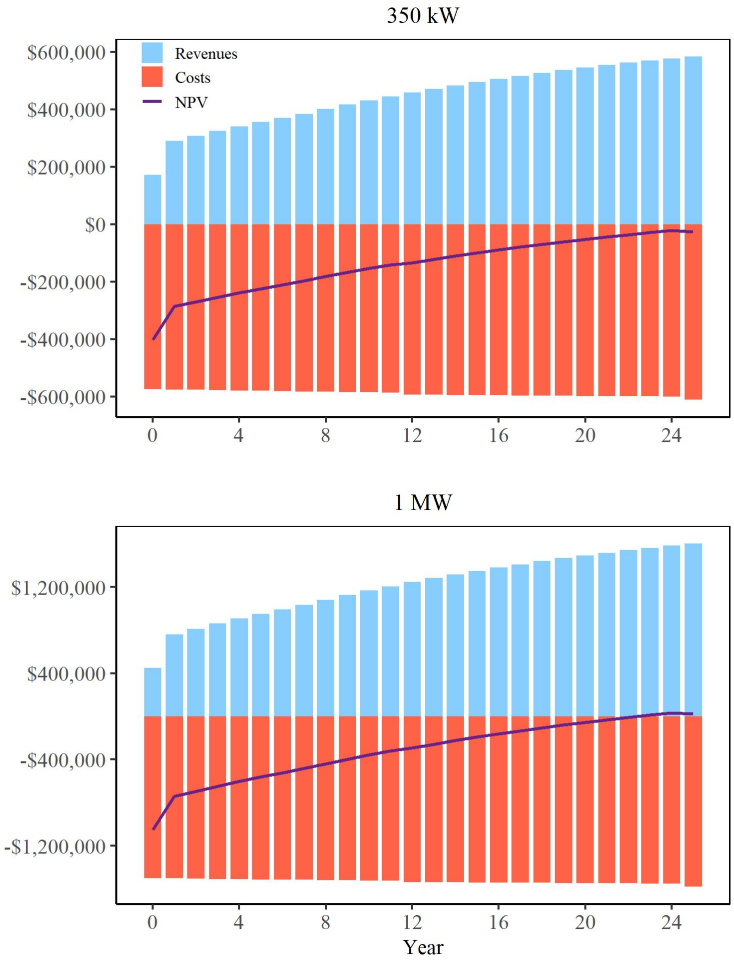


Figure 2.6: Cumulative NPV, Revenues, and Costs for 350 kW and 1 MW solar systems. Revenues are comprised of cumulative profit generated by selling solar energy to grid (begun in Year 1), 30% ITC taken in the year of installation (Year 0), and 100% federal bonus depreciation taken in first year of system use (Year 1). Costs are comprised of initial installation cost, cumulative maintenance costs (begun in Year 1), and solar panel recycling costs (Year 25). NPV is equal to the difference between Revenues and Costs each year. Note, scales differ between 350 kW and 1 MW.

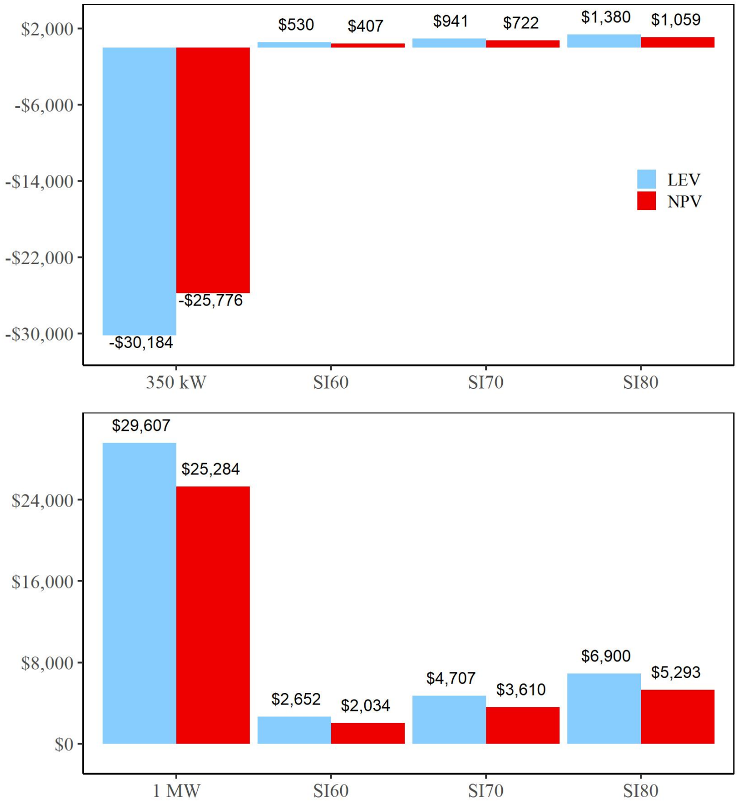


Figure 2.7: Year 25 NPV and LEV for the three site indices and 350 kW and 1 MW solar systems, compared at the acre scale.

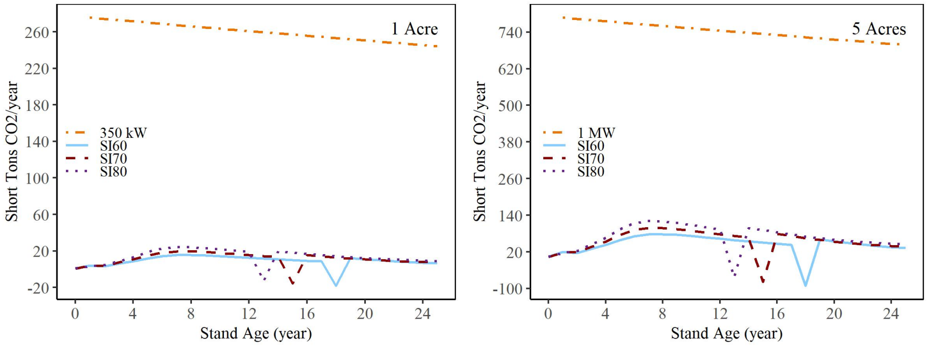


Figure 2.8: Comparison of annual CO_2 emission reduction potential for one-acre and five-acre plots. Annual CO_2 sequestered for timber sites are identified as short tons of CO_2 and annual CO_2 emissions averted for solar systems are identified as short tons of CO_2 equivalent. Note, short ton CO_2 scale between one acre and five acres differ.

2.4 Discussion

As previously discussed, few studies have compared the economics of roundwood and solar power generation using common assumptions. However, studies on the financial viability of solar arrays, whether in comparison to other land uses, have largely utilized a payback period, though the method has been criticized for not taking into account the time value of money and ignoring cash inflows which occur after the projected payback period[74]. Woodson[48] compared the financial viability of longleaf pine and behind-the-meter solar power (used to replace another form of energy) in the Southeastern United States, identifying solar power as a better financial prospect over 50 years. The author[48] identified a quicker payback period (nine years) for the solar system with a higher "payment" rate, illustrating how optimizing the system for the property or including household/property use can impact the rate of recovery. While the metric of the payback period is not directly comparable to NPV or LEV, our results for the larger solar array (1 MW) agree with the conclusion that solar power systems can be more profitable than timber stands. Farangi et al.[49] identified a five-year payback period on initial investment costs for a 1 MW system in Iran due to the lower installation costs and a government purchasing price at more than \$13/kWh. While these high prices are unlikely in the current market, it illustrates the even higher potential profits from solar power when the payment rate is increased. The GPC 25-Year PPA payment rates used are likely on the low end of rates a landowner may be able to acquire. Per correspondence with Michael Perkins at Radiance Solar[64], PPA payment rates can be negotiated, potentially giving the landowner a higher rate than advertised. An increased rate could result in reaching a positive NPV and LEV at an earlier point in the 25-Year PPA for the 1 MW solar system or a breakeven point for the 350 kW system.

While the payment rate can heavily influence the profit of solar systems, the cost of the system itself is also a major determinant, with regional variations and market pressures impacting solar installation pricing. Regional variations in solar energy pricings can occur, impacted by competition, consumer value of solar energy, and installer experience[75]. As shown in Table 2.3, NREL's estimate for a 1 MW system was significantly greater than the Radiance Solar estimate used here. NREL's cost estimate was based on national averages, illustrating the impact location has on solar installation prices[63]. The method of solar panel disposal at the end of usable life can also greatly impact the overall cost of the system. Recycling costs in the U.S. market are much higher than landfill costs (\$0.50-\$1.80/module), though recycling costs are expected to decrease over time as the demand increases and processes are improved[69]. Market forces such as inflation and supply chain disruptions can also influence solar equipment and installation costs. The economy of scale may also increase the profitability of solar investment, as illustrated by the difference in the profitability of the two solar systems studied here. Suppliers or installers can charge a lower unit price when more equipment is purchased, or a large job occurs at a single location, resulting in a lower price per Watt for larger systems. This was illustrated by the higher per Watt price for the 350 kW system as compared to the 1 MW system (Table 2.3). However, the high initial costs for solar systems may make it difficult for small acreage landowners to purchase solar power equipment at a size where prices are significantly reduced.

While sparse studies have compared these two land investment options, several studies have looked at ways to increase timberland profitability. Previous research has concluded higher site indices produce increased timber growth rates and, in turn, increased forest profitability[54, 76], as seen in our models. Paudel and Dwivedi (2021)[54], using the same growth and yield model[55] with a 5% discount rate, identified a peak loblolly LEV of $1,960/acre for SI80 at SA20, two years later than our results.

The significant CO_2 emission reduction potential of solar energy has been noted by others[48, 49]. Carbon emissions savings for a 3.5 MW solar system compared to natural gas use were determined to be approximately 950 short tons C/year by Woodson[48], much greater than the 16.5 short tons C/year saved from longleaf pine growth. Farangi et al.[49] estimated the greenhouse gas emission reduction potential of a 1 MW system at 1,216 short tons CO_2/year, with methane and nitrogen oxide emission equivalency included. The high CO_2 emission reduction potential of switching from fossil fuel electricity sources to solar power is an important factor in combating climate change. However, large land requirements for solar arrays, potentially leading to deforestation, could have consequences for other forms of atmospheric CO_2 reduction. In addition, while carbon payments were not included in our analysis, additional economic benefits to landowners could come from carbon markets. However, the economic viability of the solar arrays would likely continue to outweigh those of the loblolly pines stands based on the significant difference in annual and overall atmospheric carbon reductions between the two land uses.

CHAPTER 3

EXPLORING THE IMPACT OF SUSTAINABLE FORESTRY INITIATIVE FIBER SOURCING STANDARD ON WATER QUALITY IN GEORGIA

3.1 Forest Certification

Forest certification programs are designed to verify that certified entities, whether they be landowners or wood-consuming mills, are managing their forests and/or their timber procurement in a responsible and sustainable manner that protects water quality. Forest certification is a market-based mechanism with third-party verification used to promote sustainable forest management practices[36, 37]. While variations in standards and practices exist between different forest certification programs, the process generally involves the interested party (landowners or wood-consuming mills, depending on the applicable standard) contacting the certifying body and completing a pre-assessment, on-site verification, implementation of corrective action (if required), certification approval, and subsequent audits and inspections to ensure continued compliance[36].

The Sustainable Forestry Initiative (SFI) is endorsed by the Programme for the Endorsement of Forest Certification system and operates in the United States and Canada[38]. SFI not only certifies forest management and chain of custody but also offers a Fiber Sourcing Standard (FSS) certification in which wood-consuming mills are certified and can procure roundwood from both certified and non-certified forestlands[38]. SFI-FSS certification promotes responsible forestry practices based on 13 principles, 11 objectives, 29 performance measures, and 59 indicators which largely focus on the application of those BMPs[77]. (See Table 1.3 for examples of BMPs.) SFI-FSS certified mills require forest BMP implementation in their procurement contracts, resulting in increased BMP implementation even in non-certified forests[38]. Reviews of the large body of forestry BMP literature clearly find that implementing forestry BMPs improves water quality, reduces erosion[35, 78], and supports forest health and productivity[34].

SFI-FSS is especially relevant in the Southeast United States, where a majority (53%) of forestland is owned by family forest landowners for whom forest management certification is prohibitively expensive[1, 79]. In Georgia, the largest roundwood producer in the United States, the majority of timberland (55%) is owned by individual or family forest landowners[1, 2]. With the high costs of forest management certification[79] and a large number of family forest landowners, only about 18% of forestland in the state is certified, including those forest management certifications other than SFI[38]. However, as of 2019, 29 of the 46 large wood-consuming mills (those consuming >350,000 short tons of roundwood per year) in the state were SFI-FSS certified[61]. As the number of SFI-FSS certified mills has increased in the state over time, so has the BMP implementation rate, with 92.58% compliance with BMPs in general (up from <80% in the late 1990s) and a compliance rate of 93.9% in 2021 for specific forestry practices which impact streams[80].

Previous literature has studied various aspects of forest certification and its impacts, from BMP implementation rates to biodiversity. Newsom et al.[81] explored the impact of the Forest Stewardship Council (FSC) SmartWood forest management certification program on on-the-ground forestry operations, finding that companies seeking certification were required to implement changes, including changes for ecological improvements, to obtain or retain their certification. In Georgia, SFI-FSS certification was found to increase the mean BMP implementation rate from 90.9% for sites located outside of the roundwood sourcing area of a certified mill to 92.3% for those sites located within the sourcing radius[38].

Forest certification programs have been found to impact ecosystem services such as biodiversity. Gullison[82] identified three potential ways FSC Forest Management certification could impact biodiversity: 1) improving biodiversity through forest management, 2) reducing deforestation, and 3) reducing pressure on high conservation value forests. In addition, Kalonga et al.[83] found that FSC Forest Management certification increased tree biodiversity in Tanzania with increased adult species richness, diversity, and density. Limited work has focused on the effects of the SFI-FSS program, with none assessing the impacts on water quality. Azevedo et al.[84] simulated the effect of SFI Forest Management certification on sediment yield utilizing the Modified Universal Soil Loss Equation (MUSLE) in the Shawanee Creek watershed in East Texas. The authors concluded the SFI certification scenario resulted in reduced sediment yield in the watershed based on reductions in channel erosion. This study simulated only three BMP measures (streamside management zones, limit in harvest unit size, and three-year green-up interval) and was limited to a single watershed[84]. Karnatz et al.[85] identified similar BMP implementation rates associated with the SFI-FSS certification across varying levels of biodiversity habitat, with high and low biodiversity value tracts receiving similar adherence to BMPs. An empirical study of the impact of the SFI-FSS certification program on a multi-watershed scale has not been completed, to the best of the author's knowledge.

As the threat of deforestation increases and water quality is likely to be impacted, options other than increased forest cover to improve water quality should be explored. Based on the increased presence of the SFI-FSS certified mills and the emphasis BMPs place on protecting water quality, the relationship between SFI-FSS certification with its associated BMPs and water quality could provide a potential avenue for improving water quality using the power of markets. We explore how changes in the coverage of SFI-FSS certified mill sourcing area (termed as a wood basket) within a watershed impacts suspended sediment concentration (SSC) load in watersheds throughout Georgia, United States.

3.2 Methods

3.2.1 Study Area

Georgia has an abundance of forests, with over 24 million acres of forestland[1]. However, a growing population and increased urbanization have put those forestlands under threat from urban sprawl[7, 8]. Such land conversion has the potential to affect the state's water quality because forests have been known to protect water quality through reduced sedimentation and runoff (See Table 1.1). Because a majority of the population (58%) in the Southern United States depends on surface water withdrawal for meeting their daily domestic needs, any impact on water quality has the potential to adversely affect the state's drinking water sources[27].

3.2.2 Areas of Interest

A total of 30 United States Geological Survey (USGS) monitoring stations, located along various waterways throughout the state, were utilized for the analysis. Digital Elevation Models (DEMs) were used to approximate the drainage basin for each monitoring station. These drainage basins, termed Areas of Interest (AOIs) and depicted in Figure 3.1, were utilized as the subject areas for the analysis. At least one USGS monitoring station was located in four out of the five major physiographic regions (Coastal Plain, Piedmont, Blue Ridge, and Valley & Ridge). Furthermore, at least one USGS monitoring station was present in eight of Georgia's 14 major river basins.

3.2.3 Data Sources

To account for land cover impacts on water quality, crop and forest cover were utilized. The USGS National Land Cover Database (NLCD) was used to calculate the percent of AOI occupied by crop and forest cover. Crop cover (referred to as Crop Cover %) was considered that which was occupied by cultivated crops and pasture/hay. Forest cover (Forest Cover %) was considered land which was occupied by deciduous forest, evergreen forest, mixed forest, or woody wetlands. Crop Cover % and Forest Cover % were calculated only for those portions of the AOI located within Georgia. See Table 3.1 for the years of data availability and years of analysis used. The timeframes utilized for the analysis were set based on the years of NLCD data availability.

Table 3.1: Years of data availability. NLCD (crop and forest cover) years were used for basis of analysis years.

Crop & Forest Cover %	**Discharge & SSC data** **Single Year**	 **Three Years**	**SFI% Overlap**
2001	2001	2000-2002	2002
2004	2001	2003-2005	2004
2006	2001	N/A	2007
2008	2001	2007-2009	2009
2011	2001	N/A	2011
2013	2001	2012-2014	2013
2016	2001	2015-2017	2015
2019	2001	2018-2020	2019

SFI-FSS mill data were collected from multiple sources: SFI's online directory, certification bodies, and directly from the mills. SFI-FSS certification status was identified for the years in which Georgia Forestry Commission (GFC) survey data on BMP implementation was available and was comparable (2002,

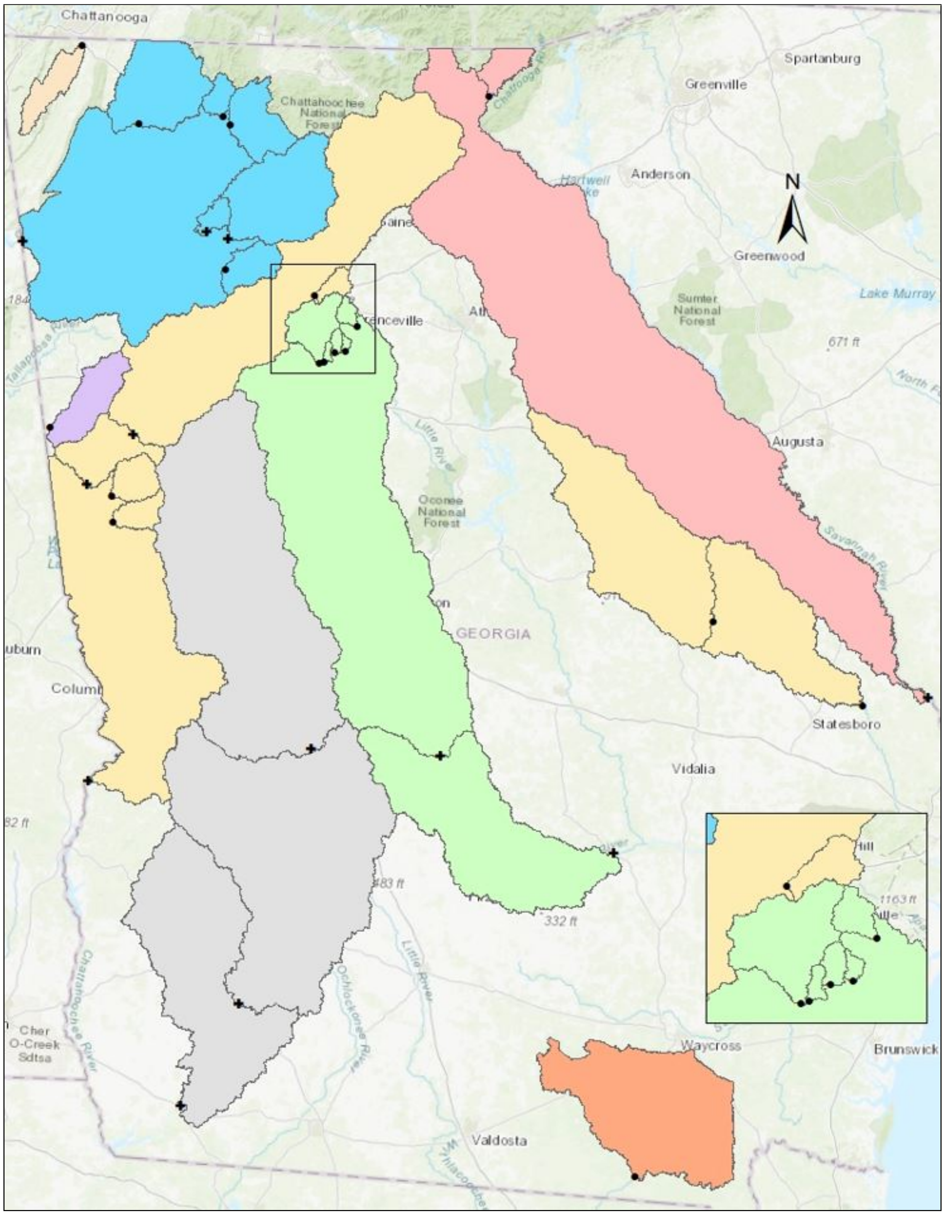


Figure 3.1: Map of AOIs. Circles and crosses indicate the location of the USGS monitoring station, with color differences in DEM-delimited watersheds indicating separate river basins. Circles represent those AOIs for which no reservoirs were located upstream of the monitoring station. Crosses represent those AOIs in which one or more reservoirs were located upstream of the monitoring station.

2004, 2007, 2009, 2011, 2013, 2015, 2017, 2019)[61]. Mill closures were identified as necessary by comparing the GFC list of primary mills to TimberMart South quarterly reports. To reflect the sourcing radius, or wood basket, of each mill, a buffer of 45 miles was created for inland mills and 65 miles for coastal mills [85](Figure 3.2). The percent of AOI occupied within SFI-FSS certified mill wood baskets (referred to as SFI % Overlap, Figure 3.3) was calculated using only the portion of the AOI located within Georgia, as information regarding the status of SFI certification in other states was not available. Only the coverage of wood baskets was considered as SFI % Overlap and not the number of mills or mill wood baskets. SFI % Overlap data was matched to the nearest year of NLCD data for the analysis (Table 3.1). Percent coverage of AOIs by non-SFI-FSS certified mills was not included in the analysis due to the high prevalence of non-SFI-FSS certified mills in the state. All AOIs were 100% occupied by these non-certified mills for the entire analysis timeframe, resulting in no variation for the variable across time or AOIs.

To account for variations in the erosion potential across AOIs, two factors from the Universal Soil Loss Equation (USLE) were included as variables. USLE is used to estimate soil loss in an area based on location specific factors (climate erosivity, erodibility of the soil, slope length and steepness) and land use and management[86, 87]. The two USLE factors utilized for the analysis are R Factor, also know as the rainfall-runoff erosivity factor, and K Factor, also known as the soil erodibility factor. R Factor identifies differences in the erosivity of an area caused by rainfall impact by representing the inputs driving sheet and rill erosion processes[86]. A GIS-compatible map of R Factors was retrieved from the National Oceanic and Atmospheric Administration's Open-source Nonpoint Source Pollution and Erosion Comparison Tool[88]. The Mean R Factor of the AOI was calculated to represent a single R Factor value for each AOI. K Factor accounts for the impact of soil properties on soil loss[87]. A map of K Factors computed by the Natural Resource Conservation Service was accessed via the ArcGIS Living Atlas of the World server[89]. The Mean K Factor of the AOI was calculated to represent a single K Factor value for each AOI. Both Mean R and K Factors were calculated only for those portions of the AOI located in Georgia.

Daily instantaneous discharge data from 2000 to 2020 was retrieved for each station from the USGS Instantaneous Values (IV) Web Service in December 2022. SSC data from 2000 to 2020 was retrieved for each monitoring station from the USGS National Water Information online portal in December 2022. For most of the USGS monitoring stations, SSC sampling occurred once a

(2002)

(2004)

(2007)

(2009)

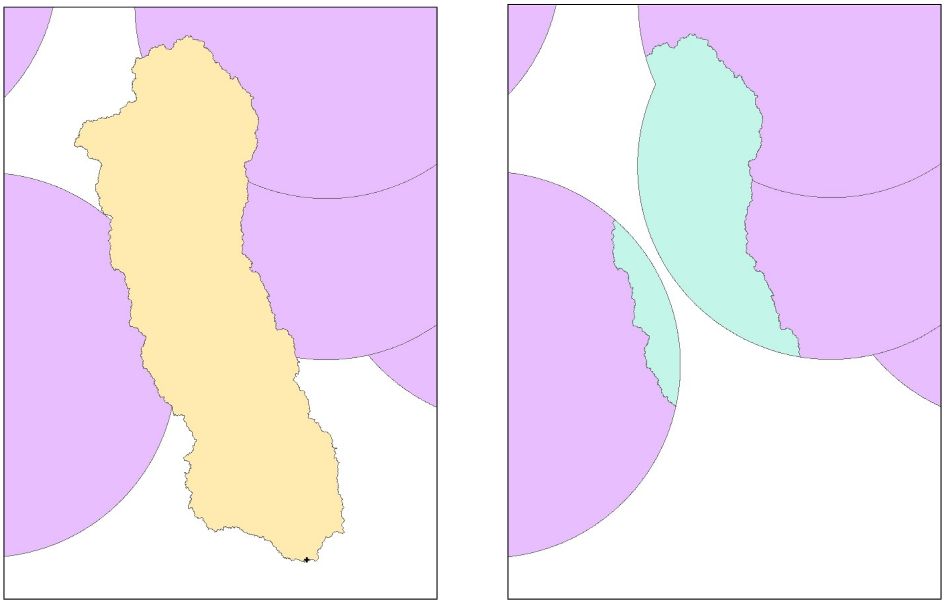
(2011)

(2013)

(2015)

(2019)

Figure 3.2: Location and range of SFI-FSS certified mills in Georgia between 2002 and 2019.



(a) (b)

Figure 3.3: Illustration of SFI % Overlap calculation, with a) depicting the full AOI in yellow with surrounding SFI FSS wood baskets as purple circles and b) depicting the area of the AOI overlapped by the wood baskets in blue. The blue area in b) was used with the full area of the AOI to determine SFI % Overlap.

month, with some stations occurring at a higher frequency (up to four times a month) or some months skipped entirely.

3.2.4 Analysis

The analysis was performed for two different timeframes, using a single year of water quality data and using a three-year span of water quality data by adding the year before and after the single year (Table 3.1). The three-year analysis was conducted so that each period would have a commensurately larger number of SSC samples. SSC and daily discharge were used to generate sediment rating curves for each time period of analysis (single vs three years). Because the timing of monthly water sampling for SSC and daily discharge measurements were not always an exact match, SSC data was matched to the daily discharge value which was measured within one hour of the SSC water sampling timestamp. The most appropriate line of best fit for the sediment rating curve was used, chosen based on the Akaike information criterion (AIC) between linear, logarithmic, and quadratic. The generated sediment rating curve was utilized to calculate predicted SSC values using the daily discharge data. Daily discharge and predicted SSC data were used to calculate sediment load (Equation 3.1), with the median sediment load value taken for each period.

$$\underset{(liter(L)/year(yr))}{Daily\ Discharge} \times \underset{(grams(g)/L)}{Predicted\ SSC} = \underset{(g/yr)}{Sediment\ Load} \tag{3.1}$$

To compare median sediment load across AOIs of varying sizes, the median sediment load was normalized using the area of the AOI (resulting in units of grams/acre/year (g/ac/yr)). This area normalized median sediment load will herein be referred to as median load. See Appendix A for example of calculations.

A minimum threshold was used to determine whether the median load value would be used in the regression analysis (discussed further below). At least six associated monthly SSC and daily discharge data points were needed to calculate the sediment rating curve to be included for the single-year period. The threshold was set at a minimum of twelve SSC and daily discharge data points for the three-year period. This was done to ensure the sediment rating curve and subsequent predicted SSC values were calculated based on more than a handful of data points, including different seasonal impacts on water quality. Three individual analyses were removed for the single-year period and two for the three-year period based on these thresholds.

A dummy variable was included indicating whether an AOI contained any reservoirs (termed Reservoir Impact), as the storage and/or timed release of water may impact discharge and SSC downstream, which is not reflective of the impact of the above variables. Two fixed-effect variables were included as dummy variables in addition to the above mentioned variables to control for time and space variations. A year dummy variable was utilized to control for variations in annual water quality data caused by weather, rainfall, and other temporal variations. A region dummy variable was utilized to control for variation in all physiographic region-specific variables relevant to the location of monitoring stations.

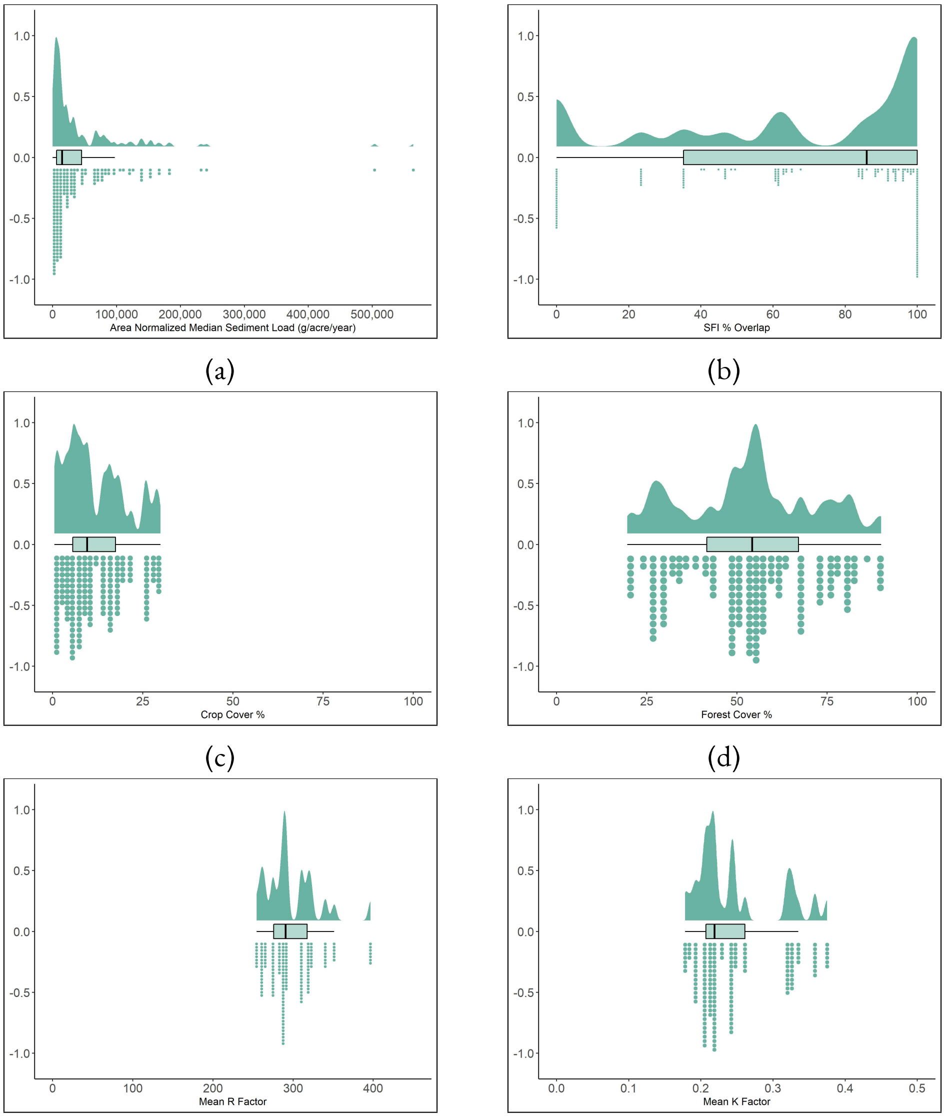
Multiple linear regression analysis was conducted comparing the impact of SFI % Overlap, Crop Cover %, Forest Cover %, Mean R Factor, Mean K Factor, Reservoir Impact, and space-time dummy variables on median load. The multiple linear regression analysis for the single-year period was performed using data from all NLCD years together, resulting in up to eight samples per AOI (water quality data was not available for all required years for all AOIs). The multiple linear regression analysis for the three-year period analysis was performed using data from all NLCD years except 2006 and 2011, resulting in up to six samples per AOI. The years 2006 and 2011 were removed from the three-year analysis to remove overlapping water quality data to ensure independence from year to year.

3.3 Results

The data distributions for the independent variables and median load can be seen in Figures 3.4 and 3.5. The range of SFI % Overlap values is skewed largely toward the upper range, with an additional spike for those with 0% of overlap. The high percentage of overlap is not unexpected as SFI-FSS certified mills covered over 90% of the state by 2019.

Crop Cover % did not exceed 30% for any AOIs. While a large portion of South Georgia is utilized for agriculture, there is not a reflectively high percentage of crop cover due to the location and extent of the AOI's watersheds. Only one AOI was located entirely in the Coastal Plain region, with the majority of AOIs whose monitoring station was located in the agriculture-heavy Coastal Plain extending into the less agricultural-intensive Piedmont and Blue Ridge regions. Forest Cover % shows a roughly normal distribution. The range and distribution of Mean R Factors are influenced by the nature of R Factors and the extent of many AOI's watersheds. R Factors are estimated based on contour lines connecting identical R Factors across an area, similar to topographic maps. The varying sizes of AOIs resulted in differences between small AOIs in which R Factors do not vary greatly and large AOIs in which a larger range of R Factors are present. In addition, higher R Factors are found largely in South Georgia, where, as previously discussed, few AOIs were located. Mean K Factors were largely divided into two groups, with the majority of AOIs falling between between 0.17 and 0.26. All Mean K Factors within the higher group (>0.3) were located within the Coosa river basin, indicating a difference in soil properties for this watershed that results in increased K Factor values.

Lastly, as seen in Figures 3.4 and 3.5, the median load for both timeframes was skewed heavily to the left, with lower values of area normalized median load dominating. This heavy skew is caused by a few outliers at the right tail. These outliers were potentially caused by large rain events across a portion of the state increasing both discharge and SSC, steep slopes within the AOI generating increased energy in water flows picking up more sediment, or releases from reservoirs upstream altering the timing of water and sediment flows. The two most extreme outliers for each analysis originated from monitoring stations located in the highly urbanized area northeast of Atlanta. The high median load values may have been generated by the absence of a permeable land surface in these areas. The mean value of the median load increased for the three-year

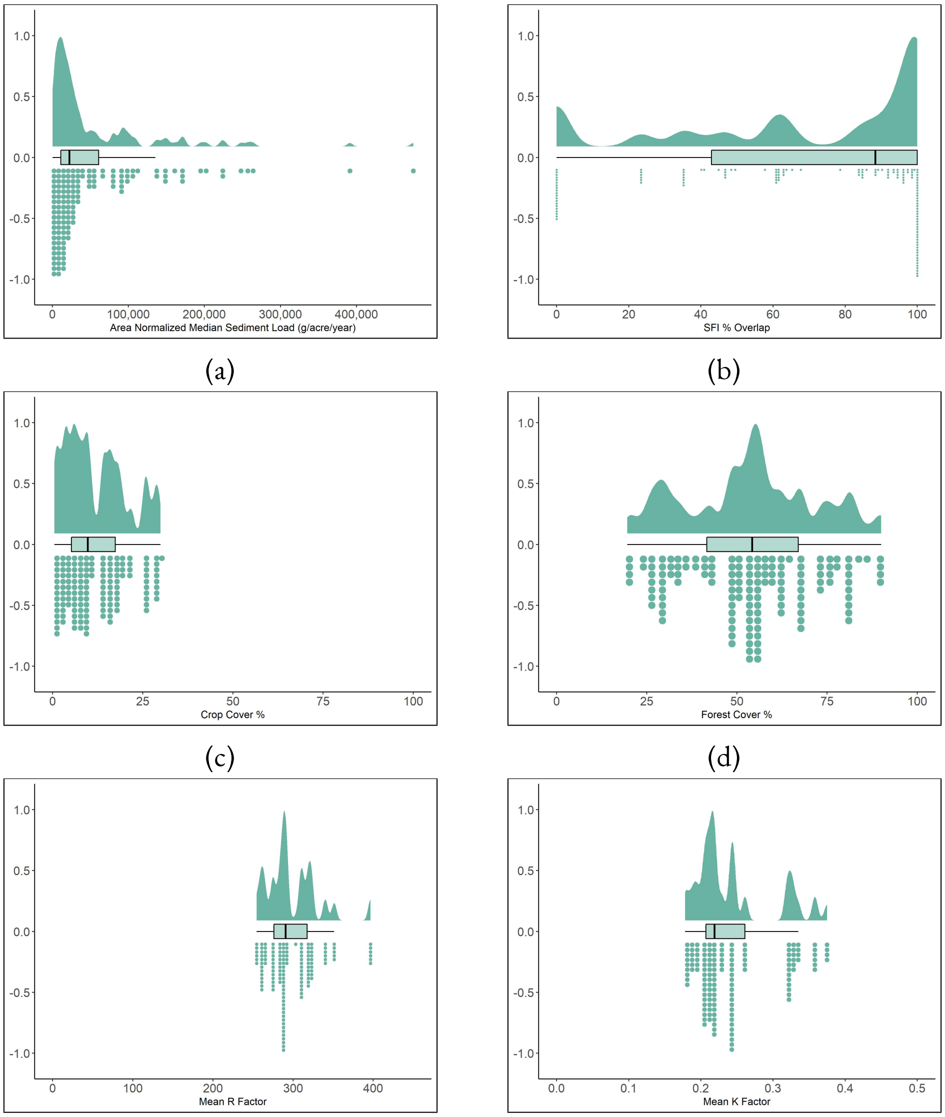


(a) (b)

(c) (d)

(e) (f)

Figure 3.4: Distribution of data used for single year analyses: a) area normalized median sediment load, b) SFI % Overlap, c) Crop Cover %, d) Forest Cover %, e) Mean R Factor, and f) Mean K Factor. The top portion of each graph illustrates the data distribution while the bottom portion depicts the raw data points for each variable. Includes all AOIs used for both single year and three-year water quality analyses and both reservoir impacted and non-reservoir impacted AOIs.



(a) (b)

(c) (d)

(e) (f)

Figure 3.5: Distribution of data used for three-year analyses: a) area normalized median sediment load, b) SFI % Overlap, c) Crop Cover %, d) Forest Cover %, e) Mean R Factor, and f) Mean K Factor. The top portion of each graph illustrates the data distribution while the bottom portion depicts the raw data points for each variable. Includes all AOIs used for both single year and three-year water quality analyses and both reservoir impacted and non-reservoir impacted AOIs.

analysis compared to the single year, increasing to 22,256 g/ac/yr from 14,785 g/ac/yr. Slight differences in the number of occurrences for all variables between the single year of water quality data (Figure 3.4) and three years of water quality data (Figure 3.5) are due to the removal of years 2006 and 2011 for the three-year analysis, as discussed above.

Table 3.2 includes the results of the multiple regression analyses. For a single year of water quality data, the independent variables significantly influence the median load. A positive relationship was identified between median load and SFI % Overlap. This implies that for a greater percentage of overlap of SFI-FSS certified mill wood baskets, the median sedimentation load was increased. Because the median load was normalized using AOI acreage and the size was therefore constant, this increase in median load indicates that SSC and/or discharge was increased. Crop Cover % and Forest Cover % were both identified to have a statistically significant, inverse relationship with median load. This relationship implies that increased crop or forest cover results in reduced SSC and/or discharge, indicating improved water quality.

Table 3.2: Results of multiple linear regression analyses, separated by years of water quality data. RSE stands for residual standard error. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

Single Year of Water Quality Data			**Three Years of Water Quality Data**		
Number of AOIs	171		Number of AOIs	139	
R^2	0.38^{***}		R^2	0.55^{***}	
Adjusted R^2	0.32^{***}		Adjusted R^2	0.50^{***}	
Independent Variable	**Coefficient**	**RSE**	**Independent Variable**	**Coefficient**	**RSE**
Intercept	154,888.6	61,481.9	Intercept	$214{,}807.1^{*}$	76,908.1
SFI %Overlap	548.3^{***}	145.2	SFI %Overlap	683.0^{***}	143.1
Crop Cover %	$-1{,}731.8^{**}$	545.6	Crop Cover %	$-1{,}161.3^{*}$	617.8
Forest Cover %	$-1{,}061.6^{*}$	451.9	Forest Cover %	$-1{,}448.3^{**}$	480.8
Mean R Factor	-337.9	182.4	Mean R Factor	-534.2	237.6
Mean K Factor	85,430.3	167,955.2	Mean K Factor	145,760.4	182,709.5
Reservoir Impact	-15,128.1	10,171.5	Reservoir Impact	-25,870.0	10,874.9
Coastal Plain	3,696.6	18,378.8	Coastal Plain	10,862.0	21,270.2
Piedmont	13,724.1	10,815.7	Piedmont	19,372.7	14,947.8
Valley & Ridge	17,103.9	20,838.5	Valley & Ridge	-19,863.2	24,733.1
2004	$37{,}170.9^{*}$	14,327.9	2004	$62{,}636.6^{***}$	24,755.1
2006	1,225.8	13,146.0	2008	-16,459.7	11,760.5
2008	-15,731.8	9,785.2	2013	-14,622.9	12,402.1
2011	-23,074.5	11,224.6	2016	-11,479.8	13,440.7
2013	6,715.4	12,384.5	2019	18,518.1	15,971.4
2016	-14,446.4	10,868.4			
2019	$32{,}946.2^{*}$	25,585.5			

The same relationships with SFI % Overlap, Crop Cover % and Forest Cover % was present for the three-year water quality analyses. The R^2 value is higher than that of the single-year analysis, indicating a more robust influence from the independent variables on median load. The more influential relationship between median load and the independent variables over the three-year timeframe may be due to the reduced number of data points included, as data from 2006 and 2011 were removed. Changes in the mean values of the variables between a single year and three years may also have played a part, with SFI % Overlap increased slightly between a single year (67%) and three years (68.3%) due to the removal of data.

3.4 Discussion

Previous research regarding the impact of SFI certification programs is limited. This previous work has recorded improvements in BMP implementation rates as a result of SFI-FSS wood baskets[38] and a positive impact on all levels of biodiversity habitat in the Southern United States from SFI-FSS certification[85]. In contrast to the results of our study, Azevedo et al.[84] identified an inverse relationship between modeled SFI Forest Management implementation utilizing specific BMPs (streamside management zones, limit in harvest unit size, and three-year green-up interval) and sediment yield. In addition to the work by Azevedo et al.[84], other studies have looked at the influence of general BMP use in the Coastal Plain region. BMPs focused on mitigating erosion, such as along skid trails or haul roads, have been found to greatly reduce sediment removal from sites, mitigating 95% of sediment delivery to waterways from a clearcut stand[35]. Hawks et al.[35] demonstrated the influence of BMP use, including the impact of appropriately applied and focused BMP implementation on areas with the greatest opportunity for erosion.

The impact on water quality identified in our study differs from those of others that have looked at the influence of SFI-FSS certified forests and general BMP use. The impact of SFI-FSS on water quality that we found could be due to the fact that forest managers and other supply chain actors who are already in the most regulated markets or have had bad sustainability practices in the past are generally more likely to seek certification[90]. Another factor may also be that BMPs are expensive to implement[91] and the added cost of certification may hinder their execution. Moreover, even though the presence of SFI-FSS certified mills has been reported to increase BMP implementation rates in Georgia between 2002 and 2015[38], overall BMP implementation rates in Georgia have ranged between approximately 90-95% since the 2007 GFC survey[80]. As such, while the number of SFI-FSS certified mills has increased over time (from 11 in 2007 to 30 in 2019), the BMP implementation rate has remained relatively stable over the past decade. This small amount of variation in statewide BMP implementation rates over much of the study timeframe may have affected our analysis. In addition, as BMP use has been found to promote forest health and productivity[34, 35], forestland managers are likely incentivized to implement BMPs for the productivity of their harvest and not solely due to the presence of SFI-FSS certified mills.

The limited research into the influence of the SFI-FSS certification program on ecosystem services makes comparisons of our study's results to others difficult. In addition, direct comparisons between different certification programs are inappropriate due to the differences in standards and implementation practices. However, exploring the current research associated with other certification programs, such as FSC, could provide insight into potential future research avenues regarding the relevance of the SFI programs to conservation and the enhancement of ecosystem services. FSC Forest Management certification has been found to positively influence both forest management practices and plant biodiversity. The process of pursuing and completing the FSC SmartWood certification (now FSC forest management) program is more than just a paper process, with Newsom et al.[81] identifying important on-the-ground changes made by forest companies seeking certification, such as changes to management plans or processes regarding high conservation value forests. In addition, FSC certification has been found to have a positive influence on biodiversity. Gullison[82] and Kalonga et al.[83] identified positive impacts to plant biodiversity, from identifying improved forest management practices to increased tree biodiversity in Tanzania through increased adult species richness, diversity, and density. This positive influence on another ecosystem service indicates that forest certification can influence the health of ecosystems in multiple ways, both through increased biodiversity and water quality improvement.

CHAPTER 4

CONCLUSIONS

While initial costs are high and the amount of time to profit is extended, there is potential for landowners to generate significant revenue by converting their small acreage timberlands to utility electricity-generating solar systems. However, smaller-scale solar systems, such as the 350 kW, with current PPA pricing, are not able to generate enough solar energy to overcome the high costs of installation, upkeep, and panel recycling. While there is potential for profit, the high upfront costs of solar arrays may make loblolly pine stands favorable for some small acreage landowners. While the profitability of solar energy generation may be positive for landowners and solar energy generation has significant CO_2 emission reduction potential, the environmental consequences of this land conversion should be considered, as not just a carbon sink is lost through deforestation, but the myriad of ecosystem services provided by forests are also lost, including water filtration.

The presence of SFI-FSS certified mills was not found to improve water quality in watersheds throughout Georgia. These results indicate a potential positive relationship between SFI-FSS certified mills and area normalized median load, meaning the increased presence and overlap of SFI-FSS certified mill wood baskets resulted in increased sedimentation in the watershed. While the presence of SFI-FSS certified mills results in increased BMP implementation, there may be additional factors that influence the use of BMPs and which affect sedimentation in waterways, impacting the identified results.

Study limitations for Chapter 2 include using cost and revenue estimates from a singular company, which may not be representative of all companies operating in Georgia. Additionally, Georgia Power Company is not the sole utility provider in the state, with other utility providers potentially offering different rates to energy generators. While costs for the transport of the panels and other equipment to the site were included in the installation quote, transportation costs of the solar panels for disposal were not included in the analysis, which represents an additional limitation.

Chapter 3 was limited by the number of AOIs present only in the Coastal Plain region, with only one AOI utilized, which may have reduced the influence of crop cover in the analysis as the majority of agriculture in the state is located in the Coastal Plain, as well as the removal of data from years 2006 and 2011 for the three-year analysis to ensure the independence of water quality data. In addition, for the five AOIs which cross state lines, only those portions of the watershed located in Georgia were included in the analysis. This may have influenced the results as the full picture regarding SFI % Overlap, and land cover for these AOIs was not available. The inexact comparison between years of SFI % Overlap and the other variables is considered a limitation to the study as differences between years may influence the relationship identified. In addition, the short timeframes used for water quality analysis (one and three years) have the potential to be heavily influenced by infrequent, large rain events. These large rain events may skew the median load, which would be leveled out over longer periods of observation.

Future research in these fields could include a lifecycle assessment of solar arrays to properly account for generated emissions throughout the lifespan of a panel and how that may impact their emission reduction potential. A closer look at size-optimized behind-the-meter systems in comparison to timber profits could illustrate the cost recovery time of smaller systems within Georgia. Additionally, utilizing different financial incentives for solar energy, such as the Modified Accelerated Cost-Recovery System (MARCS), could result in a different outcome. The water quality analysis could be performed in other states which have different bio-geography. Researchers can also explore the impact on water quality from specific BMP categories influenced by the presence of SFI-FSS wood basket presence, such as harvesting practices, to add to the increasing body of work on fiber sourcing certification impacts in the Southeastern United States. In addition, the inclusion of additional USLE factors could help to better account for the differences in erosion potential across AOIs.

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APPENDIX A

R CODE FOR SINGLE-YEAR WATER QUALITY ANALYSIS

```
##USGS_000

##Sediment Rating Curve
#Load water quality data file
USGS_000 <- read.table("USGS_000.txt", header = TRUE, sep = "\t")
AOI_Area <- read.csv("AOI_Area.csv", header = T, na.strings = c("","NA"))
Area <- subset(AOI_Area, AOI_Other == ’USGS_000’)
##Unit Conversions
#Concentration: mg/L * 1.10231e-9 ton = ton/L => concentration * 1.10231e-9
Conc_Unit_Conv <- 1.10231e-9
#Discharge: ft^3/s * 60s * 60m * 24h * 365d * 28.3168L = L/year => discharge *
     892998604.8
Dis_Unit_Conv <- 60*60*24*365*28.3168

#Rename necessary columns, get rid of E, <, and > characters, and reset variables
USGS_000 <- USGS_000[-1,] %>%
  select(c(site_no, sample_dt, sample_tm, p00530)) %>%
  rename(Station = site_no) %>%
  rename(Date = sample_dt) %>%
  rename(Time = sample_tm) %>%
  rename(SSC_mgL = p00530) %>%
  mutate(SSC_mgL = as.character(gsub("E", "", SSC_mgL))) %>%
  mutate(SSC_mgL = as.character(gsub(">", "", SSC_mgL))) %>%
  mutate(SSC_mgL = as.character(gsub("<", "", SSC_mgL)))
USGS_000$Date <- as.Date(USGS_000$Date, format = "%Y-%m-%d")
USGS_000$Year <- format(USGS_000$Date, format = "%Y")
USGS_000$Month <- format(USGS_000$Date, format = "%m")
USGS_000$Time <- format(USGS_000$Time, format = "%H:%M")
USGS_000$Hour <- str_sub(USGS_000$Time, 1, 2)
USGS_000$SSC_mgL <- as.numeric(as.character(USGS_000$SSC_mgL))
USGS_000$SSC_tL <- USGS_000$SSC_mgL * Conc_Unit_Conv
USGS_000[’AOI’] = ’USGS_000’

#Separate SSC into different tables for years and take out any NAs
USGS_000_01_SSC <- USGS_000 %>% select(c(’AOI’, ’Date’, ’Year’, ’Month’, ’Time’,
     ’Hour’, ’SSC_tL’)) %>% filter (Year == ’2001’) %>% drop_na()

##Daily Instantaneous Discharge
#Load daily instantaneous discharge txt files
USGS_000D_Dis_00_06 <- read.table("USGS_000-00_06.txt", header = TRUE, sep = "\t")
```

```
USGS_000D_Dis <- USGS_000D_Dis_00_06[!(USGS_000D_Dis_00_06$site_no=="15s"),
     -c(1,4,6)] %>%
  rename(Station = site_no) %>%
  rename(DailyDischarge_cfs = X38474_00060) %>%
  separate(datetime, c("Date", "Time")," ")
USGS_000D_Dis$Date <- as.Date(USGS_000D_Dis$Date, format = "%Y-%m-%d")
USGS_000D_Dis$Year <- format(USGS_000D_Dis$Date, format = "%Y")
USGS_000D_Dis$Time <- format(USGS_000D_Dis$Time, format = "%H:%M")
USGS_000D_Dis$Hour <- str_sub(USGS_000D_Dis$Time, 1, 2)
USGS_000D_Dis$DailyDischarge_cfs <-
     as.numeric(as.character(USGS_000D_Dis$DailyDischarge_cfs))
USGS_000D_Dis$DailyDischarge_Lyr <- USGS_000D_Dis$DailyDischarge_cfs *
     Dis_Unit_Conv
#Separate Daily Discharge into different tables for years and take out any NAs
USGS_000D_Dis_01 <- USGS_000D_Dis %>% select(c('Station', 'Date', 'Time', 'Hour',
     'Year', 'DailyDischarge_Lyr')) %>% filter (Year == '2001') %>% drop_na() %>%
     filter (DailyDischarge_Lyr > 0) %>% mutate(DailyDischarge_Lyr =
     as.numeric(as.character(DailyDischarge_Lyr))) %>% rename(Discharge_Lyr =
     DailyDischarge_Lyr) %>% mutate(Discharge_Lyr2 = (Discharge_Lyr^2))

##2001
#Match SSC and Daily Discharge Data by Date and Hour
USGS_000_01 <- sqldf("SELECT S.AOI, S.Date, S.Time, S.Hour, S.Year, S.SSC_tL,
     D.Discharge_Lyr, D.Discharge_Lyr2
                       FROM USGS_000_01_SSC S
                       LEFT JOIN USGS_000D_Dis_01 D
                         ON S.Date = D.Date AND S.Hour = D.Hour
                       GROUP BY S.Date")
#Sediment Rating Curve best fit equation calculation (linear, logarithmic, or
     quadratic)
USGS_000_01_Linemodel <- lm(SSC_tL ~ Discharge_Lyr, data = USGS_000_01) #Linear
     regression model
AIC_Linear <- AIC(USGS_000_01_Linemodel)
USGS_000_01_Logmodel <- lm(SSC_tL ~ log(Discharge_Lyr), data = USGS_000_01)
     #Logarithmic regression model
AIC_Log <- AIC(USGS_000_01_Logmodel)
USGS_000_01_Quadmodel <- lm(SSC_tL ~ Discharge_Lyr + Discharge_Lyr2, data =
     USGS_000_01) #Quadratic regression model
AIC_Quad <- AIC(USGS_000_01_Quadmodel)
#Sediment Rating Curve selection and predicted value calculation
if (AIC_Linear < AIC_Log & AIC_Linear < AIC_Quad) {
  USGS_000D_Dis_01$SSC_Predict <- predict(object = USGS_000_01_Linemodel, newdata
       = USGS_000D_Dis_01)
} else if (AIC_Log < AIC_Linear & AIC_Log < AIC_Quad) {
  USGS_000D_Dis_01$SSC_Predict <- predict(object = USGS_000_01_Logmodel, newdata =
       USGS_000D_Dis_01)
} else {
  USGS_000D_Dis_01$SSC_Predict <- predict(object = USGS_000_01_Quadmodel, newdata
       = USGS_000D_Dis_01)
}
#Calculate Load, Area Normalized Load, Median Values, and Data Counts
USGS_000D_Dis_01$Load <- USGS_000D_Dis_01$Discharge_Lyr *
     USGS_000D_Dis_01$SSC_Predict #Load from daily discharge and predicted SSC
Load_01 <- median(USGS_000D_Dis_01$Load) #Median load
Load_Area_01 <- Load_01/Area$Area_acres #Area normalizing load for comparison
     across watersheds
D_Dis_Med_01 <- median(USGS_000D_Dis_01$Discharge_Lyr) #Median daily discharge
SSC_Med_01 <- median(USGS_000D_Dis_01$SSC_Predict) #Median predicted SSC
Data_Count_01 <- length(USGS_000D_Dis_01$Discharge_Lyr) #data count of daily
     discharge values
```

```
Regression_Count_01 <- length(USGS_000_01_SSC$SSC_tL) #data count of SSC used in
     SRC
#Combine into one table
USGS_000_01 <- cbind(Load_01, Load_Area_01, D_Dis_Med_01, SSC_Med_01,
     Data_Count_01, Regression_Count_01) %>%
  as.data.frame %>%
  rename(Median_Load = Load_01) %>%
  add_column(Unit = "ton/year", .after = "Median_Load") %>%
  rename(LoadxArea = Load_Area_01) %>%
  add_column(Units = "ton/acre/year", .after = "LoadxArea") %>%
  rename(DDischarge_Med = D_Dis_Med_01) %>%
  rename(SSC_Median = SSC_Med_01) %>%
  rename(Data_Count = Data_Count_01) %>%
  rename(Regression_Count = Regression_Count_01) %>%
  add_column(AOI = "USGS_000", .before = "Median_Load") %>%
  add_column(Year = "2001", .before = "Median_Load") %>%
  add_column(Regress_Type = (if(AIC_Linear < AIC_Log & AIC_Linear < AIC_Quad)
       {"Linear"} else if (AIC_Log < AIC_Linear & AIC_Log <
       AIC_Quad){"Logrithmic"} else {"Quadratic"}), .before = "Median_Load")
```