THE IMPACT OF WOOD PELLET MANUFACTURING ON UNITED STATES SOUTHERN TIMBERLANDS

A thesis

presented to

the Faculty of the School of Natural Resources

at the University of Missouri-Columbia

In partial fulfillment

of the requirements for the degree

master of science

---

by

HOUSTON SUDEKUM

Dr. Francisco X. Aguilar, Thesis Supervisor

DECEMBER 2019

The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled:

THE IMPACT OF WOOD PELLET MANUFACTURING ON UNITED STATES SOUTHERN TIMBERLANDS

presented by Houston Sudekum, a candidate for the degree of master of science, and hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Francisco X. Aguilar

Dr. Benjamin Knapp

Dr. Zhen Cai

Dr. Ronald McGarvey

ACKNOWLEDGEMENTS

I would like to thank Dr. Francisco X. Aguilar for guiding me through my research, coursework decisions, and facilitating other academic and professional experiences. Dr. Aguilar's input was critical to many parts of this thesis project. I would like to thank Dr. Karen Abt, Dr. Ronald McGarvey, Dr. Zhen Cai, Dr. David Larsen and Dr. Benjamin Knapp for providing valuable feedback throughout the research project. Although, Dr. Abt and Dr. Larsen were not on my committee, I could not have completed this project without their help. Dr. Abt consistently spoke to me at length about my research project and offered valuable insights. Early in the research process, Dr. Larsen helped me make critical decisions regarding software for statistical analysis and data extraction. His expertise was critical to my understanding of forest inventory data and programming languages. I would also like to thank Ashkan Mirzaee and Dr. Ram Dahal for sharing data and providing occasional feedback. Lastly, I would like to acknowledge the efforts of the U.S. Forest Service employees who fielded my questions about FIA data and helped explain the dataset.

TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

Table Page

ABSTRACT

Global wood pellet production grew from an estimated 1.7 million metric tons in 2000, to 35.4 million metric tons in 2018. U.S. mills established over this period account for a large share of new supply triggered by renewable energy targets set by the European Union (EU). There is concern over the potential impacts of exponential growth in wood pellet supply on US forests. We offer a systematic quantitative analysis to assess the effects of wood pellet production on forest conditions within wood pellet mill procurement areas. We rely on plot-level information from the US Forest Inventory and Analysis (FIA) database to estimate changes in forest conditions (e.g. trees per hectare, carbon in trees, cubic-meter volume) between inventory years 2000 and 2017 across Southeastern US States. Using spatial analysis and panel-regression for samples of timberland plots we attempt to discern pellet production effects associated with pellet mill size and location. Propensity score matching was used as a re-sampling technique to select a subset of FIA plots to control for the non-random process of pellet mill sitting. Panel regression models controlled for various anthropogenic and natural factors to measure the net impact of wood pellet production on average plot-level forest conditions. Overall, we find increased carbon stocks and some evidence of increased removals associated with wood pellet production. This research will contribute to a growing body of knowledge related to the sustainability and future prospects of wood energy and wood pellets.

1 INTRODUCTION

The Food and Agricultural Organization of the United Nations estimates that wood provides around 6% of the total global primary energy supply (FAO, 2018), and wood pellets are increasingly important in meeting global wood energy demand. Global wood pellet production between 2000 and 2018 rose from 1.7 to 35.4 million tons (FAO, 2019; AEBIOM, 2018). In 2018, the European Union (EU) accounted for 75% (26.0 million tons) of global wood pellet consumption but only 55% (19.4 million tons) of production, while the United States (US) consumed 5% (1.7 million tons) and produced 21% (7.5 million tons) (FAO, 2019). Around 40% of global wood pellet consumption occurs in the industrial electricity generation sector, while residential and commercial heating accounts for the remaining 60% (Fritsche et al., 2019).

Growth of the wood pellet industry is primarily attributed to changes in EU policy promoting renewable fuel consumption (Abt et al., 2014). The 2009 EU Renewable Energy Directive (RED) set 2020 energy targets that were updated in December, 2018 for 2030 with key goals to: cut greenhouse gas emissions by 40% (from 1990 levels), increase renewable energy share to 32%, and improve energy efficiency by 32.5% (from 2007 levels) (The European Commission 2009; The European Commission 2018). European Union member states continue to address country specific energy targets with legislation to promote RED goals, some of which subsidize wood pellet consumption for residential/commercial heat production and electricity generation (Abt et al., 2014; Singh et al., 2016).

Following the EU RED implementation, the US became the largest pellet producer and exporter in the world (Figure 1) (USITC, 2019; Eurostat, 2019; Thrän et al., 2017). US pellet exports are primarily associated with supplying feedstock for electricity generation, rather than the residential and commercial heating sector (Calderon, 2016). More than 100 wood pellet

mills began operation between 2000 and 2018 in the United States Forest Service (USFS) Eastern and Southern regions[1] of the US. 96 of these pellet mills still operate today accounting for more than 10 million tons of added capacity (EIA, 2019; Forisk, 2018). More than 98% of US pellet exports since 2012 came from ports located in the Southern US (USITC, 2019). The largest pellet export ports include: Baton Rouge, Louisiana; Mobile, Alabama; Panama City, Florida; Brunswick, Georgia; Savannah, Georgia; Charleston, South Carolina; Georgetown, South Carolina; Wilmington, North Carolina; Chesapeake, Virginia (SELC, 2017; USITC, 2019).

A considerable body of research has addressed economic and environmental implications of the rapidly developing US wood pellet industry. Analyses have focused on a range of topics, including: projecting forest attributes and land use changes (Galik and Abt, 2016; Costanza et al., 2017; Duden et al., 2017; Shrestha and Dwivedi, 2017; Fingerman et al., 2017), estimating emissions associated with wood pellet supply chains/calculating carbon savings compared to fossil fuel alternatives (Hanssen et al., 2017; Jonker et al., 2014; Wang et al., 2015; Roder et al., 2015; Mitchell et al., 2012; Wihersaari, 2005; Magelli et al., 2009; Buchholz et al., 2016; Mobini et al., 2013), and the market dynamics of wood pellet production and trade (Ericsson and Nilsson, 2004; Fritsche and Iriarte, 2014; Henderson et al. 2017; Joshi et al., 2012; Junginger et al., 2011; Sun and Niquidet, 2017).

In 2008, before the EU RED, 84% of wood pellet manufacturing feedstock consisted of residues and by-products from other industrial wood-product industries, while the remaining 16% came from chips and roundwood (Spelter and Toth, 2009; Sénéchal and Grassi, 2009). The growth of the pellet industry coupled with voids left behind by slowing production and closing of pulp mills has driven pellet manufactures to increasingly substitute industrial residues for roundwood (EIA, 2019; Abt et al., 2014; Thiffault et al., 2015, Forisk, 2018). In 2019 thus far,

[1] Regions throughout this analysis will refer to United States Forest Service Regions

roundwood constituted 23% of the pellet production feedstock, while the remainder came from sawmill, wood product manufacturing, and other residues (EIA, 2019). Some predict that increased reliance on roundwood for pellet production may be adversely impacting timberland conditions through intensification of timber management where these substitutions are occurring (McGee, 2019; Greenpeace, 2011; NRDC, 2015; Strange-Olesen et al., 2015). Despite concerns, few studies have addressed the direct ecological impacts associated with existing wood pellet production in the US.

Two previous studies used Forest Inventory and Analysis (FIA) data to assess the impact of wood pellet production on US forest conditions. Dale et al. (2017) measured changes in timberland conditions within two fuelsheds, near the Savannah, Georgia and Chesapeake, Virginia export ports, defined as any county within a 75-mile radius of mills producing export wood pellets. They found steady or increasing timberland area, volume in trees and carbon stocks between 2009 and 2014 (period of major pellet growth), but found some reductions in the number of standing dead trees. Strange-Olesen et al. (2015) used FIA data to identify trends in Southern and Eastern US Forest Service regions to isolate impacts of the EU RED using counterfactual statistical models of the forests. Strange-Olesen et al. (2015) collect forest attribute data in 2006, 2009 and 2012 within a defined a procurement radii (80.47 km) around all operating pellet mills in the Eastern US. They found positive trends across time frames among many forest attributes within procurement areas (e.g. area of timberland and carbon pools), but also reported some decreases in the number of standing dead trees and live trees. They determined that capacity of wood pellet mills can explain some of the decreases in standing dead trees when controlling for regional covariates.

This analysis aims to build on previous studies in order to determine if wood pellet production is impacting US timberland[2] conditions. As opposed to the case-study approach offered by Dale et al. (2017) and the regional approach from Strange-Olesen et al. (2015), this analysis uses systematic modelling of timberland conditions to assess FIA plot-level shifts in timberland structure over a longer time frame (2000-2017). This approach intended to determine if there is an intensification of timberland management due to the presence of increased demand for wood pellet feedstock by determining the driving factors behind significant changes in timberland conditions in the Southeastern US. The primary objective was to use panel regression models to estimate if the presence of wood pellet facilities has impacted forest conditions in the Southeast US. This was done by building a database of timberland plots from the Forest Inventory and Analysis database and constructing a geographic information system to control for heterogeneity across spatial and temporal dimensions across plots. The remainder of the paper is structured as follows: a theoretical framework describes the concepts and rational supporting the analytical approach; the methods section outlines the data used for calculations/estimations of the dependent and independent plot-level attributes and the econometric tools used to model changes in timberland conditions; the results section reports the impacts of wood pellet production; and the discussion offers interpretations of the results. Lastly, the conclusion section offers future directions and implications of the research.

[2] Defined by the United States Forest Service as forest land capable of producing in excess of 20 cubic feet per acre per year and not legally withdrawn from timber production, with a minimum area classification of 1 acre

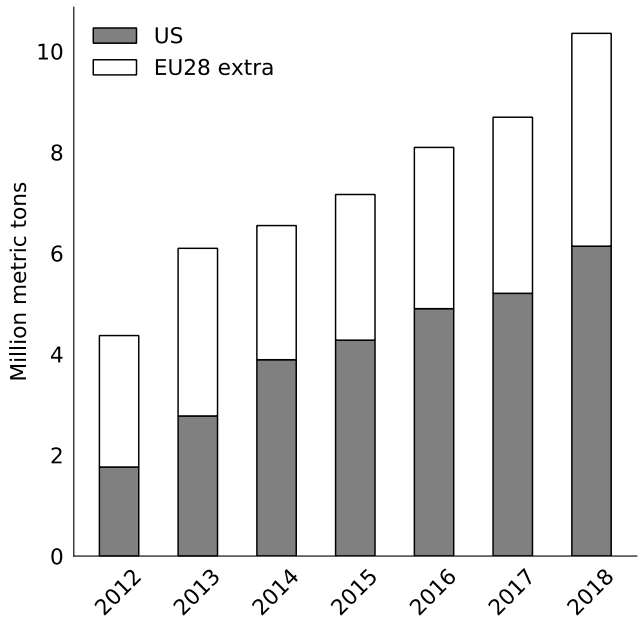


Figure 1. EU wood pellet imports between 2012 and 2018 from the US and from all other countries outside of the EU not including the US (i.e. EU28 Extra).

2 THEORETICAL FRAMEWORK

This analysis was routed in industrial location theory, regional science/economics and forest ecology. These three disciplines provided theory to justify the econometric methodology and inform interpretation of the results. The methodology was composed of a series of econometric models to estimate the impact of industrial wood-product facilities on plot-level timberland conditions. Plot-level timberland conditions are impacted by anthropogenic, and natural factors across time and space (Villalobos, 2018; Blackman et al., 2016). The extent and presence of plot-level impacts depends upon the location of industrial facilities in relation to the plot (Aguilar, 2009 & 2010; Aguilar et al., 2012), economic traits of the plot's region (Abt et al., 2014), and extrinsic and intrinsic plot-level conditions (Strange-Olesen et al., 2016; Ahmed et al.,

2017; Timilsina et al., 2012; Parish et al., 2017). This analysis controlled for these three gradients of factors to elicit the impact of wood product facilities on plot-level timberland conditions.

Traditional industrial location theory argues that facilities locate in non-random places based on a variety of factors that maximize profits (McCann, 1998). As Hoover (1948) pointed out, the location of a facility can dictate its ultimate success or failure. Weber (1909), Ross (1896) and others, introduced that the geographic fixation of input resources dictates industrial facility location. Predöhl (1928) argued that the economic traits of a location are as, if not more, important in the consideration of industrial location. Rawstron (1958) expanded to point out that both economic restrictions (regulations, labor, consumers, infrastructure etc.), and technological restrictions influence location of an industrial facility, while Isard (1956) explained that location depends upon the entire extent of spatial economic activities, with a particular focus on distribution and cost of inputs and outputs. Helburn (1943) similarly contributed that the practice of locating industrial facilities occurs across different spatial scales (e.g. national, regional and local). These traditional industrial theories fall short in applicability for some modern industries, however McCann (1998) points out that they remain appropriate for industries that rely on land-based heavy material inputs, who incur a large proportion of their expenditure from procurement and transportation costs, and especially when the manufactured products have relatively low value to weight ratios. Accordingly, wood-product facilities locate based upon principles outlined by classical industrial location theory (Boukherroub et al., 2017; Mobini et al., 2013; Singh et al., 2016; Sénéchal and Grassi, 2009).

The more modern fields of regional science/economics provided insight into the application of industrial location theory to econometric modelling. Regional scientists identify industrial location as a function of internal, external and location-specific factors (Brouwer et al. 2004; Van Dijk and Pellenbarg, 2000), and often focus on the outcome of location decisions

(Harris and Nadji, 1987). Generally, these disciplines put a large emphasis on policy factors that influence the economic activity of a region (Porter, 2003; Temple, 1994; Kain and Meyer, 1971), and present methodologies for the application of modern econometric tools for regional and spatial analyses (Arbia, 2006; Harris and Nadji, 1987; Van Dijk and Pellenbarg, 2000; Aguilar, 2008, 2009 & 2010; Aguilar et al., 2012). This analysis used the framework offered by industrial location theory and regional science/economics in order to identify the appropriate internal, external and location specific factors that impact sitting of wood product facilities. These factors were considered when controlling for the non-random placement of forest product industries. Further, after controlling for the placement of facilities, the subsequent modeling of plot-level conditions accounted for a subset of these same factors that impact timberland conditions.

The regional classifications considered in this analysis include: USFS region, ecological sections, state and county. Timberland conditions can be associated with regional ecological traits (e.g. soil types, forest types, and climate) and/or economic conditions (e.g. policy, best management practices, management tendencies etc.) (Porter, 2003). Specific reasons were identified for the inclusion of each region. At the broadest scope, this analysis focused on the USFS Southern region because of the prevalence of wood pellet manufacturing for export to the EU (EIA, 2019; Forisk, 2018). Each state within the region carries their own respective best management policies that guide timberland management decisions (USDA Forest Service, 2016). Likewise, finer-scale county level attributes like population density, and transportation infrastructure helped estimate economic activity, which can be associated with the prevalence of timberland management (Biles, 2003). Controlling for ecological section helped allow for the comparisons of timberland attributes across different forest types.

Outside of regional traits, extrinsic and intrinsic location-specific factors impact timberland conditions. The confluence of forest ecology and regional science provided insight

into how forest resources are impacted by location-specific factors. At the plot level, these factors were classified into extrinsic (anthropogenic and ecological) or intrinsic (ecological) categories. Regional science explained how location specific anthropogenic factors impact timberland conditions as a direct function of timberland location in relation to industry (Aguilar, 2010; Aguilar, 2008), while forest ecology explained how intrinsic and extrinsic location specific anthropogenic and ecological factors impact timberland conditions. The inclusion of intrinsic and extrinsic location specific factors was also informed by previous analyses that identify location specific forces behind forest change (Ahmed et al., 2017; Timilsina et al., 2012).

Extrinsic location pressures on timberland conditions fall into one of two categories: anthropogenic and ecological disturbances. A range of factors were used to estimate the presence and/or frequency of anthropogenic disturbances, and in turn explain variation in timberland conditions. Ownership of timberland can drive differences in use and management practices (Siry et al., 2010; Timilsina et al., 2012; Wear and Greis, 2002). The probability of industrial management increases as a function of distance from industrial wood-processing facilities and can be indicative of management intensity and frequency (McCann, 1998; Zhang, 2012). Extrinsic natural disturbances such as drought, weather, fire, insect, and disease also impact timberland conditions (Ahmed et al., 2017; Thornton, 2002). The differences across these extrinsic pressures were accounted for in order to estimate the impact of industrial wood facilities on timberland conditions.

Intrinsic ecological factors also play an important role in explaining the state of timberland conditions. Site quality, aspect, species richness and diversity can all help distinguish between forest types and account for differences in growing conditions. Site quality and aspect are important predictors of plot-level timberland conditions (Timilsina et al., 2012) and may also impact the probability of management (i.e. plots with high site quality are more likely to be

managed over plots with low site quality). Species richness and diversity differ across forest types and help predict differences associated with forest types (Huang et al., 2018; Morris et al., 2014). Controlling for the intrinsic ecological factors of FIA plots is essential to capturing the inherent differences between forest types due to natural variation and timberland management.

The combination of industrial location theory, regional economics/science, and forest ecology provided a foundation of theories and methodologies for estimating the impact of wood product industries on timberland conditions. The generalized equations 1 and 2 are formulated from the principles outlined in the above section.

$$pellet\ mill\ location = f(p, r, w) \tag{1}$$

$$plot - level\ timberland\ conditions = f(e, i) \tag{2}$$

Where p = proximity to timberlands, r = regional economic conditions and traits, w = the presence of other wood product facilities, e = extrinsic regional, anthropogenic and ecological factors, and i = intrinsic ecological factors. The methods section elaborates on how equation 1 was used to control for the non-random placement of wood pellet mills and subsample FIA plots. Subsequently, the methods describes how equation 2 was used to estimate the impact of wood product industries on timberland conditions.

It is expected that more management of timberland occurred near wood pellet mills (after controlling for the non-random placement of wood product facilities). Table 1 outlines the expected shifts in timberland traits in the presence of increased management intensity and/or pellet industry presence. Generally, it is expected that timberland plots with more management

would show significant reductions in volume and carbon of live and standing dead trees, and increased removals of trees and volume. In some cases, the direction of shift in timberland traits could depend upon management practices. These instances are indicated in the expected direction column.

Table 1. Timberland conditions may or may not change as a function of pellet mill presence, but it is expected that increased management of timberlands near wood pellet mills would shift timberland traits. The expected direction of change in the presence of increased management intensity is included below in the expected direction column. The expected direction of change was based off of available information from previous publications and datasets referenced in the literature cited column. A "+/-" in the expected direction column indicates that the condition could increase or decrease in the presence of management intensity.

FIA timberland attributes	Description (per hectare on timberland)	Expected direction	Literature cited
Carbon	Natural log of tons of carbon in live and standing dead trees (dbh >= 2.54 cm)	-	Timilsina et al., 2012; Galik et al., 2016 ; Jonker et al., 2014; Parish et al., 2017; Williams et al., 2016
Condition carbon	Natural log of tons of carbon in soil organic material, understory (above and belowground), organic material on the forest floor, and down and dead trees	+/-	
Carbon total	Natural log of the summation (before transformation) of carbon and condition carbon	-	
Live trees	Natural log of the number of live trees (dbh >= 2.54 cm)	+/-	Strange-Olesen et al., 2016; Parish et al., 2017; Dale et al, 2017
Live tree volume	Natural log of the gross cubic-meter volume in live trees (dbh > = 12.70 cm)	-	
Removal trees	Natural log of the number of removal trees	+	Galik et al., 2016
Removal volume	Natural log of the annual sound cubic-foot volume of a removal tree at the time of removal	+	
Standing dead trees	Change in number of standing dead trees from the previous plot measurement (dbh >= 2.54 cm)	-	Strange-Olesen et al., 2016; Dale et al., 2017; Paish et al., 2017
Standing dead volume	Change in gross cubic-meter volume in standing dead trees from the previous plot measurement (dbh >= 12.70 cm)	-	

3 METHODS

There were three primary steps in the methods of this analysis (Figure 2): FIA plot calculation and other data collection, propensity score matching, and panel regression. The FIA plot calculations were made from the open-source FIA database. All explanatory variables were also collected and estimated from open-source data, with the exception of spatially and temporally explicit information on wood pellet mill operation (Forisk, 2018). Propensity score matching was used to control for the non-random location of wood pellet mills, and panel regression was used to elicit impact of wood product industries on timberland conditions.

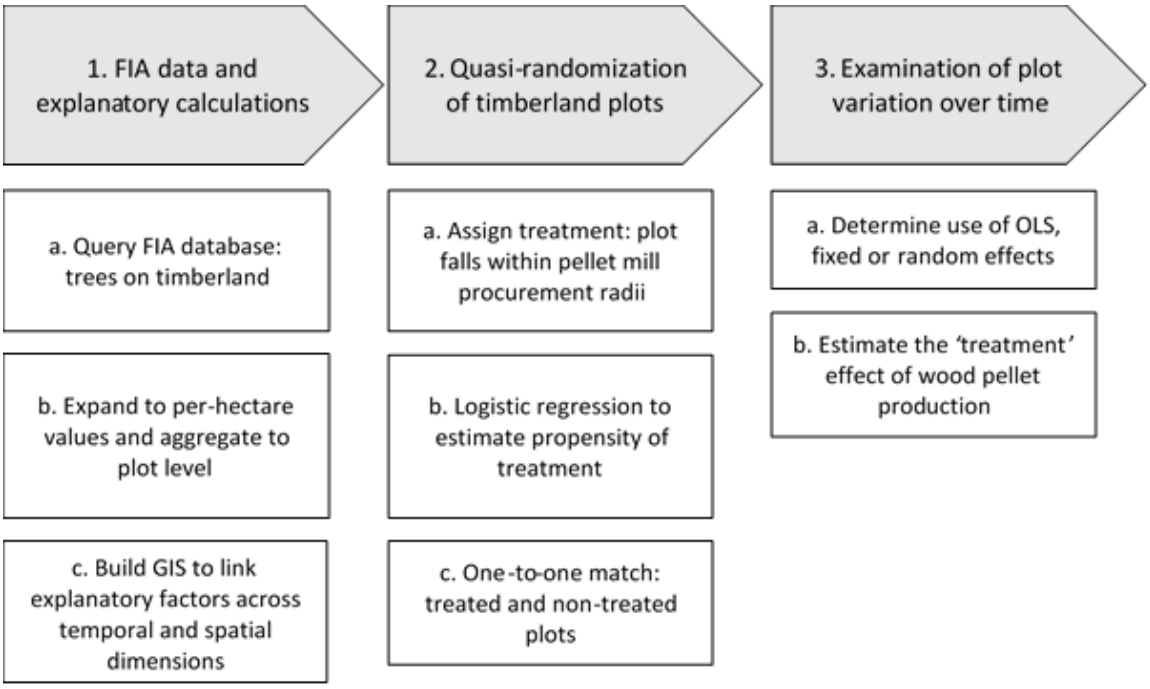


Figure 2. Outline of the methods.

3.1 FIA data and explanatory calculations

At the broadest level, this analysis included all plots with any amount of timberland. Restricting sampling to timberland plots excluded all plots that did not fit the following criteria: capable of producing in excess of 1.4 cubic meters of timber per hectare per year, not legally withdrawn from timber production, and within a minimum of .4 hectares of continuous

timberland (USDA Forest Service, 2018). The exclusion of forested plots not categorized as timberland helped to assure that anthropogenic impacts on timberland conditions were not exaggerated. At a finer scale, this analysis incorporated four separate sub-samples of FIA plots: carbon, live tree counts, and volumetric values were calculated in plots that had two measurements between inventory years 2000 and 2017, and one of the measurements must have occurred between 2012 and 2017; standing dead tree counts and volumetric values were calculated in plots that fell entirely within timberland and were remeasured between 2000 and 2017; two separate samples were collected for any plot with a recorded removal volume or recorded removal trees. In the remainder of paper, the plot samples are referenced based upon the type of attributes collected in the sample. Remeasured and removal plots more generally refer to samples that only include remeasured plots or removal observations respectively.

Remeasured plots were included in order to try and capture changes within plots over time. The time restriction for carbon and live tree remeasured plots emphasized more recent changes. A restriction of 6 years was chosen because the FIA program tries to re-measure all plots every 5 years (Roberts, 2004); expanding the restriction to 6 years captured more remeasured plots. Standing dead tree measures were only considered for plots that fall entirely within timberland to try and reduce the number of outliers derived from the expansion process (*see further description below*).

The presence of removals indicates change in plot conditions, and thus the previous observation of those plots were not included in the removal samples. There were instances in the FIA database where removal trees did not have removal volumes. This can occur when a silviculture treatment killed a tree, but did not technically remove the tree (*Consultation with USFS employees*). In these cases a removal volume was recorded for a standing dead tree (i.e. not designated a removal tree by FIA, but it is given a removal volume) (*Consultation with USFS*

employees). In these types of scenarios, it was possible for a plot to have a recorded removal volume and no recorded removal trees.

Timberland values were estimated at the plot-level using FIA data from three different FIA tables: Tree, Condition and Plot. Counts of trees, standing dead trees, removal trees and their respective volumes were aggregated to plot measurements. The FIA data was accessed using the refTable web-based API to assure that the most recent data was collected (Miles, 2018). Plot-level carbon was estimated from the aggregation of measurements given at the tree level (carbon in live and standing dead trees) and at the condition level (carbon in down and dead trees, carbon in soil organic material, carbon in litter, and above and below ground carbon in the understory) (USDA Forest Service, 2018). Plots can be divided into multiple timberland conditions based upon reservation status, owner group, forest type, stand-size class, regeneration status, stand density (USDA Forest Service, 2018). Each type of timberland condition was weighted equally. Excluding the standing dead tree measures, plot measurements were expanded to a per hectare basis while controlling for the proportion of the plot contained within timberland conditions (*Consultation with USFS employees*). Remeasured plots were linked together using plot sequence numbers and previous plot sequence numbers provided in the FIA database to determine if each plot was measured more than once within the timeframe (USDA Forest Service, 2018).

Plot-level carbon, volumetric estimates of removal and live trees and counts of removal and live trees approximately fit a log normal distribution (Figure 7), and thus were transformed by natural logs in order to retain validity of parametric statistics (McDonald, 2009). Plot observations that contained no carbon in live trees/standing dead trees, no volume in live trees and/or no trees require shifting values so that the natural log of the minimum value was defined. These observations often occurred in plots with high numbers of removals or presence

of disturbance. All of the values were shifted by ¼ of the minimum value of that attribute that was not equal to zero (McDonald, 2009). Shifting by different constants was explored, and the results remained consistent. The standing dead tree attributes did not fit a log normal distribution. To address this, first differences were calculated so that the first observation of each remeasured plot was dropped (Greene, 2012). The resulting distributions approximated a normal distribution (Figure 7). Various statistical tests of normality were calculated, but given the large size of the samples, normality was primarily assessed using visual inspection of density distributions and quantile-quantile plots (Ghasemi and Zahediasal, 2012).

The estimation of the explanatory attributes for each plot often required determining the spatial nature of the plot. Latitude and longitude provided by the FIA database made these spatial determinations possible, however each FIA plot has 'fuzzed' or 'swapped' coordinates to protect the privacy of landowners and the integrity of the data collection process (Roberts et al., 2005). The 'fuzzing' process involves randomly relocating most plots within .8 kilometers of their true location, while the 'swapping' process occurs on the remaining 0-10 % of forested plots and only for plots that fall within private land. The 'swapping' consists of exchanging coordinates with another similar plot within the same county (Roberts et al., 2005). A selection of attributes were collected and recorded at the county level which helped control for the fuzzing and swapping process, but given the scale of this analysis, it was not expected that the 'fuzzing' and 'swapping' impacted the results.

This approach accounted for the impact of wood-product related industries by calculating distances of each FIA plot to pellet mills, pulp mill facilities, power plants consuming wood fuels, ports trading wood products and major wood pellet export ports (*defined below*). If the plot fell within the procurement area of a wood demanding sectors, a binary attribute in place of a distance was estimated when the wood product industry did not exist during at least

one year of the analysis (e.g. major wood pellet export ports did not exist until 2006) (Table 2). The distances were transformed by natural logs to assign more weight to the changes in distance near the FIA plot and less weight to changes in distance far from the plot (McDonald, 2009).

Location, capacity, and operating status of wood pellet mills were supplied by Forisk Consulting LLC. Pellet mills were categorized into small capacity (less than 91 thousand metric tons) and large capacity mills (greater than 91 thousand metric tons). For each FIA plot, Distances were calculated from the nearest small and large capacity mill. Two binary values were assigned to each plot if it was within 48.28 kilometers (30 miles) from a small capacity mill or 80.47 kilometers (50 miles) from a large capacity mill (Brandeis and Abt, 2019; Spelter and Toth, 2009; Stewart, 2015, Jonker et al., 2014; Sénéchal and Grassi, 2009; Boukherroub et al., 2017; Magelli et al., 2009; Enviva, 2010; Dale et al., 2017; Strange-Olesen et al., 2015). Additionally, each plot was assigned a discrete value if the plot fell within multiple pellet mill radii. All of these attributes varied within plots across time as pellet mills open and close. Pellet mills were considered for a given inventory year if they were established in the previous year and did not close in the previous 2 years.

The distance to the nearest pulp mill (USDA Forest Service Reports), power plants consuming wood fuel (EPA and DOE Reports), and port trading forest products (USDOT, 2019; Garcia, 2018) were calculated in order to account for the impact of these industries on the selected timberland attributes. Distances to ports trading forest products was a time invariant attribute, while distance to pulp mills and power plant were time variant. A binary time variant attribute for major wood pellet export ports was determined 1 if the plot was within a 120.70 km (75 mile) radii of a major export port and 0 if outside of the radii (SELC, 2017; Garcia, 2018). Major wood pellet export port was defined as any port exporting wood pellets to the EU (SELC,

2017; USITC, 2019). A lagged palmer drought severity index (PDSI) (CDC, 2019), the population per hectare (USCB, 2019; NBER, 2019), and road length per hectare (USCB, 2018) were estimated at the county level and respectively assigned to each FIA plot. Drought and population were time-variant attributes, while road density was not.

Site index (weighted average based upon condition proportion when appropriate), fire/weather disturbance, insect/disease disturbance, large and small diameter Shannon's Diversity Index (>= 5 inches diameter breast height), cosine of aspect (so that north = 1 and south = -1) and public vs private ownership were all estimated or taken directly from the FIA database (USDA Forest Service, 2018). All of these attributes are specific to plot observations and can vary over time. The two disturbance attributes are binary: 1 if the plot was disturbed, otherwise 0. Ownership is also a binary attribute: 1 if the plot is within state or federally owned land, otherwise 0.

Table 2. Explanatory variables estimated for each FIA plot; [Φ] indicates variables used to estimate treatment of FIA plots in the propensity score matching; [⊥] indicates the explanatory variables used in the propensity score matching; [3] indicates if the measure was not used as an explanatory variable in the panel regression for any model; The first differences models excluded all time invariant attributes including the state and ecological subsection effects.

Explanatory Variables	Description	Units	Sources
Treatment			
Distance to nearest pellet mill[Φ]	Distance to the nearest pellet mill	Log of kilometers	Forisk, 2018
Large capacity pellet mill presence[Φ]	Within 80 km of a pellet mill with capacity > 100k short tons	Binary	Forisk, 2018
Additive impact of pellet presence	the number of additional pellet mill radii that the plot falls within	Discrete	Forisk, 2018
Presence of major pellet export ports[⊥]	Within 121 km of port exporting wood pellets to the EU	Binary	SELC, 2017; USITC, 2019
Time-Variant			
Distance to nearest biopower plant[⊥]	Distance to the nearest power plant producing 25,000 Mwh from wood fuels	Log of kilometers	EIA reports from 2001, 2004,2005,2007, 2009, 2010, 2012, 2014, 2016; DOE eGRID reports from 2000, 2004, 2005, 2007, 2009, 2010, 2012, 2014, 2016
Distance to nearest pulp mill[⊥]	Distance to the nearest pulp mill	Log of kilometers	USDA Forest Service, 2019b
PDSI	Lagged palmer drought severity index (-10: dry to 10: wet) of the plots county	Continuous index	CDC, 2019
Population density	Population in the county of the plot	Population per hectare	UCSB, 2019; NBER, 2019
Artificial regeneration	Evidence of artificial regeneration on the plot	Binary	USDA Forest Service, 2019a
Large diameter diversity	Large diameter Shannon's Diversity Index	Continuous index	USDA Forest Service, 2019a
Small diameter diversity	Small diameter Shannon's Diversity Index	Continuous index	USDA Forest Service, 2019a
Fire or weather disturbance	Plot impacted by fire or weather	Binary	USDA Forest Service, 2019a
Insect or disease disturbance	Plot impacted by insect or disease	Binary	USDA Forest Service, 2019a
Time-Invariant			
Adjusted site index	Weighted average of site index based upon proportions of conditions within the plot	Continuous index	USDA Forest Service, 2019a
State or federal ownership	State or federal ownership of the largest condition in the plot	Binary	USDA Forest Service, 2019a
Aspect	Cosine of aspect of the largest condition in the plot	Cosine of degree	USDA Forest Service, 2019a
Distance to nearest forest product port[⊥]	Distance to the nearest port trading forest products	Log of kilometers	USDOT, 2019
Road density[⊥3]	The length of primary and secondary roads in the plot's county	Kilometers per square kilometer	USCB, 2018
Time and Group Effects			
Inventory year	The inventory year that the plot observation was measured in	Categorical	USDA Forest Service, 2019a
State[⊥]	The state that the plot falls within	Categorical	USDA Forest Service, 2019a
Ecological Section	The ecological section that the plot falls within	Categorical	USDA Forest Service, 2019a

3.2 Quasi-randomization of timberland plots

This analysis accounts for the non-random location of wood pellet mills by using propensity-score matching to subsample FIA plots before the estimation of a panel regression model. Using propensity score matching can reduce initial observable heterogeneity in explanatory factors and lead to more accurate estimations of panel regression models (Ravallion, 2005; Rodriguez et al., 2007). The propensity score method controlled for various spatial and economic factors that impact pellet mill sitting. These factors fall into the following categories: the presence of wood-processing facilities, transportation infrastructure, population, and region. This method intended to randomize on the non-randomized locations of pellet mills and gain a sub-sample of comparable treated, within pellet mill procurement radii, and non-treated plots, outside of pellet mill procurement radii. Equation 3 estimated the observed relationships to treatment where the independent variables were observable explanatory attributes that influence treatment, and equation 4 was used to estimate a propensity score from the probability of treatment (Becker and Ichino, 2007; Greene, 2012; Rodriguez et al., 2002). The fundamental approach is given by equation 3 and 4:

$$Probit(T) = \delta x_i + \varepsilon \qquad i = 1, \ldots, n \tag{3}$$

$$f(x) = E(T = 1|x_i) \qquad i = 1, \ldots, n, \tag{4}$$

where there were M regressors in x_i including a constant term and n plots. Regressors and plot definition differ between the removal plots and the remeasured plots.

The propensity score matching for carbon and live tree remeasured observations included 27,878 plots, and 5830 of them were designated treated because they were within the

procurement radii of a large or small capacity wood pellet mill between 2012 and 2017 in their respective inventory year. The model's estimation of x_i (3,4) included six explanatory variables that did not vary over time: log of distance to nearest port trading forest products, log of distance to nearest pulp mill in 2000, log of distance to nearest biopower facility in 2000, population density of the county in 2000, road density of the county, and a dummy variable for state. Training of the probit model used all 27,878 eligible plots. The propensity scores given by $f(x)$ (4) were matched one-to-one without resampling between the treated and non-treated samples to the plot with the closest propensity score to its own (Becker and Ichino, 2002). All measurements of the matched plots were collected as the final sub-sample of remeasured carbon and live tree plots.

The propensity score matching for standing dead observations included 18,397 remeasured plots, and 4,965 of them were designated treated because they were within the procurement radii of a large or small capacity pellet mill between 2000 and 2017. The model estimation of x_i (3, 4) included seven time variant explanatory variables: log of distance to nearest port trading forest products, log of distance to nearest pulp mill, log of distance to nearest biopower facility, population density of the county, road density of the county, a dummy variable for state and a binary if within 121 km of a major wood pellet export port. The subsequent collection of remeasured samples in the dead-tree plots matched the method of the carbon and live tree plots.

All removal tree and volume plots were used for the initial estimation of the two respective models. Propensity scores were calculated from $f(x)$ (4) and each treated remeasured observation was matched one-to-one with a non-treated observations without resampling (Becker and Ichino, 2002). Treatment of removal plots was also defined as being within the procurement radii of a pellet mill at the time of inventory. The initial sample of

removal volume plots contained 918 and 11,785 treated and total observations respectively. The initial sample of removal tree plots contained 867 and 11,289 treated and total observations respectively. For both removal models, x_i (3, 4) included seven time variant explanatory variables: log of distance to nearest port trading forest products, log of distance to nearest pulp mill, log of distance to nearest biopower facility, population density of the county, road density of the county, a dummy variable for state and a binary if within 121 km of a major wood pellet export port. Propensity scores were calculated from $f(x)$ (4) and each treated removal observation was matched one-to-one with a non-treated observations without resampling (Becker and Ichino, 2002).

3.3 Examination of variation in plot conditions over time

This analysis used a panel regression framework to can control for the multi-dimensional differences between regional and location specific extrinsic and intrinsic pressures on plot-level timberland conditions in order to elicit the specific impact of wood-pellet production on timberland conditions (Villalobos, 2018; Blackman et al., 2016). The general panel model was fit to timberland plot conditions where y_{it} was a value of the plot-level timberland measure (Table 1) within the plot i in inventory year t. x_{it} (Table 2) included a matrix that encompassed human and non-human factors that systematically impact timberlands. y could change over the plot i and/or time t as a function of the explanatory factors. Hence, changes in y were associated with changes in x (Greene, 2012). Linear panel regression provided the tools to model changes in a matrix of explanatory factors across both time and space (Greene, 2012). Thus, the statistical framework of this analysis is founded in the generalized panel model given by equation 5.

$$y_{it} = x'_{it}\beta + c_i + \varepsilon_{it} \qquad i = 1, \ldots, n; t = 1, \ldots, T \tag{5}$$

There were K regressors in x_{it} including a constant term, *n* plots in the area of analysis, and *T* inventory years (Greene, 2012). ε_{it} was an error term for random events that impact timberland attributes across time and space. c_i was a plot- or group- specific effect that did not change over time. Alternatively, v_t could be substituted for c_i as a time specific effect that does not change across plots. Two-way effect models incorporate the estimation of both time-specific and plot- or group-specific effects. If c_i and/or v_t contain only a constant term such that for c_i $E[c_i|x_{it}] = \rho$, where ρ is a constant value, then pooled ordinary least squares (OLS) estimation provides consistent, unbiased estimation. Alternatively, a fixed effects model estimates a plot- or group-specific mean ρ_i in place of c_i (6), where ρ_i is non-stochastic, and controls for all plot- or group-effects, and a random effects model estimates c_i with $(\alpha + u_i)$ (7), where α is a constant and u_i is a stochastic plot- or group- specific element (Greene, 2012).

$$y_{it} = x'_{it}\beta + \rho_i + \varepsilon_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{6}$$

$$y_{it} = x'_{it}\beta + (\alpha + u_i) + \varepsilon_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{7}$$

A mixed-effects model incorporates both fixed and random effects, so that some effects can be modeled as $(\alpha + u_i)$, and others as ρ_i (Harrison et al., 2018). A general mixed effects model is given by:

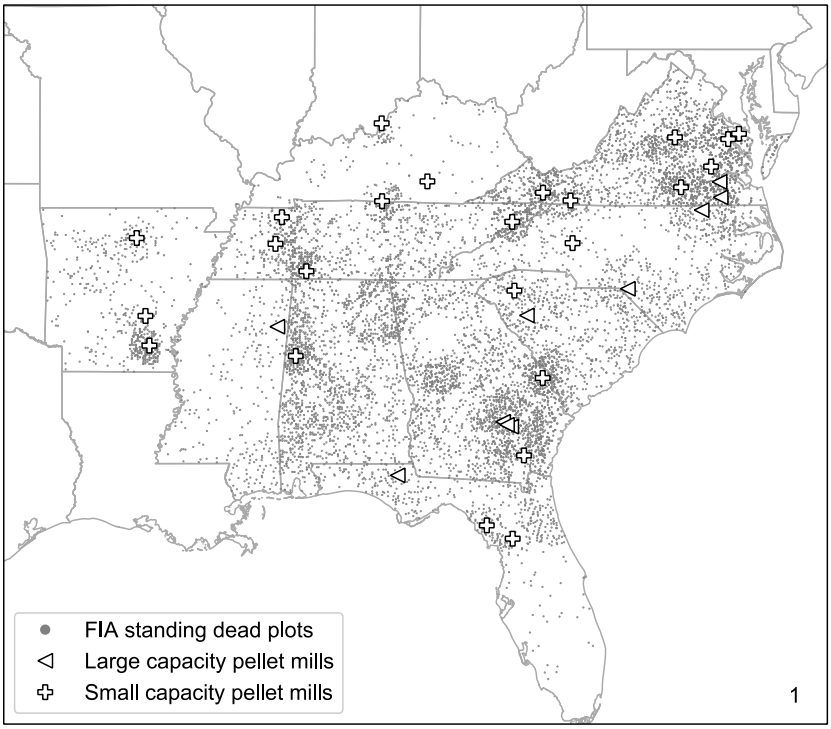
$$y_{it} = x'_{it}\beta + \rho_i + (\alpha + u_i) + \varepsilon_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{8}$$

where ρ_i is the fixed effects term and is estimated as the plot- or group-specific mean for i, and u_i is the plot- or group-specific random element for i (Harrison et al., 2018). We considered two groups and one time effect in the model specification: inventory year, ecological section (Cleland et al., 2007) and state. F-tests and Haussmann tests were used to determine the model specification of OLS, fixed effects, random and mixed effects (Greene, 2012).

4 RESULTS

4.1 Propensity score matching

The average standardized differences of treatment and control means were calculated for all continuous variables to assess the effectiveness of the matching for the removal samples and the remeasured samples. All standardized values were less than .06 in the remeasured samples and less than .10 in the removal samples. The standardized difference in proportions of plots within each southern state was less than .2 for all four subsamples. Generally, these metrics indicate that the matching produced balanced samples of treated and non-treated plots (Garrido, et al., 2014). The final sample of carbon and live tree remeasured plots contained 31,188 observations of 11,660 plots. After dropping the first measurement for first differences and the propensity score matching the final sample of standing dead tree plots included 9,930 observations of 7,942 plots. Figure 3 maps 1 and 2 show the spatial distribution in relation to the small and large capacity pellet mills of the standing dead first difference remeasured plots and the carbon/live tree remeasured plots respectively. The resulting removal volume and removal tree samples contain 1,836 and 1,734 observations respectively. Figure 4 maps 1 and 2 show the spatial distributions of the removal count and volumes respectively. Figures 5 and 6 show mean change before and after transformations by natural logs and first differences respectively.



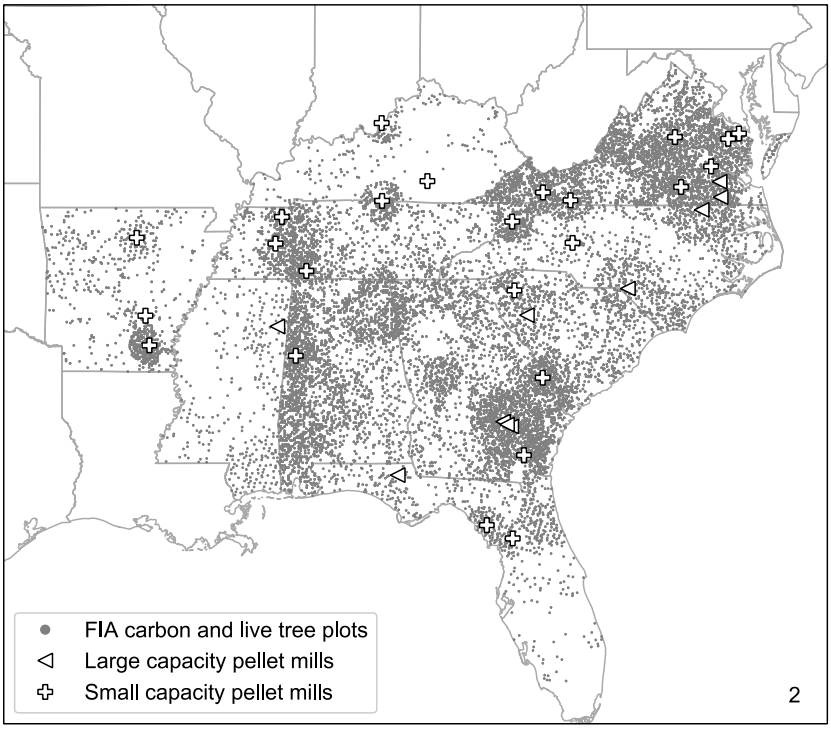
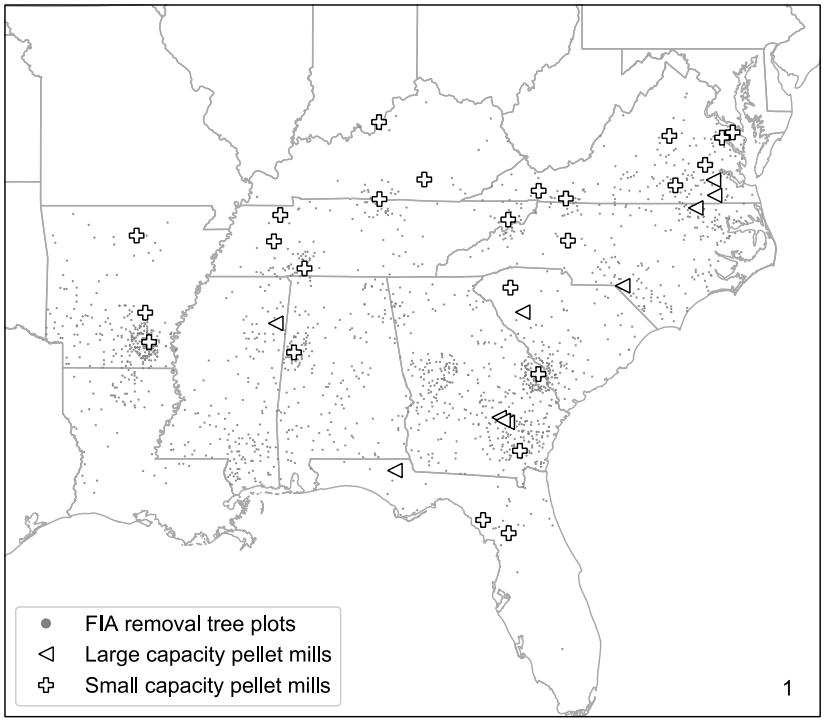


Figure 3. All remeasured FIA plots after propensity score matching. Map 1 includes all standing dead tree first differences remeasured plots and map 2 includes all carbon and live tree remeasured plots.



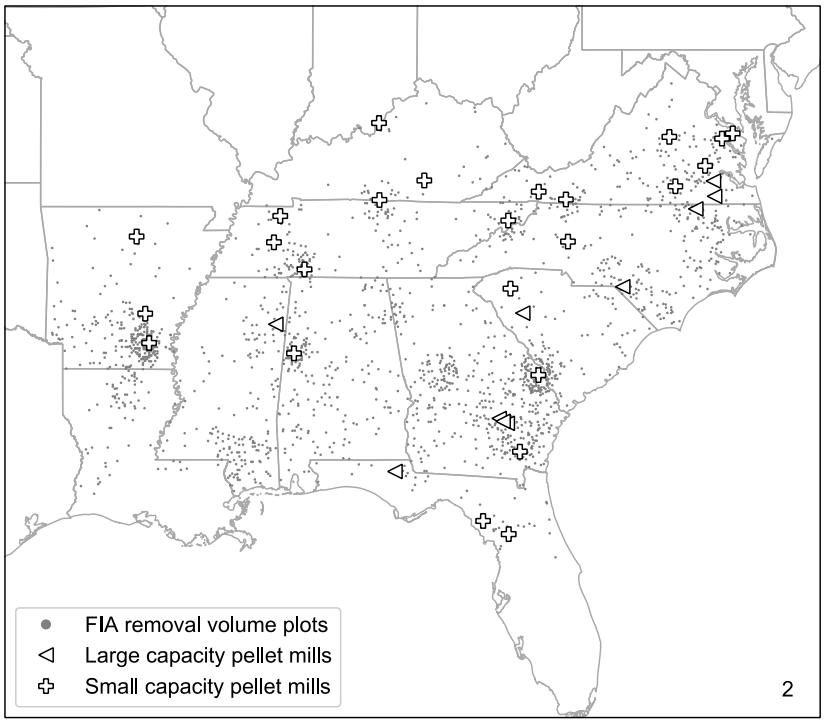


Figure 4. All removal FIA plots after propensity score matching; Map 1 includes all removal tree plots and map 2 includes all removal volume plots.

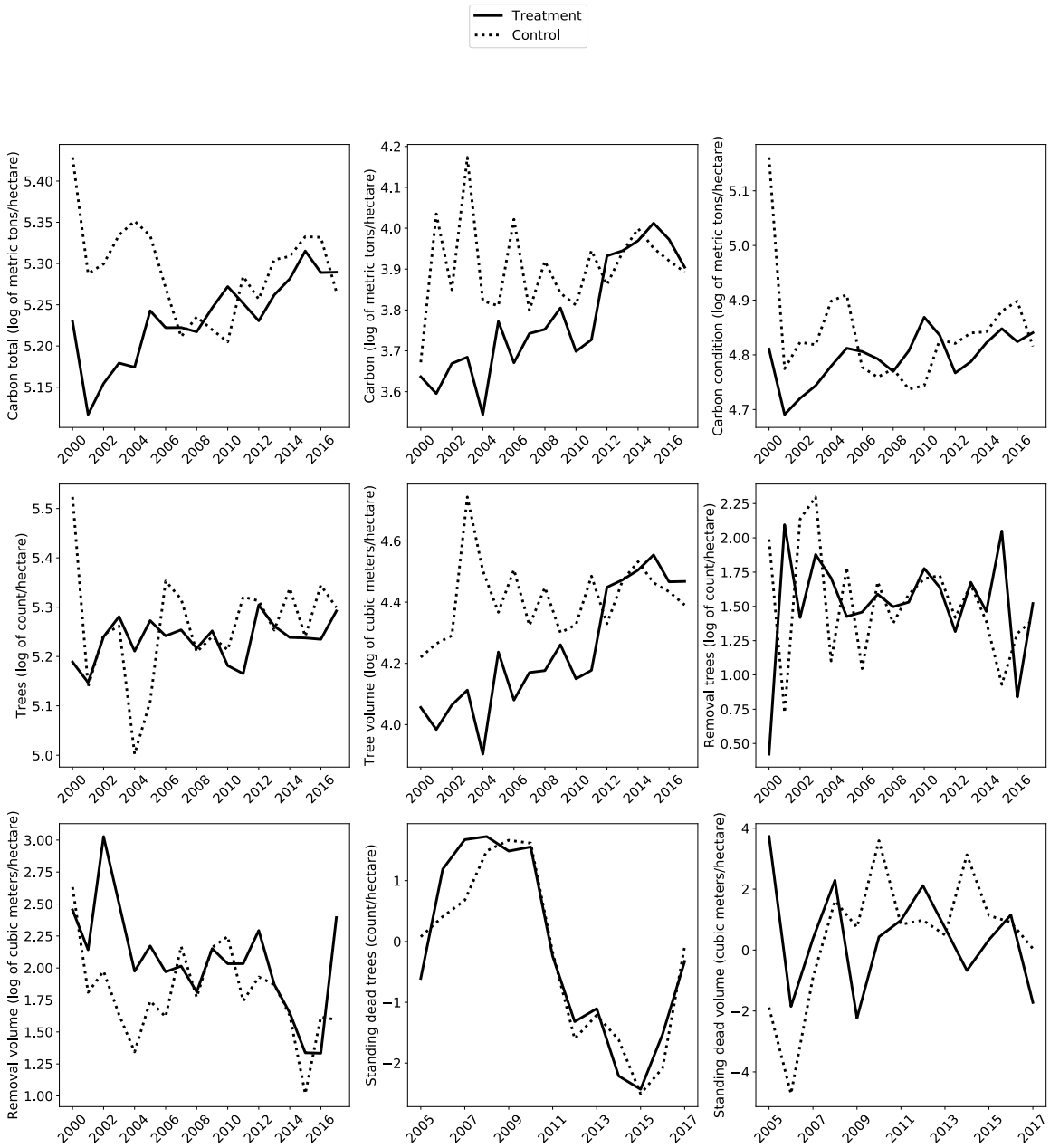


Figure 5. Means of all FIA attributes across all inventory years of the analysis; respective transformations described in the methods and Table 1; the means are calculated after propensity score matching and grouped based on treatment described in the propensity score matching methods.

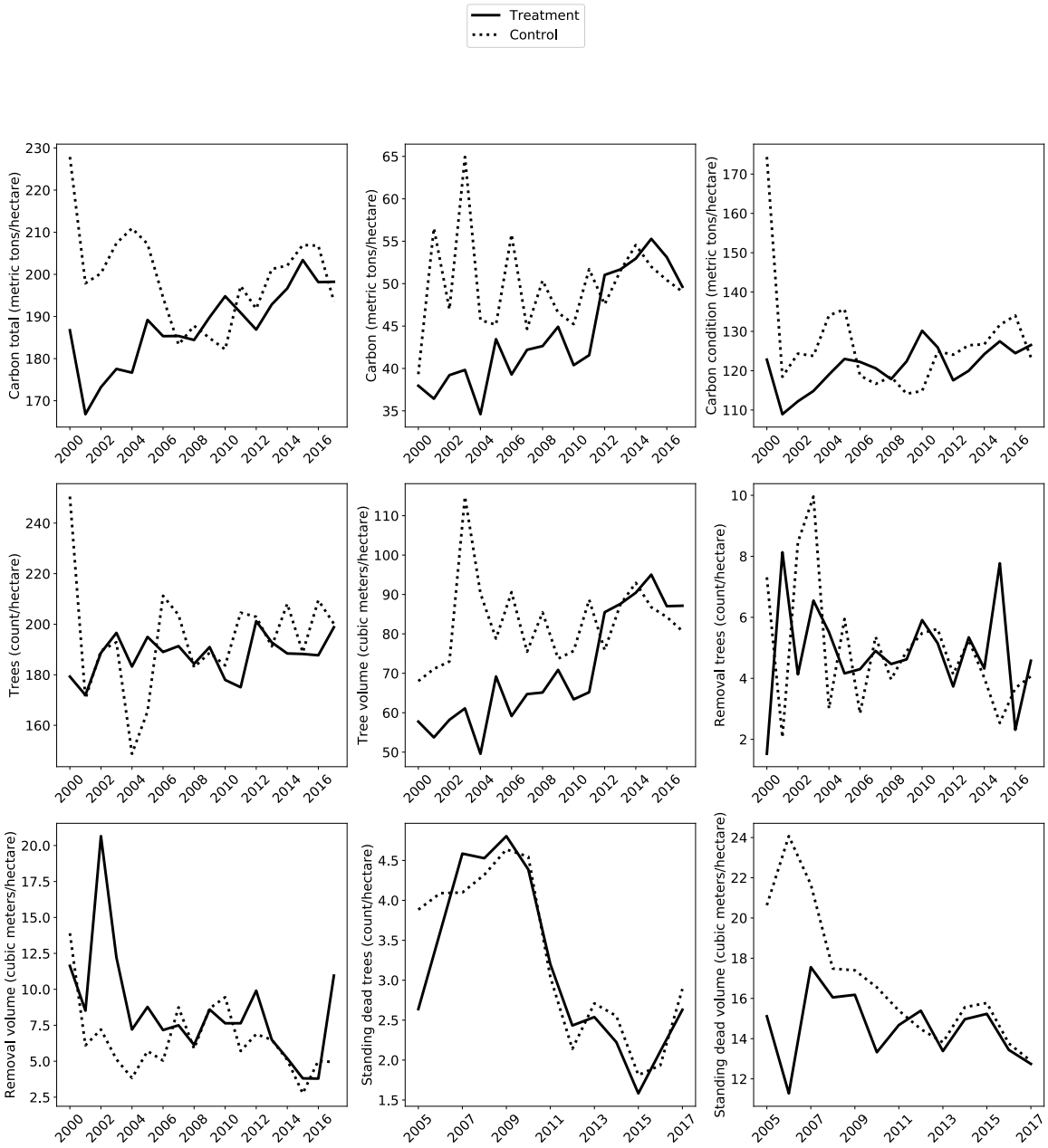


Figure 6. Means of all FIA attributes across all inventory years of the analysis before transformations; the means are calculated after propensity score matching and grouped based on treatment described in the propensity score matching methods.

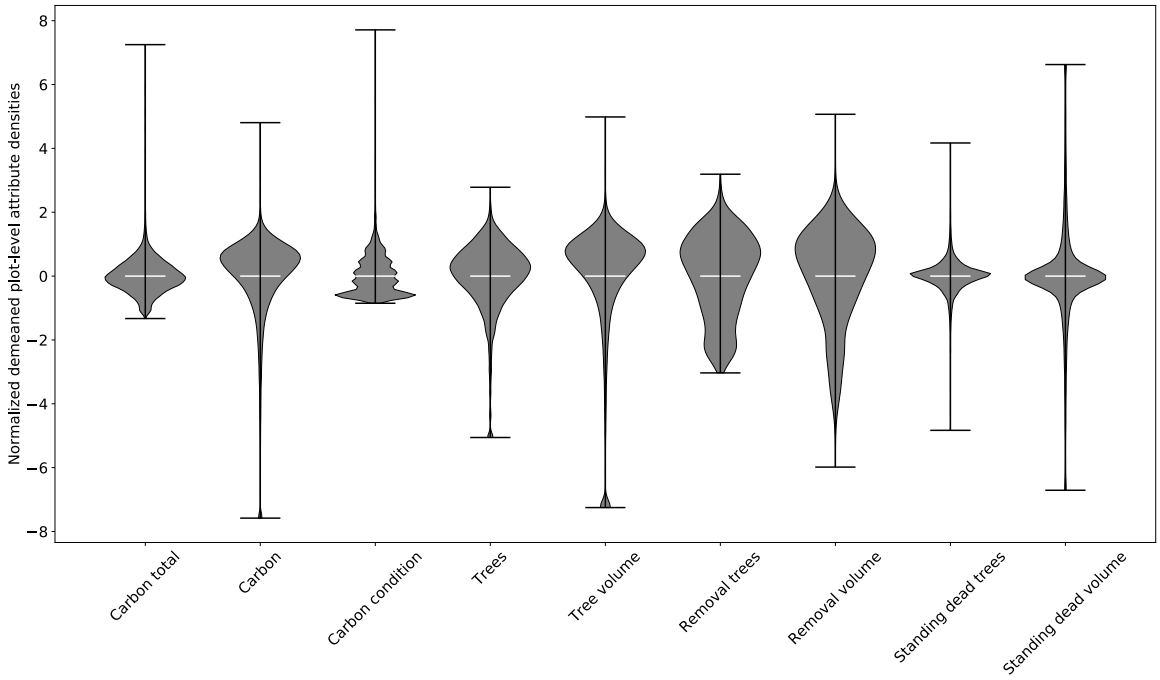


Figure 7. Standardized distributions of all FIA attributes for all plots after propensity score matching. All values are scaled so mean is 0 and standard deviation is 1. The top and bottom bars of distribution indicate the minimum and maximum values after transformations.

4.2 Panel regression

The propensity score matching assured that the sampled plots included in the regression were representative of plots with similar locations in relation to wood product facilities. The spatial relationship of the plot in relation to wood pellet mills accounted for the primary differences between the locations of treated and the non-treated subsamples. The regression model also controlled for a variety of other explanatory factors that can impact plot-level timberland conditions outside of the wood product facility and regional traits used in the propensity score matching. Some of the strongest predictors of plot conditions were: the presence of insect or disease disturbance, fire or weather disturbance, artificial regeneration, and state or federal ownership. These traits were found to be highly significant with many of the FIA attributes. The model also identified a variety of significant relationships between wood product industries and FIA attributes. These relationships differed based upon the industry type

and the interaction of that industry with wood pellet facilities. This section focused on significant relationships considered at the .05 level, but all regression results were reported in the regression tables found in the appendix. Special attention was paid to significant relationships at the .01 level because of the large sample sizes (Biau et al., 2008). This section also placed more emphasis on the models with R-squared greater than .1 (all except standing dead tree count, standing dead tree volume and removal volume models), as it is expected that these models were more appropriately specified (Table 3) (Greene, 2012).

Figures 8, 9 and 10 show standardized regression coefficients for a variety of the explanatory variables. In these figures, regression coefficients are standardized in order to make comparisons across regressions more appropriate. The regression coefficients are transformed by multiplying the coefficient values by the ratio of standard deviation of the explanatory variable divided by the standard deviation of the response variable (Bring, 1994). The results and discussion sections use the untransformed regression coefficients for interpretations (see appendix), and the standardized figures are intended to provide a visual comparison of the impact of an explanatory variable across all regression models.

The regression model identified significant positive relationships between the presence of large capacity wood pellet mills and plot-level carbon stocks (Table 5; Figure 9). Similarly, a one percent decrease in the average distance to the nearest small and large capacity pellet mill was associated with 10%, 3% and 2% increases in average carbon in live/standing dead trees, total carbon and condition level carbon respectively (Table 5; Figure 8). The regression model also captured a statistically significant positive relationship between plot-level carbon in live trees and the additive impact from the presence of multiple pellet mills. The model found positive relationships between the presence of a major wood pellet export port and all plot level carbon attributes (Table 5). The presence of major wood pellet export ports, additive pellet mill

impact and the reduction in distance of plot to wood pellet mill were all associated with increased volume in live trees. However, the additive impact of multiple wood pellet mills showed a strongly significant relationship with increased removal trees, such that the increase in one additional pellet mill was associated with a 34% increase in the average amount of removal trees (Table 7; Figure 9).

The regression model also captured a variety of statistically significant relationships as distances of plot to other wood product industries changed. A 1% decrease in the distance of a plot to a pulp mill was associated with a 1% decrease in the average amount of total carbon, and a 3% increase in the average number of live trees (Table 5). Alternatively, a 1% decrease in the distance to biopower facilities was associated with a 3% decrease in the average number of live trees and a 4% decrease in the average carbon stored in live and standing dead trees (Table 5). A 1% decrease in the distance of a plot to a port trading forest products was associated with a 10% increase in the average number of removal trees. Additionally, a decrease in distance to port trading forest product was also associated with a reduction in the amount of carbon stored in live and standing dead trees, but an increase in overall plot-level carbon.

The interaction terms between wood product industries and two of the treatment variables, distance to nearest pellet mill and within procurement radii of a large capacity pellet mill, provide insight to how the added pressures of other wood product industries impact treated plots. Notably, the model captured many significant relationships between the interactions and the number of standing dead trees. A 1% decrease in distance to biopower facility and the distance to the nearest pellet mill was on average associated with a .0037 reduction in the average number of standing dead trees per plot. Similarly, the presence of large capacity pellet production and a 1% decrease in the distance of plot to a biopower plant was associated with a .0073 reduction in the average number of standing dead trees per plot. The

presence of large capacity pellet production and a reduction in distance to ports trading forest products was also associated with reduced standing dead trees and reduced removal trees. On average there were positive impacts on carbon in live and standing dead trees associated with reduced distance to pulp mills and the presence of large capacity pellet mills.

Other extrinsic anthropological explanatory variables included: the presence of artificial regeneration, population density, and the presence of state or federal ownership. State or federal ownership was associated with increases in the average plot-level carbon stocks, volumes in live trees, and a 27% reduction in the average number of removal trees. Population density exhibited statistically significant positive relationships with volume in live trees and carbon and an 18% decrease in the amount of removal volume. The presence of artificial regeneration was associated with 25%, 13% and 12%, 26% and 9% reduction in carbon in live/standing dead trees, total carbon, and condition level carbon stocks, volume in live trees and count of live trees. Additionally, there was a 27% increase in the number of removal trees on plots with artificial regeneration.

The extrinsic disturbance attributes also exhibited highly significant relationships with plot-level forest conditions. Insect or disease disturbance and fire or weather disturbance generally exhibited stronger relationships than the lagged PDSI attribute. A low PDSI is indicative of drought conditions, and thus an increase in PDSI produced the expected result of a reduction in standing dead trees and increased carbon stocks. The impact of disturbance on carbon stocks varies based upon the type of damage. The presence of insect and disease damage was associated with significant average increases in carbon stocks, counts of live trees, and a 48% increase in the volume in live trees, while fire damage was associated with a 12.5% significant decrease in carbon stored in live/standing dead trees (Figure 10). The fire and weather attribute was also associated with significant reductions in live trees. Both insect/disease and

fire/weather attributes strongly predict the increases in volume and counts of standing dead trees.

The aspect and site index attributes were positively associated with plot level carbon stocks and volume in live trees. The diversity indices also showed many significant relationships with timberland traits. Higher large diameter Shannon indices were associated with higher carbon stocks and volume in live trees and a reduction in number of trees, while small diameter Shannon indices were associated with lower carbon stocks and a 92% increase in the number of trees per acre.

Table 3. Descriptive statistics for the nine regressions included in the analysis.

Model	R-squared	Adjusted R-squared	F statistic	P-value	DF-residual
Standing dead trees	0.03	-0.132	13.1	<.001	8510
Standing dead volume	0.009	-0.157	3.7	<.001	8510
Carbon	0.185	0.184	7048.9	<.001	31123
Carbon total	0.163	0.162	6049.7	<.001	31106
Condition carbon	0.223	0.222	8908.1	<.001	31106
Live tree volume	0.209	0.208	8207.9	<.001	31106
Trees	0.291	0.29	12745.5	<.001	31106
Removal volume	0.056	0.04	108.0	<.001	1804
Removal trees	0.189	0.174	396.7	<.001	1702

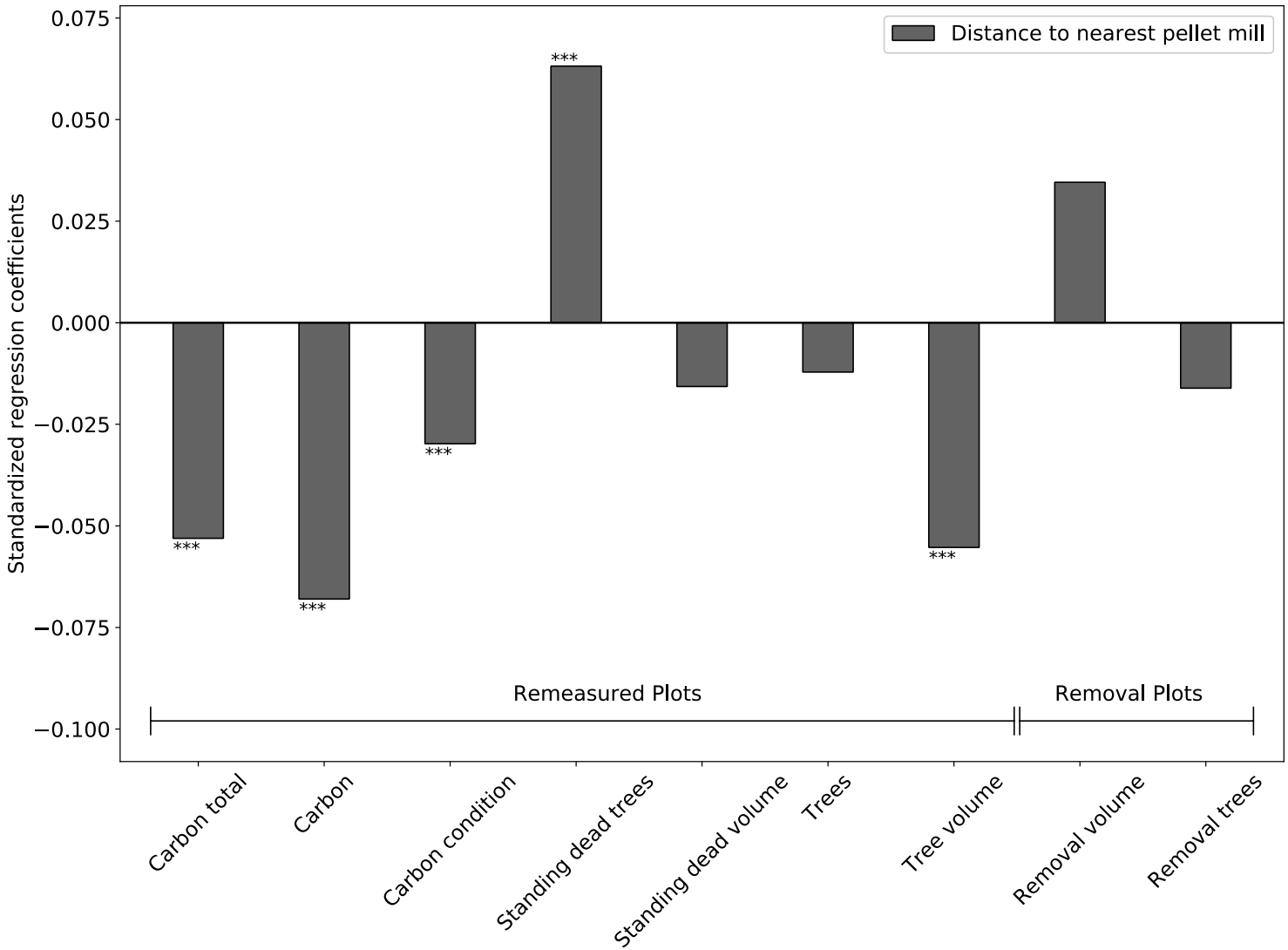


Figure 8. Standardized regression coefficients for all FIA attributes and the distance to nearest pellet mill.

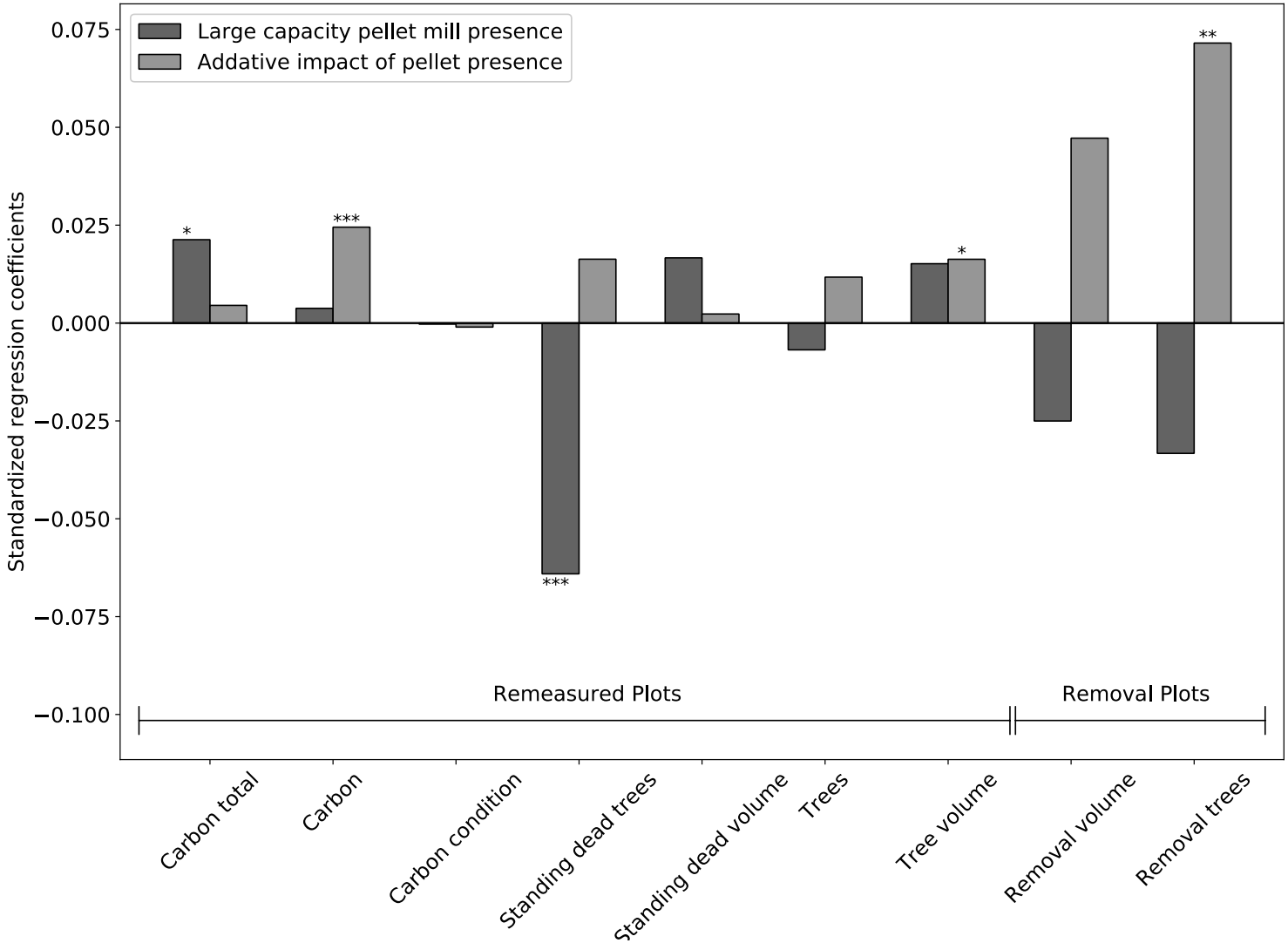


Figure 9. Standardized regression coefficients for all FIA attributes and presence of large capacity pellet production and additive pellet mills

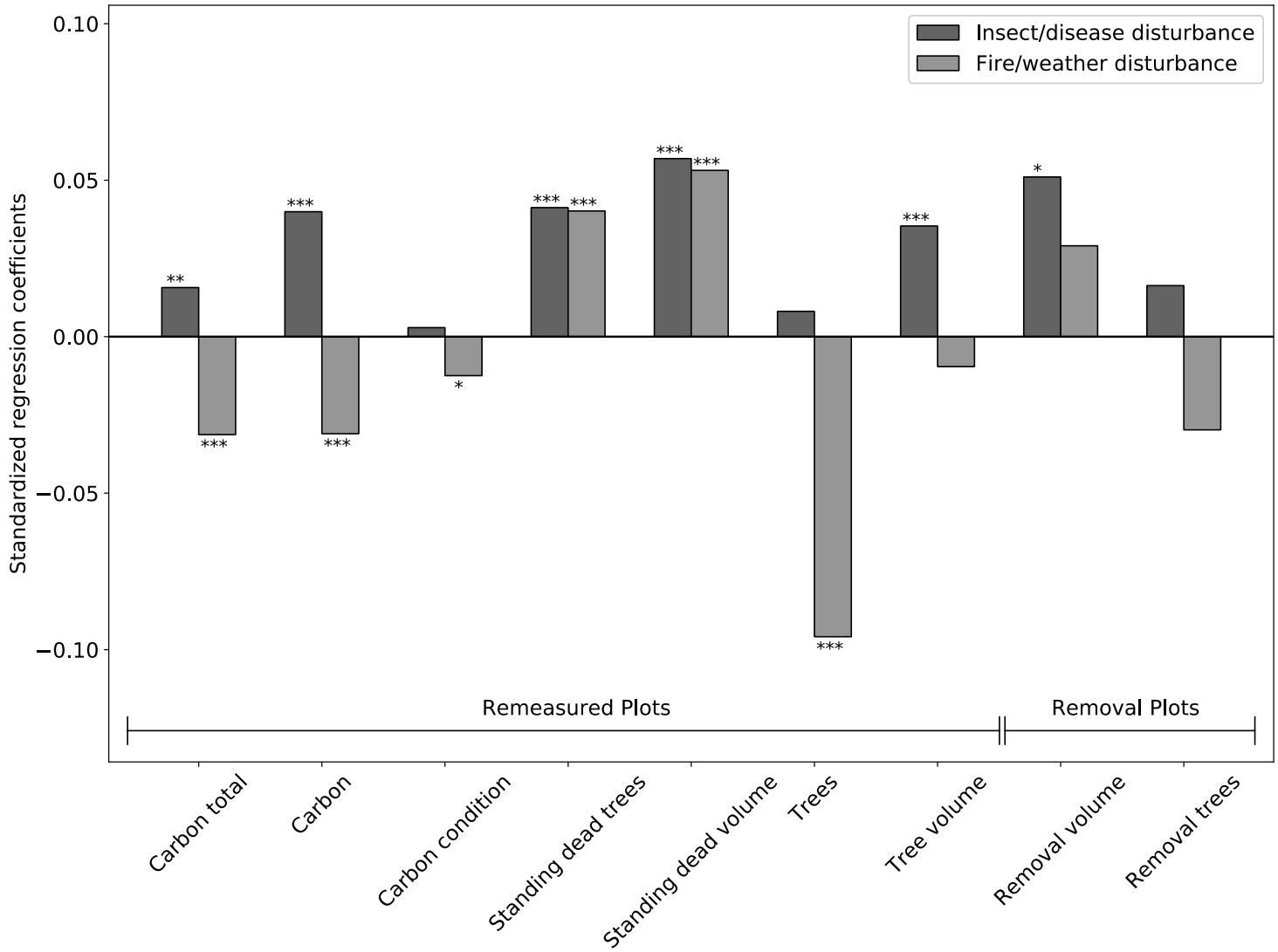


Figure 10. Standardized regression coefficients for all FIA attributes and presence of insect or disease and fire or weather disturbance.

5 DISCUSSION

Long-term timberland management can lead to increased productivity of forests (Grier et al., 1989; McEwan et al., 2019), however, in the short term management practices manifest themselves in different ways across a landscape. Management changes timberland attributes through harvests and silviculture treatments. These practices can lead to long term shifts in timberland structure and change in forest type (Grier et al., 1989; Bravo-Ovideo et al., 2015), but these long-term shifts are generally not captured in a 17 year window. Given that the largest intensification of wood pellet production occurred within the last 10 years, this analysis did not capture long-term shifts associated with the presence of wood pellet production, but it may have captured the differences associated with the long-term presence of established wood product industries. The resulting relationships between treatment variables and timberland attributes are interpreted as the short-term shifts across a landscape associated with wood pellet production.

The coefficients on forest product industry variables can help explain the differences in management intensity in the presence of wood product facilities. As outlined in the theoretical framework, plots with higher gross carbon stocks, more volume in live trees, more standing dead trees and less removal trees were expected to have less or no timber management. The results also may provide insight into how long-term management induced by the sustained presence of facilities (pulp mills) has impacted timberland traits compared to the newer facilities (pellet mills and biopower).

The presence of wood pellet production was associated with increased plot level carbon stocks. This could be the result of less timber management occurring in plots near wood pellet mills compared to non-treated plots falling within similar distances from other wood processing facilities. The reduction in total plot-level carbon with reductions in distance to pulp mill may be

associated with more management near pulp mills in the short-term or long-term. If in the short-term, the difference between pulp and pellet mill relations to carbon stocks could be explained by larger capacity for consumption of feedstock/roundwood in pulp mills compared to pellet mills, and the longer tenure of the pulp facilities (Forisk, 2018). The stronger demand of feedstock at pulp mills likely drives increased and more intensive management of timberland near those facilities, and has done so for a longer time. Increased trees per hectare and reductions in total carbon with decreasing distance to pulp mill is also indicative of more intensive management (i.e. abundance of smaller diameter trees). Likewise, reductions in tree counts and carbon stored in live and standing trees associated with decreasing distance to power plants consuming wood fuels may be associated with some type of increased timberland management. Biopower plants create a stronger market for woody byproducts, and this may induce more intermediate silviculture treatments or harvest of lower quality timber for utilization by biopower facilities. Alternatively, biopower plants may locate near marginal timberlands (compared to other industries) that have better access to other fuels (e.g. coal or natural gas), however, controlling for site index, artificial regeneration, diversity indices and others should help to limit capturing this relationship in the results. The increase in removals associated with decreasing distance to port indicate that transportation infrastructure may be an important predictor of timber harvests. The opposite of this trend is observed within large capacity pellet radii, indicating that the proximity to port may not be heavily influencing wood pellet mill location, even though many large capacity mills are using the export ports.

The model also captured evidence of increased removals associated with pellet mill presence. The additive presence of multiple pellet mills can explain some of the increases in the amount of removal trees (i.e. as the number of pellet mill radii that the plot falls within increases, the number of removal operations harvest more trees). Outside of the ports distance

and interaction with large capacity pellet mills mentioned above, the additive impact of multiple pellet mills was the only other forest product industry variable that exhibited statistically significant positive associations with removals. This implies that the amount of removal trees in relation to location of other wood product industries (pulp mills and biopower plants) were relatively evenly distributed. However, the relationship observed with pellet mills did not translate to a significant reduction in carbon. Given that the model does not generally capture significant impacts of wood product industries on removals, it is probable that the carbon and volumetric trends associated with wood product industries have developed over longer time frames. This suggests that it may be too early to rule out the possibility that the intensification of pellet production could begin to shift standing carbon stocks in a negative direction through more intensified management, however, this is yet to be seen. For now, the pellet industry is not negatively impacting timberland carbon stocks when compared to other forest product industries.

Otherwise, some of the strongest predictors of removal tree count include artificial regeneration presence and the diversity indices. The Shannon diversity index is a standardized measure that can be compared across different plots with different proportions of timberland. The index responds to both evenness and richness. Interpretations of the driving forces behind the observed relationships could vary, however, there are likely explanations. There is a statistically significant positive correlation between live and standing dead tree and total carbon stocks and the large diameter Shannon index, and a negative correlation between removals and the indices. These relationships are likely explained by management styles in the US South that are characterized by short rotation pine forests and pine plantations. Generally, managed forests have lower Shannon indices (Tenzin and Hasenauer, 2016; Polyakov et al., 2008).

Although the standing dead tree models have a relatively poor fit, across wood pellet treatment variables, the model fairly consistently capture impacts on the number of standing dead trees. The results suggest that, on average, the presence of multiple wood pellet mills was associated with reduction in the amount of standing dead trees. However, many of the treatment variables showed positive associations with standing dead trees. It is expected that wood pellet mills utilize standing trees for production, and this could likely be associated with the negative trends observed in the treatment variables. However, the discrepancies observed may be indicative of the difficulty in modeling these attributes at the plot-level.

The presence of fire/weather and insect/disease disturbances were strong positive predictors of the number and volume in standing dead trees. There was also a strong positive correlation between the presence of insect and disease with plot level carbon and volume in live trees. This is expected because timberlands with less management and more volume are often more susceptible to insect and disease disturbance (Byler and Hagle, 2000). Fire and weather damage had significant negative correlations with plot level carbon stocks and the number of live trees. These results reinforce that the relationships between disturbances and carbon stocks play an important role in estimating forest related carbon emissions. The significant reduction in total carbon in the presence of fire and weather damage is likely explained by combustion where and when fires occur. Ultimately disturbances can reallocate carbon in live trees to carbon in dead trees, soil and the atmosphere. The proportional distributions of carbon after disturbance is dependent upon the type and severity of disturbance. The significant relationships between disturbance and plot level carbon reinforce the importance of these relationships.

6 RECOMMENDATIONS

Future research can use this analysis as a model to assess the impact of wood product industries across landscapes. For instance, past research has shown fire-preventative forest management can benefit both short term and long term carbon stocks (North et al., 2009; Hurteau and North, 2010), and future research can continue to explore if the presence of wood product industries reduces risk of natural disturbances across landscapes. Future research could also address how forest product industries directly impact the diversity of forests, and discuss the ecological implications of these impacts. Alternatively, models similar to this analysis could be used to forecast changes in forest conditions in the presence of existing wood product industries by estimating location specific factors that increase the likelihood of management and removals. These types of models could help to more clearly identify driving forces behind wood product industry management.

7 CONCLUSION

Assessing the utilization of woody biomass for energy production is a question of determining the tradeoffs associated with the industries involved. This analysis used regression models to assess the impact of wood pellet industries on timberland conditions in order to help inform these debates in the future. We found that wood pellet production was not negatively impacting forest conditions near wood pellet facilities based on forest inventory data. Overall, timberlands contain significantly more carbon as the average distance to pellet mill decreases. We found some evidence of increased number of removals within the radii of multiple pellet mills, but this did not translate to significant impacts on other timberland conditions. Overall, wood pellet production has not negatively impacted timberland conditions within the first decade or two of major industry growth. It will be important to continue to monitor the wood

pellet industry, especially in the case of changes to domestic policy that reduce protect areas. In the event that the United Kingdom leaves the European Union, it will be interesting to see whether United Kingdom energy policy shifts away from the EU renewable energy directive, which could intern have significant impacts on the US wood pellet industry.

APPENDIX

Table 4. Fixed inventory year effects for first-differences standing dead tree plots.

	Change in Standing Dead Trees		Change in Volume in Standing Dead Trees	
	Estimate	**P**	**Estimate**	**P**
Treatment				
Distance to nearest pellet mill	0.367	**<.001**	-0.594	0.205
Large capacity pellet mill presence	-0.751	**<.001**	1.274	0.226
Additive impact of pellet presence	0.212	0.239	0.197	0.871
Presence of major pellet export ports	-0.536	**0.001**	-0.6	0.564
Interactions				
Distance to nearest pellet mill : distance to nearest biopower plant	0.376	**0.006**	0.086	0.926
Distance to nearest pellet mill : large capacity pellet mill presence	-0.584	**0.013**	2.837	0.073
Distance to nearest pellet mill : distance to nearest port trading forest products	-0.341	**<.001**	0.504	0.332
Distance to nearest pellet mill : distance to nearest pulp mill	-0.051	0.743	-0.416	0.69
Large capacity pellet mill presence : distance to nearest biopower plant	0.732	**0.014**	1.219	0.544
Large capacity pellet mill presence : distance to nearest port trading forest products	0.639	**<.001**	1.132	0.332
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.554	0.087	-1.247	0.566
Time-Variant				
Distance to nearest biopower plant	-0.087	0.474	0.168	0.837
Distance to nearest pulp mill	-0.021	0.872	0.624	0.464
Population density	0.039	0.725	0.62	0.406
Artificial regeneration	-0.138	0.386	-1.723	0.108
PDSI	-0.166	**<.001**	0.001	0.997
Large diameter diversity	-0.266	**0.01**	0.33	0.634
Small diameter diversity	0.716	**<.001**	-1.528	**0.016**
Fire or weather disturbance	0.76	**<.001**	6.559	**<.001**
Insect or disease disturbance	1.329	**<.001**	11.971	**<.001**

Table 5. Fixed and mixed inventory year, ecological section, and state effects for remeasured carbon plots.

	Carbon		Total Carbon		Condition Carbon	
	Estimate	P	Estimate	P	Estimate	P
Treatment						
Distance to nearest pellet mill	-0.098	**<.001**	-0.028	**<.001**	-0.018	**<.001**
Large capacity pellet mill presence	0.016	0.699	0.033	**0.035**	0	0.977
Additive impact of pellet presence	0.125	**<.001**	0.008	0.52	-0.002	0.878
Presence of major pellet export ports	0.084	**<.001**	0.054	**<.001**	0.055	**<.001**
Interactions						
Distance to nearest pellet mill : distance to nearest biopower plant	-0.008	0.574	-0.004	0.479	-0.009	0.136
Distance to nearest pellet mill : large capacity pellet mill presence	0.058	0.165	-0.008	0.599	-0.032	0.057
Distance to nearest pellet mill : distance to nearest port trading forest products	-0.005	0.581	-0.002	0.603	-0.002	0.649
Distance to nearest pellet mill : distance to nearest pulp mill	0.024	0.128	0.005	0.363	0.008	0.223
Large capacity pellet mill presence : distance to nearest biopower plant	0.113	**0.036**	0.015	0.457	-0.043	0.053
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.053	0.117	0.003	0.825	0.031	**0.026**
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.132	**0.024**	0.013	0.558	0.077	**0.001**
Time-Variant						
Distance to nearest biopower plant	0.042	**0.001**	0.001	0.897	-0.001	0.807
Distance to nearest pulp mill	0.008	0.582	0.012	**0.023**	0.008	0.165
Population density	0.041	**0.001**	0.007	0.121	0.003	0.588
Artificial regeneration	-0.246	**<.001**	-0.127	**0**	-0.123	**<.001**
PDSI	0.009	**0.005**	0.003	**0.004**	0.004	**0.006**
Large diameter diversity	0.494	**<.001**	0.059	**<.001**	-0.071	**<.001**
Small diameter diversity	0.087	**<.001**	-0.133	**<.001**	-0.147	**<.001**
Fire or weather disturbance	-0.174	**<.001**	-0.063	**<.001**	-0.029	**0.016**
Insect or disease disturbance	0.384	**<.001**	0.054	**0.003**	0.011	0.569
Time-Invariant						
Adjusted site index	0.008	**<.001**	0.001	**<.001**	-0.001	**<.001**
State or federal ownership	0.324	**<.001**	0.026	**0.003**	-0.071	**<.001**
Aspect	0	0.969	0.028	**<.001**	0.031	**<.001**
Distance to nearest forest product port	0.033	**<.001**	-0.013	**0.001**	-0.005	0.236

Table 6. Fixed and mixed inventory year, ecological section, and state effects for remeasured live tree plots.

	Volume in Live Trees		Trees	
	Estimate	**P**	**Estimate**	**P**
Treatment				
Distance to nearest pellet mill	-0.112	**<.001**	-0.014	0.059
Large capacity pellet mill presence	0.092	0.119	-0.024	0.472
Additive impact of pellet presence	0.117	**0.016**	0.048	0.068
Presence of major pellet export ports	0.116	**0.001**	0.066	**<.001**
Interactions				
Distance to nearest pellet mill : distance to nearest biopower plant	0.001	0.972	-0.018	0.099
Distance to nearest pellet mill : large capacity pellet mill presence	0.07	0.229	-0.036	0.27
Distance to nearest pellet mill : distance to nearest port trading forest products	-0.007	0.6	0.008	0.277
Distance to nearest pellet mill : distance to nearest pulp mill	0.03	0.181	0.008	0.528
Large capacity pellet mill presence : distance to nearest biopower plant	0.142	0.06	0.024	0.57
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.05	0.298	-0.006	0.803
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.135	0.101	-0.046	0.302
Time-Variant				
Distance to nearest biopower plant	0.035	0.064	0.03	**0.005**
Distance to nearest pulp mill	0.038	0.067	-0.033	**0.004**
Population density	0.044	**0.013**	-0.013	0.16
Artificial regeneration	-0.26	**<.001**	-0.091	**<.001**
PDSI	0.008	0.074	0.001	0.743
Large diameter diversity	0.765	**<.001**	-0.121	**<.001**
Small diameter diversity	0.013	0.452	0.925	**<.001**
Fire or weather disturbance	-0.076	0.064	-0.435	**<.001**
Insect or disease disturbance	0.479	**<.001**	0.063	0.095
Time-Invariant				
Adjusted site index	0.012	**<.001**	0	0.292
State or federal ownership	0.327	**<.001**	0.026	0.132
Aspect	0.02	0.183	0.006	0.459
Distance to nearest forest product port	-0.035	**0.025**	0.013	0.07

Table 7. Fixed and mixed inventory year, ecological section, and state effects for remeasured live tree plots.

	Volume in Removal Trees		Removal Trees	
	Estimate	**P**	**Estimate**	**P**
Treatment				
Distance to nearest pellet mill	0.052	0.189	-0.02	0.53
Large capacity pellet mill presence	-0.098	0.437	-0.109	0.274
Additive impact of pellet presence	0.266	0.094	0.339	**0.009**
Presence of major pellet export ports	-0.201	0.088	0.12	0.194
Interactions				
Distance to nearest pellet mill : distance to nearest biopower plant	0.095	0.21	-0.02	0.735
Distance to nearest pellet mill : large capacity pellet mill presence	0.052	0.767	0.174	0.186
Distance to nearest pellet mill : distance to nearest port trading forest products	-0.019	0.681	0.045	0.263
Distance to nearest pellet mill : distance to nearest pulp mill	-0.127	0.166	-0.052	0.464
Large capacity pellet mill presence : distance to nearest biopower plant	0.218	0.333	0.053	0.77
Large capacity pellet mill presence : distance to nearest port trading forest products	0.327	**0.021**	0.323	**0.005**
Large capacity pellet mill presence : distance to nearest port trading forest products	-0.319	0.196	-0.183	0.362
Time-Variant				
Distance to nearest biopower plant	-0.151	0.064	0.099	0.134
Distance to nearest	0.215	**0.019**	-0.057	0.456
Population density	-0.182	**0.028**	-0.038	0.616
Artificial regeneration	0.084	0.317	0.273	**<.001**
PDSI	-0.031	0.061	-0.013	0.317
Large diameter diversity	-0.076	0.211	-0.419	**<.001**
Small diameter diversity	-0.269	**<.001**	0.006	0.893
Fire or weather disturbance	0.177	0.213	-0.145	0.187
Insect or disease disturbance	0.557	**0.028**	0.147	0.465
Time-Invariant				
Adjusted site index	-0.002	**0.008**	-0.002	**0.016**
State or federal ownership	-0.235	0.189	-0.27	0.055
Aspect	0.062	0.272	0.049	0.263
Distance to nearest forest product port	-0.109	**0.037**	-0.102	**0.02**

BIBLIOGRAPHY

Abt, K.L. 2014. Effect of policies on pellet production and forests in the U.S. South: a technical document supporting the Forest Service update of the 2010 RPA Assessment. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station, 2014.

Aguilar, F. X. 2008. Effect of centrifugal forces on cluster patterns in the softwood lumber industry of the United States. Forest Science. 54(2).

Aguilar, F. X. 2009. Spatial econometric analysis of location drivers in a renewable resource-based industry: the U.S. South lumber industry. Forest Policy and Economics. 11: 184-193.

Aguilar, F.X. 2010. Conjoint analysis of industry location preferences: evidence from the softwood lumber industry in the US. Applied Economics. 1-10.

Aguilar, F.X., M. Goerndt, N. Song, S. Shifley. 2012. Internal, external and location factors influencing cofiring of biomass with coal in the US northern region. Energy Economics. 34:1790-1798.

Ahmed, M. A. A., A. Abd-Elrahman, F. Escobedo, W. Cropper Jr., T. Martin, N. Timilsina. 2017. Spatially-explicit modeling of multi-scale drivers of aboveground forest biomass and water yield in watersheds of the Southeastern United States. Journal of Environmental Management. 199:171.

Arbia, G. 2006. Spatial Econometrics: Statistical Foundations and Applications to Regional Convergence. Advances in Spatial Science. Springer-Verlag Berlin Heidelberg.

Biau, D. J., S. Kerneis, R. Porcher. 2008. The importance of sample size in the planning and interpretation of medical research. Clinical Orthopedics and Related Research. 466:2282-2288.

Biles, J. 2003. Using Spatial Econometric Techniques to Estimate Spatial Multipliers: An Assessment of Regional Economic Policy in Yucatán, Mexico. The Review of Regional Studies. 33(2): 121-141.

Blackman, A., L. Corral, E. S. Lima, G. Asner. 2016. Titling indigenous communities protects forests in the Peruvian Amazon. PNAS. 114(16): 4123-4128.

Boukherroub, T., L. LeBel and S. Lemieux. 2017. An integrated wood pellet supply chain development: Selecting among feedstock sources and a range of operating scales. Appl. Energy. 198:385-400.

Bravo-Oviedo, A. R. Ruiz-Peinado, P. Modrego, R. Alonso, G. Montero. 2015. Forest thinning impact on carbon stock and soil condition in Southern European populations of *P. sylvestris* L. Forest Ecology and Management. 2015. 357:259–267.

Bring, J. 1994. How to Standardize Regression Coefficients. The American Statistician. 48(3):209-213.

Brouwer, A., I. Mariotti, J. N. van Ommeren. 2004. The firm relocation decision: an empirical investigation. The Annals of Regional Science. 38:335-347.

Buchholz, T., M.D. Hurteau, J. Gunn and D. Saah. 2016. A global meta-analysis of forest bioenergy greenhouse gas emission accounting studies. GCB Bioenergy. 8(2):281-289.

Byler, J., S. Hagle. 2000. Succession Functions of Pathogens and Insects. 2015. United States Forest Serivce Forest Health and Protection.

Calderon, G., G. Gauthier, J.M. Jossart. 2016. European Biomass Association (AEBIOM). European Bioenergy Outlook.

Center for Disease Control (CDC). 2019. Palmer Drought Severity Index, 1895-2016. Available at: https://data.cdc.gov/Environmental-Health-Toxicology/Palmer-Drought-Severity-Index-1895-2016/en5r-5ds4/row-px7u.qh2v~ry2a

Cleland, D. T., J.A. Freeouf, J.E. Keys, G.J. Nowacki. Ecological Subregions: Sections and Subsections for the conterminous United States. Available at: https://www.fs.usda.gov/treesearch/pubs/48672

Cornwall, W. Is wood a green source of energy? Scientists are divided. Science 2017, 355:18–21.

Costanza, J.K., R.C. Abt, A.J. McKerrow and J.A. Collazo. 2017. Bioenergy production and forest landscape change in the southeastern United States. GCB Bioenergy. 9(5):924-939.

Dale, V.H., E. Parish, K.L. Kline and E. Tobin. 2017. How is wood-based pellet production affecting forest conditions in the southeastern United States? For. Ecol. Manage. 396:143-149.

Duden, A. S., Verweij, P. A., Junginger, H. M., Abt, R. C., Henderson, J. D., Dale, V. H., Kline, K. L., Karssenberg, D. , Verstegen, J. A., Faaij, A. P. and van der Hilst, F. 2017. Modeling the impacts of wood pellet demand on forest dynamics in southeastern United States. Biofuels, Bioprod. Bioref. 11: 1007-1029. doi:10.1002/bbb.1803

Ericsson, K., L.J. Nilsson. 2004. International biofuel trade—a study of the Swedish import. Biomass Bioenergy. 26:205-220.

Eurostat. 2019. EU trade since 1988 by HS6. Product 440131 and 440130.20. Available at: http://ec.europa.eu/ eurostat/web/international-trade-in-goods/data/database

Food and Agriculture Organization of the United Nations (FAO). 2018. Wood Energy. Available at: http://fao.org/forestry/energy/en/

Food and Agriculture Organization of the United Nations (FAO). 2019. FAOSTAT Database. Available at: http://www.fao.org/forestry/statistics/84922/en/

Fingerman Kevin, R., Nabuurs Gert-Jan, I. Leire, R. Fritsche Uwe, S. Igor, V. Lotte, Mai--Moulin Thuy and J. Martin. 2017. Opportunities and risks for -sustainable biomass export from the south-eastern United States to Europe. Biofuels, Bioproduction Bioref. 0(0).

Forisk Consulting LLC. 2018. Wood bioenergy US. Wood Bioenergy Quarterly Report. (Q1, 2018). Available: http://forisk.com/products/category/bioenergy-2/.

Fritsche, U., L. Iriarte. 2014. Cost supply curves for medium- to longer-term potentials for sustainable biomass and bioenergy (pellets, biomethane, liquid biofuels) imports to the EU-27. Task 2.4: Sustainable Imports. International Institute for Sustainability Analysis and Strategy.

Fritsche, U., C. Hennig, J. R. Hess, R. Hoefnagels, P. Lamers, C. Li, O. Olsson, F. Schipfer, D. Thrän, J. Shankar Tumuluru, L. Visser, M, Wild, H. Haufe. 2019. Margin potential for a long-term sustainable wood pellet supply chain. IEA Bioenergy Task 40: 5/2019. IEA Bioenergy.

Galik, C.S. and R.C. Abt. 2016. Sustainability guidelines and forest market response: an assessment of European Union pellet demand in the southeastern United States. GCB Bioenergy. 8(3):658-669.

Garcia, O. W., T. Amann, J. Hartmann. 2018. Increasing biomass demand enlarges negative forest nutrient budget areas in wood export regions. Scientific Reports. 8:5280.

Ghasemi, A., S. Zahediasel. 2012. Normality tests for statistical analysis: a guide for non-statisticians. International journal of endocrinology metabolism. 10(2): 486-489.

Greene, William H. Econometric Analysis. 7th ed., Pearson, 2012.

Greenpeace. 2011. Fuelling a BioMess. Available at: https://www.greenpeace.org/nl/natuur/5080/fuelling-a-biomess/

Grier, C., K. Lee, N. Nadkarni, G. Klock, P. Edgerton. 1989. Productivity of Forests of the United States and Its Relation to Soil and Site Factors and Management Practices: A Review. United States Forest Service General Technical Report

Hanssen, S.V., A.S. Duden, M. Junginger, V.H. Dale and F. Hilst. 2017. Wood pellets, what else? Greenhouse gas parity times of European electricity from wood pellets produced in the

south-eastern United States using different softwood feedstocks. GCB Bioenergy. 9(9):1406-1422.

Harris, C., M. Nadji. 1987. Regional Economic Modeling in Theory and In Practice.

Helburn, S. 1943. Location of industry. J. Land Public Util. Econ. 19: 253–263.

Henderson, J.E., O. Joshi, R. Parajuli and W.G. Hubbard. 2017. Research paper: A regional assessment of wood resource sustainability and potential economic impact of the wood pellet market in the U.S. South. Biomass Bioenergy. 105:421-427.

Hoover, E., 1948. The Location of Economic Activity. McGraw-Hill, New York.

Hurteau, M., M. North. 2010. Carbon recovery rates following different wildfire risk mitigation treatments. Forest Ecology and Management. 260:930-937.

Isard, W. 1956. Regional science, the concept of region and regional structure. Papers in Regional Science. 2(1):13-26.

Jonker, J.G.G., M. Junginger and A. Faaij. 2014. Carbon payback period and carbon offset parity point of wood pellet production in the South-eastern United States. GCB Bioenergy. 6(4):371-389.

Joshi, O., D. Grebner, J. Henderson, S. Grado, I. Munn. 2012. Input-Output Modeling of Wood-Based Bioenergy Industries in Mississippi. Forest Products Journal. 62(7/8).

Junginger, M., J. van Dam, S. Zarrilli, F. Ali Mohamed, D. Marchal and A. Faaij. 2011. Opportunities and barriers for international bioenergy trade. Energy Policy. 39:2028-2042.

Kain, J., J. Meyer. 1971. Essays in Regional Economics. Harvard University Press. Cambridge, Massachusetts.

Lamers, P., E. Thiffault, D. Par and M. Junginger. 2012. Feedstock specific environmental risk levels related to biomass extraction for energy from boreal and temperate forests. Biomass and Bioenergy. 55:212-226.

Lubowski, R., A. Plantinga, R. Stavins. 2006. Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function. Journal of Environmental Economics and Management. 51:135-152.

Magelli, F., K. Boucher, H.T. Bi, S. Melin and A. Bonoli. 2009. An environmental impact assessment of exported wood pellets from Canada to Europe. Biomass Bioenergy. 33:434-441.

Miles, P. 2018. Forest Inventory and Analysis Database – Application Programming Interfaces. Available at: https://apps.fs.usda.gov/fia/datamart/images/FIADB_API.pdf

McCann, P. 1998. The Economics of Industrial Location. Springer.

McEwan, A., E. Marchi, R. Spinelli, M. Brink. 2018. Past, present and future of industrial plantation forestry and implication on future timber harvesting technology. Journal of Forestry Research.

McDonald, J. H. 2009. Handbook of Biological Statistics. Sparky House Publishing.

McGee, C. 2019. Wood Pellets Draw Fire as Alternative to Coal. The Wall Street Journal. Available at: https://www.wsj.com/articles/wood-pellets-draw-fire-as-alternative-to-coal-11565175605

Mitchell, S.R., M.E. Harmon and K.E.B. O'Connell. 2012. Carbon debt and carbon sequestration parity in forest bioenergy production. GCB Bioenergy. 4(6):818-827. Mundlak, Y., "On The Pooling of Time Series and Cross Sectional Data," Econometrica, 46(1):69-85.

Mobini, M., T. Sowlati, S. Sokhansanj. 2013. A simulation model for the design and analysis of wood pellet supply chains. Applied Energy. 11(1): 1239-1249.

National Bureau of Economic Research (NBER). 2019. Census. U.S. Intercensal County Population Data, 1970-2014. Available at: https://data.nber.org/data/census-intercensal-county-population.html

National Resources Defense Council (NRDC). 2015. In the U.S. Southeast, natural forests are being felled to send fuel overseas. Natural Resources Defense Council (NRDC), Report R-15-10-A.

North, M., M. Hurteau, J. Innes. 2009. Fire suppression and fuels treatment effects on mixed-conifer carbon stocks and emissions. Ecological Applications. 19(6):1385-1396.

Porter, M. 2003. The economic performance of regions. Regional studies. 37(6-7):449-578.

Predohl, A. 1928. The theory of location in its relation to general economics. Journal of Political Economy 36 (3), 371–390.

Strange-Olesen A. S., S. L. Bager, B. Kittler, W. Price, F.X. Aguilar. 2015. Environmental Implications of Increased Reliance of the EU on Biomass from the South East US. European Commission Report ENV.B.1/ETU/2014/0043, Luxembourg. pp. 357 [Online] Available at: http://www.aebiom.org/wp-content/uploads/2016/08/ DG-ENVI-study-imports-from-US-Final-report-July-2016.pdf.

Polyakov, M., I. Majumdar, L. Teeter. 2008. Spatial and temporal analysis of the anthropogenic effects on local diversity of forest trees. Forest Ecology and Management. 255:1379-1387.

Prestemon, J., J. Pye, J. Barbour, G. Smith, P. Ince, C. Steppleton, W. Xu. 2005. U.S. Wood-Using Mill Locations. Available at: https://www.srs.fs.usda.gov/econ/data/mills/

Rawstron, E.M., 1958. Three principles of industrial location. Transactions and Papers (Institute of British Geographers), pp. 135–142.

Roder, M., C. Whittaker, P. Thornley. 2015. How certain are greenhouse gas reductions from bioenergy. Life cycle assessment and uncertainty analysis of wood pellet-to-electricity supply chains from forest residues. Biomass Bioenergy. 79:50-63.

Ross, E.A., 1896. The location of industries. The Quarterly Journal of Economics 10 (3), 247–268.

Shrestha, S., P. Dwivedi. 2017. Projecting Land Use Changes by Integrating Site Suitability Analysis with Historic Land Use Change Dynamics in the Context of Increasing Demand for Wood Pellets in the Southern United States. Forests; 8, 381.

Sénéchal, S., and G. Grassi. 2009. Logistic management of wood pellets: Data collection on transportation, storage and delivery management. EUBIA intelligent Energy Europe.

Singh, D., F. Cubbage, R. Gonzalez and R. Abt. 2016. Locational Determinants for Wood Pellet Plants: A Review and Case Study of North and South America.

Siry, J., F. Cubbage, D. Newman, R. Izlar. 2010. Forest Ownership and Management Outcomes in the U.S., in Global Context. International Forestry Review. 12(1).

Spelter, H., and Toth, D. 2009. North America's wood pellet sector. Research Paper FPL-RP-656. Madison, WI: U.S. Department of Agriculture, Forest Service, Forest Products Laboratory. 21 p.

Southern Environmental Law Center (SELC). 2017. Southeast U.S. Wood Pellet Plants Exporting to Europe. Accessed: September 26, 2019. Available at: https://www.southernenvironment.org/uploads/maps/SELC_WoodPelletExportMap_2017_0707_map+table.pdf.

Stewart, Pete. 2015. Wood Supply Trends in the US South. Forest2Market.

Sun, L. and K. Niquidet. 2017. Elasticity of import demand for wood pellets by the European Union. Forest Policy and Economics. 81:83-87.

Temple, M. 1994. Regional Economics. St. Martin's Press Inc. New York, New York.

Tenzin, J., H. Hasenauer. 2016. Tree species composition and diversity in relation to anthropogenic disturbances in broad leaved forests of Bhutan. International Journal of Biodiversity Science, Ecosystem Services & Management.

Timilsina, N., F. Escobedo, W. Cropper Jr., A. Abd-Elrahman, T. Brandeis, S. Delphin, S. Lambert. 2012. A framework for identifying carbon hotspots and forest management drivers. Journal of Environmental Management. 114 : 293-302.

The European Commission. 2009. Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. Official Journal of the European Union.

The European Commission. 2018. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. Official Journal of the European Union.

Thornton, P. E., B. E. Law, H. L. Gholz, K. L. Clark, E. Falge, D. S. Ellsworth, A. H. Goldstein, R. K. Monson, D. Hollinger, M. Falk, J. Chen, J. P. Sparks. 2002. Modeling and measuring the effects of disturbance history and climate on carbon and water budgets in evergreen needleleaf forests. Agriculture and Forest Meteorology. 113:185-222.

Thrän D., D. Peetz, K. Schaubach, S. Backéus. Global Wood Pellet Industry and Trade Study. IEA Bioenergy Task 40. 2017.

United States Department of Agriculture (USDA) Forest Service. 2016. Status of state forestry best management practices for the southern United States. Available at: https://www.fs.usda.gov/treesearch/pubs/50266

United States Department of Agriculture (USDA) Forest Service. 2018. The Forest Inventory and Analysis Database. Database Description and User Guide for Phase 2 (version 7.2;

05.2018 revision). Available at: https://www.fia.fs.fed.us/library/database-documentation/pulpm

United States Department of Agriculture (USDA) Forest Service. 2019a. The Forest Inventory and Analysis Database. Available at: https://www.fia.fs.fed.us/tools-data/

United Sates Department of Agriculture (USDA) Forest Service. 2019b. Southern pulpwood production (*compiled information from pulpwood production reports was provided by a USDA Forest Service employee*). Reports available at: https://www.fs.usda.gov/treesearch/search?keywords=%22Southern+pulpwood+production%22&authorlname=&yearfrom=2000&yearto=&station=&series=&volume=&items_per_page=20&sort_by=search_api_relevance&searchwithin=

United States Census Bureau (USCB). 2018. Primary and Secondary Roads in 2018. Available at: https://www2.census.gov/geo/tiger/TIGER2018/PRISECROADS/

United States Census Bureau (USCB). 2019. County Population Totals and Components of Change: 2010-2018. Available at: https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html

United States Department of Transportation (USDOT). 2019. Ports. Available at: https://data-usdot.opendata.arcgis.com/datasets/ports?geometry=-121.366%2C18.791%2C-24.071%2C44.574&orderBy=COMMODITIE&orderByAsc=false

United States Energy Information Administration (EIA). 2019. Monthly Densified biomass Fuel Report (September 18, 2019). Available at: https://www.eia.gov/biofuels/biomass/

United States International Trade Commission (USITC) Database. 2019. Available at: https://dataweb.usitc.gov/

Van Dijk, J., P.H. Pellenber. 2000. Firm relocation decisions in the Netherlands: An ordered logit approach. Papers in Regional Science. 79: 191-219.

Villalobos, L., J. Coria, A. Norden. 2018. Has Forest Certification Reduced Forest Degradation in Sweden. Land Economics. Volume 94:2, p. 220-238.

Wang, W., M. Khanna, P. Dwivedi, R. Abt. 2015. Carbon savings with transatlantic trade in pellets: accounting for market-driven effects. Environmental Research Letters. 10(11).

Wear, David N.; Greis, John G., eds. 2002. Southern forest resource assessment. Gen. Tech. Rep. SRS-53. Chapter 9: Motivation for Private Forest Landowners. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station.

Williams, C., H. Gu, R. MacLean, J. Masek, G. J. Collatz. 2016. Disturbance and the carbon balance of US forests: a quantitative review of impacts from harvests, fire, insects, and droughts.

Zhang, D., B. Butler, R. Nagubadi. 2012. Institutional Timberland Ownership in the US South: Magnitude, Location, Dynamics, and Management. Journal of Forestry.