



# Impact of biopower generation on eastern US forests

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## Abstract

Biopower, electricity generated from biomass, is a major source of renewable energy in the US. About ten percent of US non-hydro renewable electricity in 2020 was generated from biomass. Despite significant growth in woody biomass use for electricity in recent decades, a systematic assessment of associated impacts on forest resources is lacking. This study assessed associations between biopower generation, and selected timberland structure indicators and carbon stocks across 438 areas surrounding wood-using and coal-burning power plants in the Eastern US from 2005 to 2017. Timberland areas around plants generating biopower were associated with more live and standing-dead trees, and carbon in their respective stocks, than comparable areas of neighboring plants only burning coal. We also detected an inverse association between the number of biopower plants and number of live and dead trees, and respective carbon stocks. We discerned an upward temporal trajectory in carbon stocks within live trees with continued biopower generation. We found no significant differences related to the amount of MWh biopower generation within the analysis areas. Net impacts of biopower descriptors on timberland attributes point to a positive trend in selected ecological conditions and carbon balances. The upward temporal trend in carbon stocks with longer generation of wood-based biopower may point to a plausibly sustainable contribution to the decarbonization of the US electricity sector.

**Keywords** Biopower · Woody biomass · Renewable energy · Forest inventory · Electric power sector

## 1 Introduction

The decarbonization of the electricity sector requires greater reliance on renewable and clean resources to reduce dependence on fossil fuels. Among fossil fuels, coal has been the predominant feedstock in the US electric sector for over a century (EIA, 2021f). Over the last decade, the quantity of electricity generated from coal has declined extensively while consumption of other resources, including natural gas and renewable energies, has experienced steady expansion. Recent forecasts suggest that coal's share of US electricity generation is expected to fall from 19% in 2020 to 11% by 2050 (EIA, 2021a). In comparison, US

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renewable electricity generation is expected to rise from 21% of total generation in 2020 to more than 42% by 2050 (EIA, 2021a). Among renewable electricity sources, woody biomass has experienced about 40% growth over the last two decades (EIA, 2021d). In 2020, about ten percent of non-hydro renewable US electricity generation was supplied by biomass including non-wood waste (5.5%), and wood (4.5%) resources (EIA, 2021g).

Many coal-fired plants have been retired or repurposed to burn other feedstocks in efforts to reduce dependence on fossil fuels and their carbon footprint—supported by improved financial competitiveness of low-carbon sources. By 2020, more than 100 coal-fired plants were converted to or replaced by natural gas-fired plants (EIA, 2020). As a result, coal's share of  $CO_2$  emissions in the electric power sector declined from 1,828 million tons to 786 million tons per year, while  $CO_2$  emissions from natural gas grew over 50% and reached 635 million tons per year over the last decade (EIA, 2021e). Another alternative for repurposing coal-fired plants is using biomass for fuel. This can be an appealing alternative since biomass can be a carbon neutral energy source under certain conditions (Sedjo, 2012). Upgrading boilers in coal-fired generating plants to burn biomass can be a financially sound approach to advance net-zero emissions goals for the electricity sector and support bioenergy markets (The White House, 2021; Dundar et al., 2016, 2019).

Nonetheless, the role of biopower in the decarbonization of the electricity sector can be a contested issue. Since 2010 there has been much debate regarding carbon neutrality when burning biomass to produce electricity (Sedjo, 2013; Walker et al., 2013; Sedjo & Tian, 2012). For instance, the US Environmental Protection Agency (EPA) released the first "Framework for Assessing Biogenic  $CO_2$  Emissions from Stationary Sources" in order to provide a more accurate measurement of  $CO_2$  emissions from non-fossilized and biodegradable organic materials in 2011 (EPA, 2011). The revised EPA framework (EPA, 2014) alongside two Science Advisory Board (SAB) reviews (SAB, 2012; 2015) were reflected in the Clean Power Plan (CPP) Final Rule, published in August 2015, to establish an accounting framework for bioenergy emissions from biomass. The CPP Final Rule "recognizes that the use of some biomass-derived fuels can play a role in controlling increases of  $CO_2$  levels in the atmosphere" (EPA, 2015). The CPP also recognizes the potential of "a wide range of environmental benefits, including carbon benefits" for using biomass if "feedstocks are sourced responsibly." The CPP Final Rule was stayed by the US Supreme Court, and a later EPA rule (Affordable Clean Energy) did not qualify biomass used for electricity production as a system of emissions reduction (EPA, 2019), but the suggested model in the CPP to lower air pollutants has been applied by many US states.

Sourcing woody biomass for electricity generation can have impacts that extend beyond its carbon footprint. For instance, removal of low value trees from high-risk wildfire areas can provide a significant source of woody biomass (Rummer, 2005) and simultaneously support efforts to restore habitats and reduce risk of devastating wildfire and disease (Polagye et al., 2007; Neary & Zieroth, 2007). However, large-scale tree harvesting changes forest structure, and can directly or indirectly alter biodiversity of both plants and wildlife species (Cornwall, 2017; Birdsey et al., 2018). As the CPP and other studies have suggested, the long-term benefits of using biomass for electricity generation can be maintained only under the creation of a sustainable cycle of  $CO_2$  capture and release, and preservation of forests' biodiversity (Sterman et al., 2018; Verschuyl et al., 2011). Although there is widespread use of biopower across the US, there is no large-scale, systematic review of changes in forest resources associated with increases (or decreases) in wood combustion by power plants.

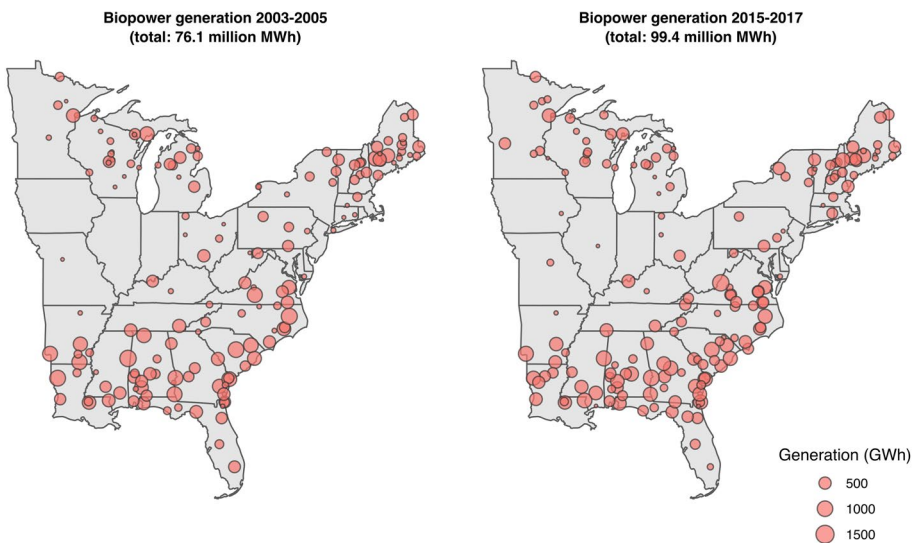
We examine *ex post* changes in fundamental timberland structure attributes (number of live trees and standing-dead trees) and respective carbon stocks (carbon in live and

standing-dead trees), associated with different biopower generation intensities. Net biopower impacts were discerned when contrasting differences in localized areas surrounding hundreds of wood-using electric plants against landscape areas where no biopower was generated (Fig. 1). Timberland attributes were collected from forest inventory data containing over one hundred thousand plots measured every three years from 2005 to 2017 in the Eastern US. This study contributes to the state of knowledge of environmental impacts of biopower generation by: (1) developing and implementing a framework to assess changes in timberland attributes associated with biopower generation; (2) introducing an empirical estimation method to discern plant-specific effects within overlapping procurement areas; (3) reviewing and identifying other significant factors related to forest changes including wood industries, land use changes, and natural disasters.

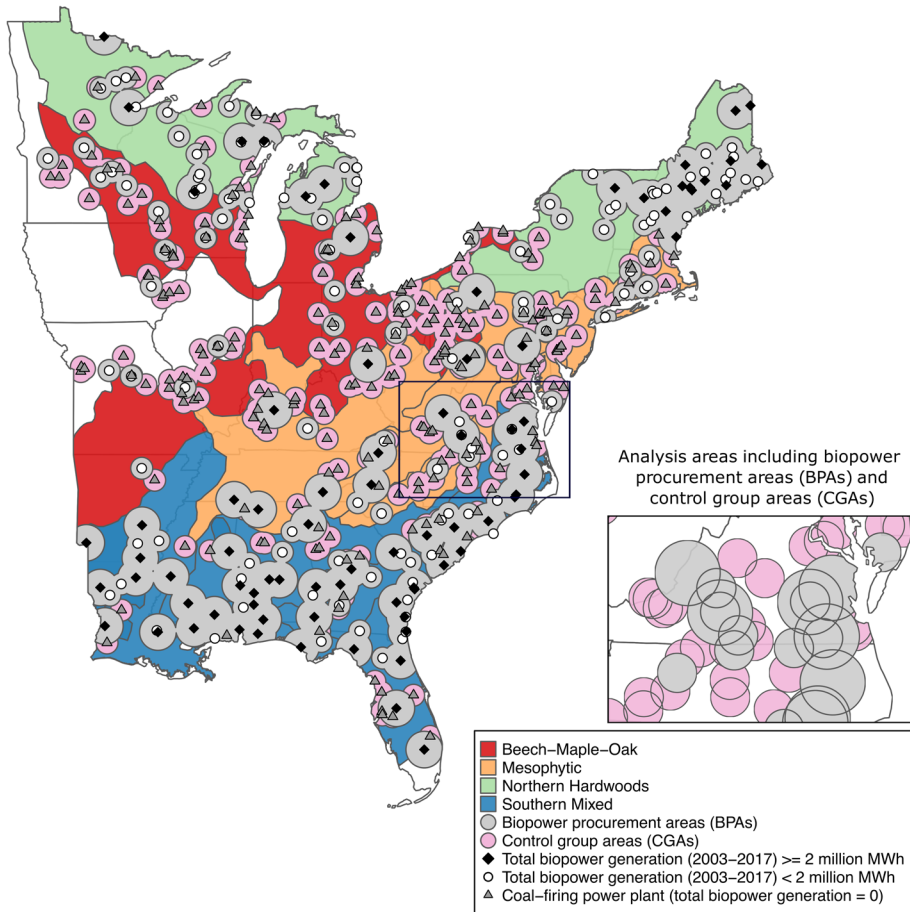
## 2 Methods

### 2.1 Biopower procurement and control group timberland areas

We identified 211 woody-biomass-using power plants that were operational between 2005 and 2017 over 27 states in the Eastern US (Figs. 1 and 2). Power plants combusting woody biomass were found across each state in the US East with the exception of Delaware, Indiana, New Jersey, and Rhode Island. Information about the power plants, including geographical coordinates, fuel types, and annual MWh generation was collected from the US Energy Information Administration (EIA) (EIA, 2021b, c). We selected power plants (including combined heat-and-power facilities) that burned woody biomass including wood/wood waste solids and liquid mixture of pulping residues from wood pulp and paper production, i.e., wood waste liquids and black liquors. In order to obtain level of



**Fig. 1** Location of wood-using power plants and corresponding biopower generation in the Eastern US for the first and last studied time window



**Fig. 2** Locations of 211 wood-using power plants dispersed in the Eastern US that were operational between 2005 and 2017 and the corresponding forest ecological regions. The inset illustrates how overlapping procurement zones were mapped and partitioned

biopower generation within every three-year interval starting with 2005, we have collected EIA information from year 2003.

Our sampling approach takes into consideration woody biomass market and power plant characteristics discerned from a review of the literature and expert validation, as well as available data on forests and biopower generation. It is worth noting that power plants procure woody biomass through contractors and do not engage directly in forest management (Coffin, 2014). Moreover, there is no available database that systematically records plant-level volumes of woody biomass (Goerndt et al., 2013) which prompted our need to derive localized timberland conditions from available forest inventory records and established mensuration methods (Sect. 2.3). We assess changes in timberland attributes and carbon stocks and net of other related covariates. We derive timberland conditions within procurement landscapes motivated by the fact that the low energy density of woody biomass and its high transportation cost severely limit the geographic area from which it is procured (Aguilar et al., 2012;

Goerndt & D'Amato, 2014). Based on a review of the literature, we selected a procurement Euclidean radius of 80 km (50 miles) for power plants having at least two million MWh biopower generation between 2003 and 2017, and a radius of 48 km (30 miles) for biopower plants with less than two million MWh total generation (Aguilar et al., 2020; Goerndt et al., 2013; Perez-Verdin et al., 2008). These procurement radii take into consideration tortuosity factors common across the US East and defined biopower plant *procurement zones* (Fig. 2).

The geographical proximity of power plants results in the frequent overlap of procurement zones. Hence, we partitioned the spatial region into 530 mutually exclusive and exhaustive *biopower procurement areas* (BPAs) (each having at least 50 km<sup>2</sup> area). Each BPA represents a unit of observation during our study period (Fig. 2, inset). Our control group denoted comparable timberland landscapes where no biopower was generated during our study period. We selected 297 power plants that solely burned coal during our study period that were located within 128 km (80 miles) of one of the biopower plants under consideration. We used a concentric circle of radius km (30 miles) centered at each coal-burning power plant to define a control zone. From the overall list of candidate controls, 70 coal-burning plants were excluded due to either having their area contained entirely within one or more BPAs, or collocation with another coal-burning plant, or multiple control zones having tangent circles. We were left with a control zone for each of 227 coal-burning power plants, defining 386 mutually exclusive and exhaustive *control group areas* (CGAs) (each having at least 50 km<sup>2</sup> area). Taken together, BPAs and CGAs defined our *analysis areas* consisting of 916 mutually exclusive areas. Within each analysis area, the impact of the associated power plants on timberland is assumed to be homogenous. For each area analyzed, we computed selected timberland attributes and assigned measures of biopower generation.

## 2.2 Timberland attributes

We relied on forest attribute estimates from the US Forest Service's National Forest Inventory and Analysis (FIA) Program to assess the associated impacts of power plants on forest conditions (USDA, 2021b). FIA estimates of forest conditions consist of three phases, including Phase 1—spatially explicit forest type and size-class estimates based on aerial photographs and satellite imagery; Phase 2—field samples of forest attributes on inventory plots comprising a subset of forest areas from Phase 1; Phase 3—a more detailed inventory of forest health attributes for one out of every 16 Phase 2 sample plots. Full details about FIA sampling, plot design, measurements and data collection are available in the FIA program documentation (USDA, 2020; Burrill et al., 2018; Bechtold & Patterson, 2015).

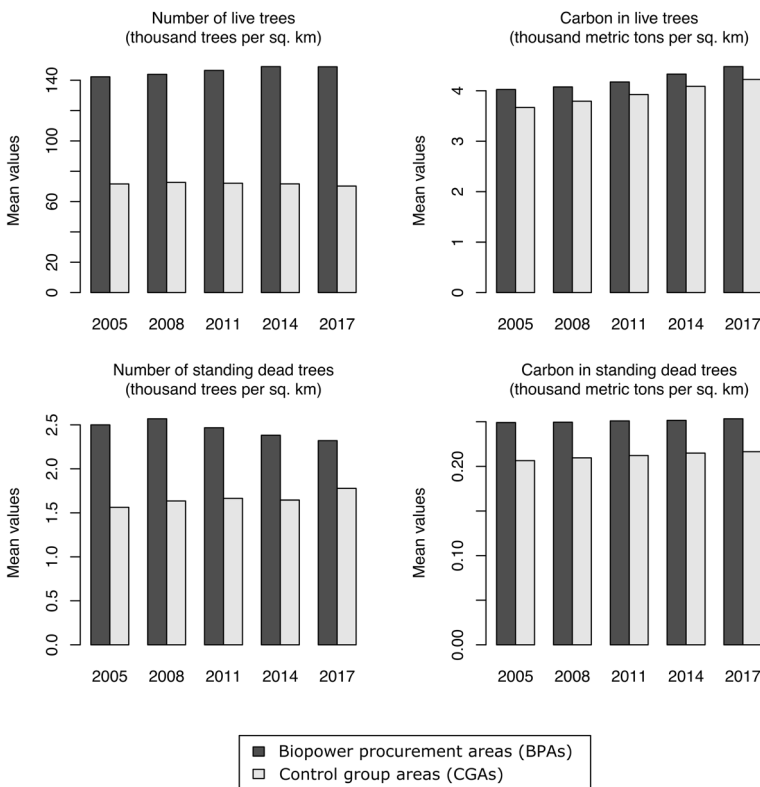
We assessed fundamental timberland attributes including two forest structure attributes (i.e., number of live trees, number of standing-dead trees) and two carbon pools (i.e., above- and below-ground carbon in live trees, and above- and below-ground carbon in standing-dead trees). Forest structure attributes were examined for potential concerns over wildlife habitats and forest biodiversity; carbon pool attributes were examined in the context of carbon neutrality and sustainability of timberland resources (Table 1).

We obtained estimates of timberland attributes for all BPAs and CGAs using the FIA forest inventory query system based on power plant coordinates and desired procurement radii for years 2005, 2008, 2011, 2014 and 2017. A three-year measurement interval allowed us to capture trends in timberland attributes. We developed a Python data-scraping

**Table 1** Selected fundamental descriptors of timberland structure and carbon stocks

Attributes	Description
Number of live trees ( <i>trees/km<sup>2</sup></i> )	Number of all live trees (at least 2.54 cm diameter at 1.37 m above the forest floor)
Number of standing-dead trees ( <i>trees/km<sup>2</sup></i> )	Number of standing-dead trees (at least 12.7 cm in diameter at 1.37 m above the forest floor)
Carbon in live trees ( <i>tons/km<sup>2</sup></i> )	Metric tons of carbon in aboveground and belowground (coarse root) biomass of live trees. The estimated volumes of wood and bark are converted to biomass based on the density of each. Additional components (e.g., tops, branches, and coarse roots, estimated according to adjusted component estimates)
Carbon in standing-dead trees ( <i>tons/km<sup>2</sup></i> )	Metric tons of carbon in aboveground and belowground (coarse root) biomass of standing dead trees

program to collect the most recent available data from the FIA database (Mirzaee, 2021). Figure 3 shows the mean of the selected timberland attributes within BPAs and CGAs from 2005 to 2017.



**Fig. 3** Annual average values of selected timberland attributes in biopower procurement areas (BPAs) and control group areas (CGAs)

### 2.3 Estimation of timberland attributes and biopower generation within analysis areas

To mitigate inherent dependence in timberland attributes that result from individual FIA plots being located in multiple procurement zones and control zones, we apportion these timberland attributes across the 916 mutually exclusive analysis areas. For procurement/control zone  $i$  (a circular area), let  $h_i$  denote the area ( $km^2$ ) of  $i$  and let  $g_i$  denote the level of the attribute in  $i$ . For analysis area  $j$  (a Venn diagram subarea), let  $v_j$  denote the square kilometers of the analysis area. Let  $z_{ij} = 1$  if area  $j$  is located within zone  $i$ ; let  $z_{ij} = 0$  otherwise. For each pair of  $i$  and  $j$  we define  $w_{ij} = z_{ij} \times (v_j/h_i)$  denoting the proportion of zone  $i$  included in analysis area  $j$ . Now consider two cases: either  $j$  is located in multiple zones, or  $j$  is located in a single zone  $i$ . For the first case, the level of attribute in analysis area  $j$  is calculated as:

$$t_j = \min_{i: z_{ij}=1} \{w_{ij} \times g_i\}. \quad (1)$$

For the second case, the remaining amount of the attribute in zone  $i$  is apportioned as:

$$t_j = \sum_i (z_{ij} \times [g_i - \sum_{\hat{j} \neq j} z_{i\hat{j}} \times t_{\hat{j}}]). \quad (2)$$

We compute timberland attributes per square kilometer by dividing  $t_j$  by  $v_j$  to remove bias in the estimates due to size of the analysis areas. To find the level of corresponding biopower generation for the BPAs, we applied the following method. For biopower plant procurement zone  $i$ , let  $e_i$  denote the level of the biopower generation in  $i$ . Then, the level of biopower generation in BPA  $j$  is calculated as:

$$q_j = \sum_i (w_{ij} \times e_i). \quad (3)$$

Note that Eq. 3 uses a different approach than used for Eqs. 1 and 2. This is because unlike the timberland attributes, we do not have any potential over-counting of electricity generation across zones.

### 2.4 Explanatory variables associated with changes in timberland attributes

Changes in forest resources around wood-using power plants are caused by many factors including forest management and policies, land use changes, forest types, natural disasters, wood industries, and the power plants themselves. To have a comprehensive understanding, we gathered a set of explanatory variables that represent the most influential factors related to landscape changes within the analysis areas (Table 2).

We included four variables to determine changes in timberland conditions associated with biopower generation. These were as follows: a dichotomous variable distinguishing biopower generators from non-biopower generators to discern overall biopower effects, total biopower generation over each three-year forest inventory window to evaluate effects of bioenergy generation, average years of biopower operation to control temporal effects of the biopower plants' presence, and number of biopower plants whose

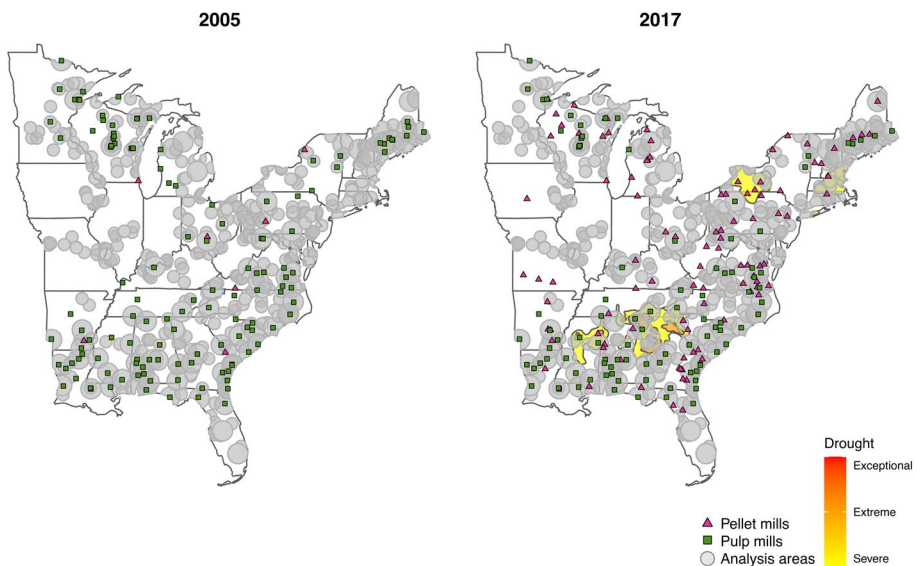


procurement zones intersect with an analysis area to estimate the effect of increased pressure on forest resources.

Competition for fibers by other wood-using industries was also identified by considering overlapping procurement zones of pellet and pulp mills within the analysis areas (FORISK, 2018; Johnson & Stepleton, 2007; Johnson et al., 2010; Piva et al., 2014; Bentley & Stepleton, 2013; Gray et al., 2018a, b). Commercial procurement zones, with a radius of 80 km and 120 km, were assigned to wood pellet and pulp industries. We calculated intersection variables by aggregating the overlap ratio between pellet or pulp mills' procurement zones with analysis areas (Fig. 4).

Natural disturbances can affect forest resources. To find the most relevant natural events, we reviewed historical maps for wildland fires, hurricanes, tornadoes, droughts, and insects and forest diseases in the Eastern US for 1-year lagged timepoints (USDA, 2021c). The analysis revealed widespread severe drought in much of the Southeast in years 2007 and 2016, motivating the addition of an extreme drought variable to account for the effect of these natural disasters (U.S. Drought Monitor, 2021) (Fig. 4). Moreover, forest vegetation types have intrinsic dissimilarities to each other causing many timberland attributes to naturally vary from one another. To account for characteristics intrinsic to different forest vegetation types (as shaped by weather, altitude, latitude, topography, hydrology, and site quality), we included indicator variables for each of the four major ecological regions that encompass our study region (Dyer, 2006).

By accounting for the human population density within the analysis areas, we included indicators for potential forest degradation due to land use changes to developed areas. Specifically, we estimated population densities by aggregating the proportional population of counties within analysis areas (U.S. Census Bureau, 2020b, a). We derived proportional population estimates by multiplying counties' populations to the ratio of the counties' area that lies inside the analysis area. Land use changes from forest resources to farmlands were



**Fig. 4** Location of wood pellet mills, pulp mills, and areas of reported extreme weather conditions (lagged 1 year) in 2005 and 2017



monitored by considering cropland ratio changes. We estimated cropland ratios (USDA, 2021a) by aggregating the proportional crop acreage of counties within the analysis areas. Exports to overseas wood pellet and other forest products markets can also impact forest resources. We added a dichotomous variable to distinguish analysis areas that have access to a major port exporting forest products (USDOT, 2019). Descriptive statistics and explanations for the variables are given in Table 2.

## 2.5 Linear mixed model

We investigated the relationship between timberland attributes and variables listed in Table 2 within the selected locations over five-time intervals. The linear mixed model (LMM) was used to model the longitudinal data in order to capture correlation between observations over time (Laird and Ware, 1982; Schabenberger & Pierce, 2001). The LMM includes both fixed effects and random effects in a panel model structure. There were  $p = 13$  fixed effects included in our model: biopower procurement area, total biopower generation in each three-year window, years of biopower operation, number of biopower plants, competing pellet production intersection, competing pulp production intersection, extreme drought, forest eco-regions (four categories), population density, cropland ratio, and port access. We specify the LMM for each timberland attribute separately and model each on a log-scale with normally distributed errors. Let  $y_i^t$  denote generally one of the estimated timberland attributes for analysis area  $i$  at time  $t$  where  $i \in \{1, \dots, 916\}$  and  $t \in \{1, \dots, 5\}$ . We write the LMM as:

$$\ln(y_i^t) = \beta_0 + \sum_k \beta_k v_{ik}^t + \sum_u \beta_u h_{iu} + \epsilon_i^t, \quad (4)$$

and

$$\epsilon_i^t = b_i + \varepsilon_i^t, \quad (5)$$

where  $\beta_0$  is a global intercept,  $v_{ik}^t$  and  $h_{iu}$  denote time-variant and time-invariant fixed effects for  $uth$  and  $kth$  variables, respectively,  $b_i$  is the analysis area-specific random effect (for each observation,  $q = 916$ ) and  $\varepsilon_i^t$  is an independent error term assumed to be normally distributed with mean zero i.e.,  $\varepsilon_i^t \sim N(0, \sigma^2)$ . The capacity of our model to assess changes within the  $i$ th analysis area, and between them, taking into consideration time variant and invariant factors allowed discerning biopower effects when comparing BPAs against CGAs.

Regression parameter estimates were obtained using restricted maximum likelihood (REML) (Harville, 1977), utilizing the *lme* function from the *nlme* package in R (R, 2021; Pinheiro et al., 2014). Note that intercept values are computed by summation of fixed intercept and mean of the random intercepts ( $\hat{\beta}_0 = \beta_0 + \sum_i b_i/q$ ). To represent percentage of changes on  $y$ , coefficients transformed by:

$$\exp(\beta_j x_j) - 1 \quad j = \{1, \dots, p\}, \quad (6)$$

where  $j$  represents any of the time variant or invariant covariates ( $x_j$ ) and associated coefficient ( $\beta_j$ ). These values correspond to expected changes with respect to the geometric means of the timberland attribute,  $\exp(\hat{\beta}_0)$ . Note that the intercept parameter  $\hat{\beta}_0$  defines the *baselevel* of the model that corresponds to an analysis area containing a coal-burning

**Table 2** Descriptions and descriptive statistics for model explanatory variables ( $n = 4580$ )

Variables	Description	Min	Mean	Max	SD
Total generation in 3-year window	Estimated bioenergy generation (GWh) in the analysis area within a three-year period starting 2003	0.00	97.29	1756.03	195.19
Years of biopower operation	Average years of operation of biopower plants whose procurement zone intersects with the analysis area since 1990	0.00	11.76	28.00	10.97
Number of biopower plants	Number of biopower plants procurement zones contained in the analysis area	0.00	1.27	7.00	1.40
Wood pellet mills intersection	Total percentage of the analysis area covered by wood pellet plants procurement zones (percent, can be greater than 1 if area intersects with more than one zone)	0.00	0.33	4.72	0.62
Pulp mills intersection	Total percentage of the analysis area covered by pulp mills procurement zones (percent, can be greater than 1 if area intersects with more than one zone)	0.00	1.59	10.28	1.78
Population density	Estimated population per $km^2$ within the analysis area	0.72	53.28	1969.21	108.27
Cropland ratio	Estimated ratio of cropland areas within the analysis area	0.00	0.10	5.10	0.11
Biopower procurement area	Dichotomous variable: 1 if the analysis area is a biopower procurement area (BPA), 0 otherwise	BPA: 58%		No: 42%	
Drought	Dichotomous variable: 1 if severe, extreme, or exceptional drought reported for in at least 5% of the analysis area in August preceding a given year, 0 otherwise	Drought: 7%		No: 93%	
Export market access	Dichotomous variable: 1 if centroid of the analysis area was located within 100 km of a major port exporting forest products, 0 otherwise	Access: 39%		No: 61%	
Forest ecological regions (FR)	Categorical variable including four major ecological regions (Fig. 2); the forest region covering the largest share of the analysis area was selected as the corresponding FR	South, Mixed: 28%	Beech-Maple-Oak: 23%	Meso-phytic: 24%	North-Hardwoods: 25%

power plant in the Southern Mixed forest region. The following transformation was applied to find  $(1 - \alpha)$  percent confidence intervals of timberland attributes change:

$$\exp(\beta_j x_j \pm Z_{(1-\alpha/2)} \times se_j) - 1 \quad j = \{1, \dots, p\}, \quad (7)$$

where  $se_j$  is the standard error of the estimate of coefficient  $j$ . Of particular interest in response to our study objectives, we calculated *net biopower impact* by adding up the estimated coefficients of variables capturing biopower plant effects. These were as follows: biopower plant presence, years of biopower operation, and number of BPA overlaps. For the last two variables, respectively, we estimated effects at 20 years of operation and a BPA with one additional overlap.

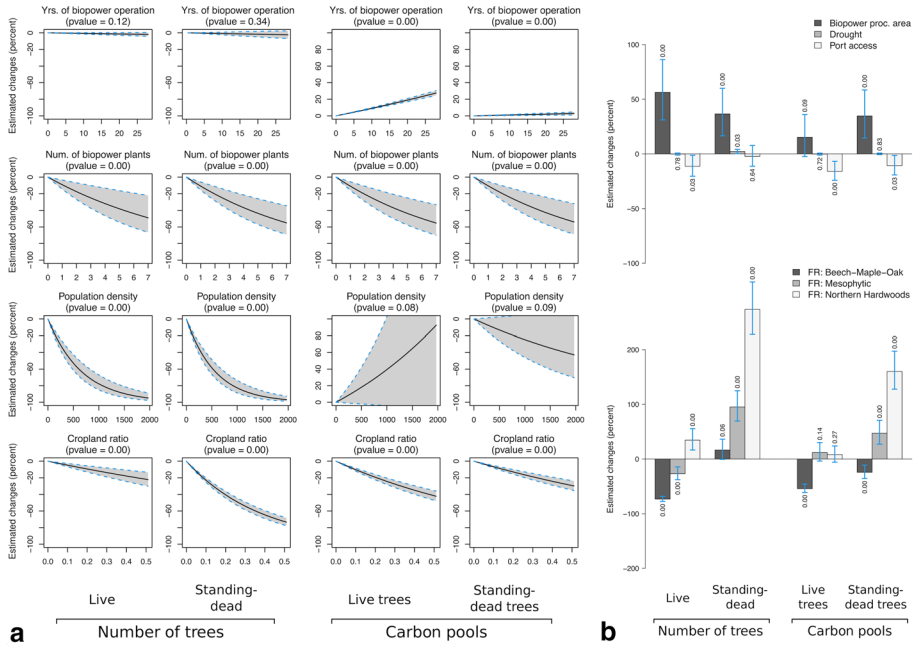
To evaluate the proposed LMM, we compare it to two other modified forms of the model. The first model (M1) is a simplified version of the model where we remove the random effects resulting in a more traditional linear model and is fitted with ordinary least squares. The second model (M2) incorporates an autoregression correlation structure and is fitted using generalized least squares. The LMM outperforms M1 in terms of lower residual standard deviation as well as AIC and BIC values. The LMM results are close to M2 in terms of these metrics of comparison while it has a significantly lower sum of squared residuals (Appendix A, Fig. A1). Therefore, we chose the LMM over the M2 as it is more parsimonious.

### 3 Results

Estimated coefficients,  $p$  values, and standard errors from the Linear Mixed Model are presented in Appendix A (Table A1). Next, we present the estimated changes of timberland attributes in analysis areas, calculated by Eq. 5, for statistically significant ( $p$  value  $\leq 0.05$ ) outcomes. Corresponding estimated changes, confidence intervals and  $p$  values are shown in Fig. 5.

The number of biopower plants within analysis areas was negatively associated with the number of trees and corresponding carbon pools (Fig. 5a). For instance, the presence of two biopower plants in analysis areas was associated with approximately 20 percent lower number of live and standing-dead trees and their respective carbon pools. In contrast, the results show carbon pool in live trees to be positively related to the average years of operation of biopower plants. Expected number of carbon stocks in live trees would increase 20 percent, for every 20-year continued biopower plants' operation. Moreover, we observed a greater number of live and dead trees and higher associated carbon stocks in the analysis areas supporting biopower generation. The results show about 60 and 40 percent more live and dead trees and about 15 and 30 percent higher associated carbon pools in the BPAs (Fig. 5b). We did not find a significant correlation between level of biopower generation and level of timberland attributes within the analysis areas.

Our results show relatively small effects of fiber competition between biopower plants and wood pellet and pulp industries. We estimated a 2 percent reduction in the number of standing-dead trees and about 2 percent increase in carbon stocks in live and dead trees within analysis areas containing a wood pellet mill procurement zone. The presence of a pulp mill also resulted in a 2 percent decrease in the estimated number of live trees and about 1 percent reduction in carbon in live and dead trees. Moreover, we detected an inverse association between proximity to an exporting port and the number of live trees and carbon in live trees. We estimated about 10 percent

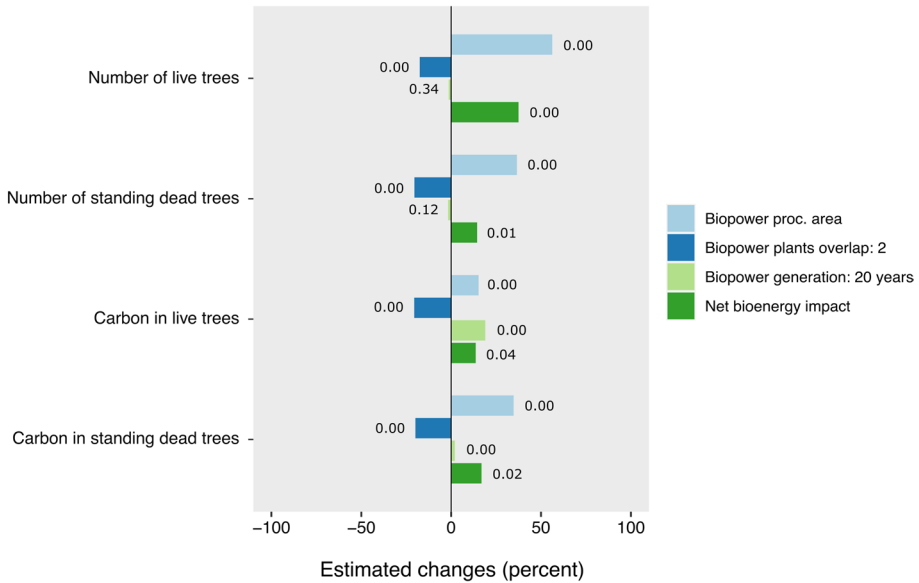


**Fig. 5** Estimated changes, 95% confidence intervals (CI), and *p* values for **a** continuous variables capturing effects of power plants operation, population density, and cropland ratio, and **b** dichotomous variables for BPAs, severe weather condition, access to export market, and differences within forest regions (FR)

decrease in the number of live trees and carbon in live and dead trees in the analysis areas within 100 km of an exporting port. We also estimated a 2 percent increase in the number of standing-dead trees in analysis areas that experienced drought in the preceding year (Fig. 5b).

An increase in human population density within analysis areas was also found to have important associations with the number of live and dead trees, but not significant on the respective carbon pools. An increase in population of 100 per km<sup>2</sup> was associated with an estimated 15 percent decrease in live and dead trees. Croplands also showed significant impacts in our attribute estimates. A 10 percent increase in cropland area within the analysis areas resulted in an estimated 5 and 20 percent decrease in number of live and standing-dead trees and approximately 5 and 10 percent decrease in carbon pools in live and dead trees, respectively (Fig. 5a).

Results also indicate that the level of timberland attributes may vary significantly among different ecological regions. For instance, we expect three times more standing-dead trees in the Northern Hardwoods ecological region than the Southern Mixed region. The presence of large and significant estimated values for forest regions suggests the ability of the model to discern timberland attribute differences across different geographical areas. Figure 6 compares the estimated changes in timberland attributes due to biopower plant activity, including areas supporting biopower generation, presence of two biopower plants, and 20 years of operation of biopower power plants.



**Fig. 6** Estimated changes and *p* values for analysis areas supporting biopower generation, containing two biopower plants and 20 years of biopower operation, with average net bioenergy impact

## 4 Discussion

Electricity generation from woody biomass in the Eastern US increased more than 30% from 2005 to 2017 (EIA, 2021b). Many concerns regarding using woody biomass for electricity generation relate to the sustainability of its procurement including potential impacts to forest structure and biodiversity (Kline et al., 2021a). Declines in the number of live and standing-dead trees can point to unsustainable forest management practices that may lead to changes in forest structure that affect plant and wildlife diversity. Lower carbon levels in live and dead trees might call into question the capacity of woody biomass for energy to support decarbonization.

Here, we found wood-using power plants did not have a negative net impact on the number of live and dead trees and corresponding carbon stocks. Our statistical analyses suggest that BPAs had a higher number of trees and carbon pools in comparison to CGAs (Fig. 6). Our *ex post* analysis also shows that both number of live trees and level of carbon in live trees experienced growth from 2005 to 2017 within the BPAs (Fig. 3). We detected a significant increase in the level of carbon in live trees as the years of biopower plants operation increased. This suggests that the carbon neutrality of biopower generation can be more likely achieved over longer time horizons.

Lack of a strong correlation between level of biopower generation and timberland attributes changes can be interpreted as allowing for the possibility of biopower generation expansion without violating key sustainability assumptions. Also, a negative relationship between the number of biopower plants present in an area and the level of forest resources can incentivize expansion of current biopower plants over building new facilities. In areas having high quantities of woody biomass; however, a reduction in live and dead trees through biopower in the short-term could reduce the risk of devastating wildfire and help forest preservation (Neary & Zieroth, 2007).

Strong inverse association of increases in population density and cropland areas with level of the timberland attributes shows the significance of the land cover changes to more developed and agricultural areas (Homer et al., 2020) across the analysis areas. The substantial value added to local economies by producing wood-based biomass (Dahal et al., 2020) can play a key role in preventing forest land cover changes. If the investments and jobs associated with biomass production can help sustain rural communities, the presence or expansion of biopower plants can incentivize rural communities to maintain forests and decelerate forest conversion to agriculture or developed land.

The lucrative European market for the US wood pellets industry has shaped a new demand paradigm for forest products in the Southeastern US (Abt et al., 2014). Recent studies on impacts of increased wood pellet production point to mostly positive effects on level of timberland attributes while generating more affordable and clean energy (Dale et al., 2017; Aguilar et al., 2020; Kline et al., 2021b). In this study, we detected relatively minor yet positive impacts associated with areas located within wood pellet mill procurement. With the caveat that our research was designed to assess changes within BPAs, our results show that access to an exporting port is associated with decreased live trees and carbon pools in the studied timberland areas. Although the studied areas are mostly used by domestic power plants, the lower level of the timberland attributes near exporting ports can reflect an effect of more competition for producing wood-based biofuel for both local and European markets.

Shifting from coal to clean sources of energy to decarbonize the national economy is a stated goal for the US electricity sector. With current technologies, simply repurposing coal-fired plants to use natural gas would likely not significantly cut carbon emissions in the long term. EIA projections show that by 2050 energy-related carbon emissions from natural gas combusting could exceed 2010's level of emissions from coal (EIA, 2021a). Biomass can be a renewable source of energy in the transitional path toward zero-emitting renewable energy technologies. Moreover, woody biomass procurement can facilitate forest restoration and management objectives by providing markets to help offset the cost of removing low value trees in conjunction with silvicultural prescriptions intended to improve forest health, diversity, resilience, and fire resistance. This is the most likely market-based mechanism underpinning the net growth in carbon stocks over time detected in our study.

## 5 Conclusions

Analysis of timberlands in the Eastern US between 2005 and 2017 within areas surrounding wood-using and non-wood-using power plants indicates net positive trends in timberland structure and carbon stocks near to wood-using power plants. Areas supporting biopower generation showed more live and dead trees and carbon in their respective pools, than neighboring areas around coal-burning power plants. Biopower procurement areas also showed an upward temporal trend in the level of carbon pools in live trees. Conversely, analysis areas with a greater number of biopower plants were associated with fewer live and dead trees and less carbon in their corresponding stocks. The amount of MWh bioenergy generation was not significantly correlated to timberland attribute changes. Positive net effects associated with biopower plants may point to the potential of using woody biomass to support decarbonization goals for the electricity sector, and its prospective role in a transitional path toward zero-emitting renewable energy.

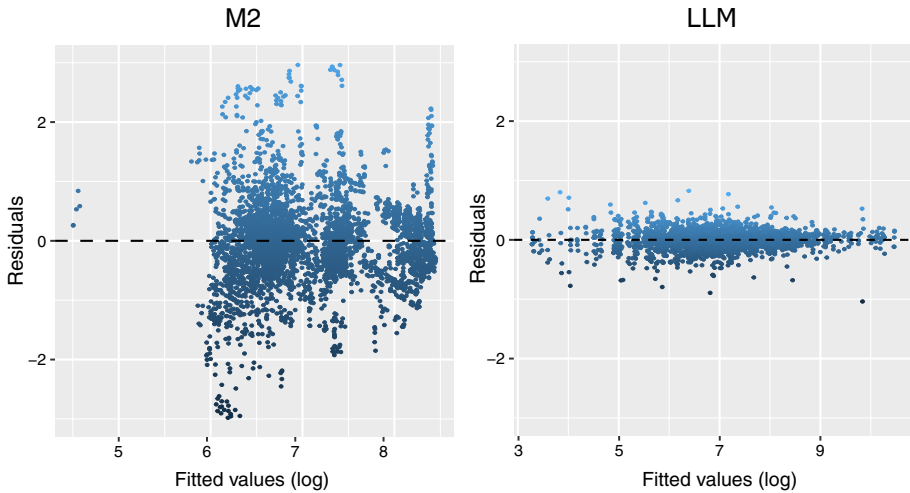
## Appendix A

See Table A1.

**Table A1** Regression coefficients (log-transformed) of bioenergy generation, wood competition, extreme weather, forest ecological regions, population density, cropland ratio, and export, along with standard errors (SE), and *p* values (*n* = 4580)

	Number of live trees ( <i>trees/km<sup>2</sup></i> )		Number of standing-dead trees ( <i>trees/km<sup>2</sup></i> )	
	Coeff. [ <i>p</i> value]	SE	Coeff. [ <i>p</i> value]	SE
Intercept	11.5059 [ $<0.001$ ]	0.082	6.9393 [ $<0.001$ ]	0.076
Biopower plant	0.4464 [ $<0.001$ ]	0.090	0.3116 [ $<0.001$ ]	0.081
Total gen. in 3-year window	-0.0001 [0.009]	0.000	0.0000 [0.747]	0.000
Yrs. of biopower operation	-0.0007 [0.121]	0.000	-0.0008 [0.337]	0.001
Num. of biopower plants	-0.0960 [0.002]	0.031	-0.1142 [ $<0.001$ ]	0.028
Wood pellet mills intersection	-0.0014 [0.642]	0.003	-0.0223 [ $<0.001$ ]	0.006
Pulp mills intersection	-0.0212 [ $<0.001$ ]	0.003	0.0062 [0.280]	0.006
Drought	-0.0013 [0.782]	0.005	0.0216 [0.029]	0.010
FR: Beech-Maple-Oak	-1.3187 [ $<0.001$ ]	0.089	0.1514 [0.061]	0.081
FR: Mesophytic	-0.3144 [ $<0.001$ ]	0.081	0.6685 [ $<0.001$ ]	0.072
FR: Northern Hardwoods	0.2966 [ $<0.001$ ]	0.074	1.3165 [ $<0.001$ ]	0.066
Population density	-0.0015 [ $<0.001$ ]	0.000	-0.0018 [ $<0.001$ ]	0.000
Cropland ratio	-0.4915 [ $<0.001$ ]	0.107	-2.5946 [ $<0.001$ ]	0.174
Exporting port access	-0.1200 [0.030]	0.055	-0.0228 [0.644]	0.049
	Carbon in live trees ( <i>tons/km<sup>2</sup></i> )		Carbon in standing-dead trees ( <i>tons/km<sup>2</sup></i> )	
	Coeff. [ <i>p</i> value]	SE	Coeff. [ <i>p</i> value]	SE
Intercept	8.1790 [ $<0.001$ ]	0.078	4.8848 [ $<0.001$ ]	0.075
Biopower plant	0.1418 [0.095]	0.085	0.2980 [ $<0.001$ ]	0.083
Total gen. in 3-year window	0.0000 [0.859]	0.000	0.0000 [0.606]	0.000
Yrs. of biopower operation	0.0087 [ $<0.001$ ]	0.000	0.0010 [0.002]	0.000
Num. of biopower plants	-0.1149 [ $<0.001$ ]	0.029	-0.1108 [ $<0.001$ ]	0.029
Wood pellet mills intersection	0.0165 [ $<0.001$ ]	0.003	0.0082 [ $<0.001$ ]	0.002
Pulp mills intersection	-0.0084 [0.002]	0.003	-0.0122 [ $<0.001$ ]	0.002
Drought	-0.0017 [0.716]	0.005	0.0008 [0.831]	0.004
FR: Beech-Maple-Oak	-0.7806 [ $<0.001$ ]	0.084	-0.2787 [ $<0.001$ ]	0.082
FR: Mesophytic	0.1123 [0.144]	0.077	0.3873 [ $<0.001$ ]	0.075
FR: Northern Hardwoods	0.0773 [0.269]	0.070	0.9562 [ $<0.001$ ]	0.068
Population density	0.0003 [0.082]	0.000	-0.0003 [0.094]	0.000
Cropland ratio	-1.0738 [ $<0.001$ ]	0.101	-0.6942 [ $<0.001$ ]	0.082
Exporting port access	-0.1730 [0.001]	0.052	-0.1133 [0.026]	0.051





**Fig. A1** Residuals versus fitted values for M2 and LMM models

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**Code and data availability** Data, results, and graphics that support the findings of this study can be reconstructed by running the source code. The source code is openly available at a software repository at the following URL: <https://gitlab.com/ashki23/rc-biopower>.

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