Energy Economics 136 (2024) 107672

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Feasibility of satisfying projected biopower demands in support of decarbonization interventions: A spatially-explicit cost optimization model applied to woody biomass in the eastern US

Ashkan Mirzaee [a,d,1], Ronald G. McGarvey [b], Francisco X. Aguilar [c,*]

[a] Department of Industrial and Manufacturing Systems Engineering, University of Missouri, Columbia, MO 65211, USA
[b] IESEG School of Management, Univ. Lille, CNRS, UMR 9221 - LEM - Lille Economie Management, F-59000 Lille, France
[c] Department of Forest Economics, Swedish University of Agricultural Sciences, SE 901 83, Umea, Sweden
[d] Global Data Insight & Analytics, Ford Motor Company, Dearborn, MI 48126, USA

ARTICLE INFO

Dataset link: https://gitlab.com/ashki23/rc-biopower

JEL classification:
C33
C44
Q23
Q42
Q56
R19

Keywords:
Biopower
Spatial-explicit optimization
Forest
Biomass

ABSTRACT

Power generation from biomass (biopower) has experienced substantial growth in the United States. Although renewable and sustainably sourced biopower can reduce the carbon footprint of the electricity sector, there is a scarcity of analyses that simultaneously consider the financial feasibility and sustainability criteria of procured biomass. We developed a spatially-explicit optimization model to minimize the cost of meeting projected biopower demand while ensuring carbon neutrality and biomass sustainability constraints. The optimization model was applied to projected biopower demand scenarios in the eastern US, considering various public policy decarbonization interventions. Modeling woody biomass procured from local forests as the source of biopower was chosen due to its dominant role as a renewable energy source, regional availability, and lower risk of violating carbon neutrality objectives. Initially, we projected the net growth of woody biomass in trees and their carbon pools by 2035, as a function of biopower generation, utilizing data from 2009–2017. Subsequently, forecasted woody biomass and projected biopower demand through 2035 were employed to determine optimal levels of biopower generation and estimate the corresponding resource impacts within procurement forests. The results suggest the potential for substantial increases in sustainable biopower generation in the eastern US. However, the feasibility of this expansion depends on the continued economic viability of biopower generation in the future. It is worth noting that the largest increases, surpassing threefold, in biopower generation over the 2020–2030 decade could potentially compromise the carbon neutrality of locally procured woody biomass.

1. Introduction

Biopower, which involves generating electricity from biomass feedstocks, typically through combustion or co-firing with other fuels like coal, plays a significant role in the renewable energy mix of the United States. Wood and waste materials, including wood pellets and biomass waste from landfills, collectively contribute 17% and 4% to US renewable energy consumption, respectively (EIA, 2019, 2020b). The eastern US region is particularly prominent for biopower generation using wood as the primary feedstock (Fig. 1), characterized by low carbon and energy intensity and localized socio-economic and environmental impacts (Saunders et al., 2012; Ansari et al., 2023; He et al., 2016; Susaeta et al., 2011). Wood procurement in this region typically involves short transport distances, minimizing additional greenhouse gas emissions. Harvesting often occurs alongside the extraction of higher-value wood products to ensure economic viability, with minimal additional energy consumption required for processing and drying (Goerndt et al., 2013a; Abt et al., 2014; Dwivedi et al., 2011; Röder et al., 2015). Co-firing woody biomass with coal presents an environmentally beneficial alternative for existing coal-fired power plants, aiding in the transition to renewable energy sources (Gugler et al., 2021).

Beyond environmental considerations, biopower also holds promise for rural economic development. Studies suggest that investments in wood-based biopower can yield significant returns in local rural economies (Dahal et al., 2020). Moreover, biopower utilization has the

* Corresponding author.
E-mail address: francisco.aguilar@slu.se (F.X. Aguilar).
[1] Present affiliation (d). Work was completed while at (a) and (d).

https://doi.org/10.1016/j.eneco.2024.107672
Received 12 September 2023; Received in revised form 3 April 2024; Accepted 28 May 2024
Available online 4 June 2024

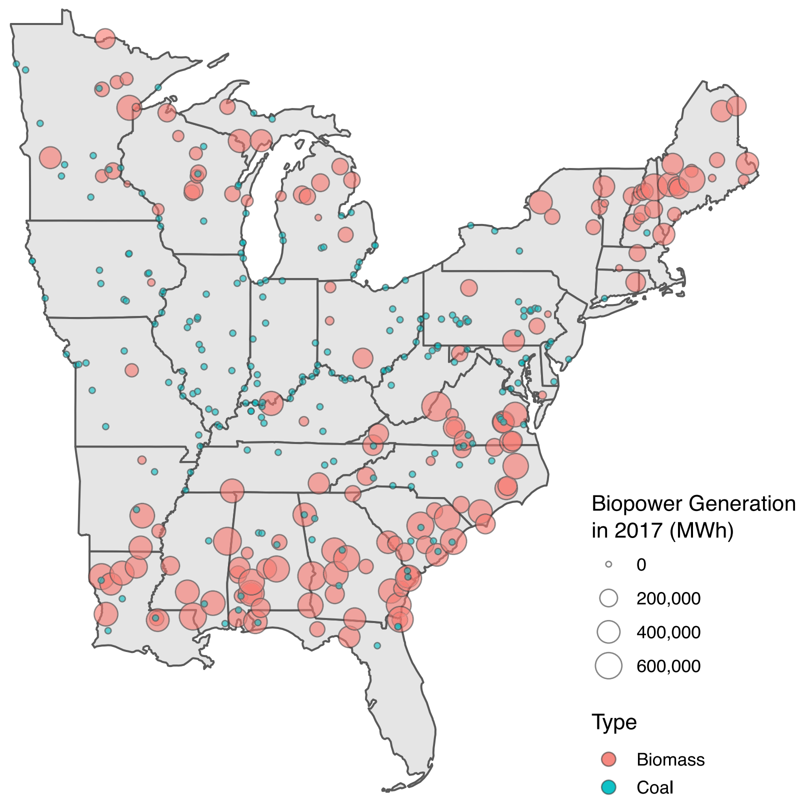

Fig. 1. Wood-using and coal-burning power plants in the eastern US that were in operation in 2017. Biopower generations are reported for year 2017. *Data source:* EIA (2021b,a).

potential to contribute to decarbonization efforts by promoting forest regrowth and incentivizing sustainable forest management practices that enhance carbon sequestration (Aguilar et al., 2012; Amigues and Moreaux, 2019). Evidence from the US indicates that the use of wood as a renewable energy feedstock has not depleted local forest carbon stocks, a crucial factor for sustainability and carbon emissions reduction compared to fossil fuels (Aguilar et al., 2022). Similar findings from studies conducted in the European Union highlight the potential for carbon emission reductions through supportive policies promoting the use of woody biomass, such as the EU Emissions Trading System (Dechezleprêtre et al., 2023).

The assessment of resource impacts in energy generation has been a subject of study in various research endeavors. Dincer (1999) was among the early studies that considered environmental impacts related to generating energy. The operations research/operations management literature includes many applications of optimization methods to reduce the environmental impacts of energy generation and minimize carbon emissions from the power sector (Hashim et al., 2005; Henning et al., 2006; Omu et al., 2013; Chen et al., 2013; Kang et al., 2020; Álvarez-Miranda et al., 2018). Several authors have focused on mitigating the carbon footprint from biomass-based heat and power generation. Chinese and Meneghetti (2005) proposed a mixed integer linear programming optimization model for local biomass-based heating networks with a goal of maximizing profits and minimizing GHG emissions. Bentsen et al. (2014) discussed optimal biomass allocation for energy generation in the EU and its potential GHG benefits. Kim et al. (2011) presented an optimization model for minimizing the cost of a biomass processing network and reducing its carbon footprint. There is a large body of literature on biomass supply chain modeling and optimization for minimizing related GHG emissions. For instance, Ekşioğlu et al. (2009) analyzed the logistical challenges related to biomass supply chains along with the optimal number and capacity of biofuel production plants. De Meyer et al. (2015) developed a generic mathematical model to optimize strategic decisions such as facility location and resource allocation in biomass-based supply chains. Dundar et al. (2016) presented minimum cost approaches to reduce CO_2 emissions from co-firing woody biomass in a set of candidate coal burning power plants across five Midwestern US states. Liu et al. (2014) studied the cost feasibility and environmental impacts of co-firing biomass for electricity. Hu et al. (2011) presented linear models analyzing the impact of biomass co-firing for electricity generation on carbon dioxide and sulfur dioxide. Dundar et al. (2021) developed a robust mixed-integer nonlinear programming model that involves multi-state partnership to minimize cost and CO_2 emissions related to co-firing woody biomass.

In this study, the analysis focuses on the potential for increasing biopower generation and its impact on timberland resources in the eastern US through 2035. Contributions to the literature concerning the optimal level of biopower generation, considering resource impacts, include: (1) the formulation of a multi-objective optimization model to determine the minimum cost of generating biopower while meeting carbon neutrality and sustainability constraints; (2) the development of a forecasting model to predict the level of timberland attributes (specifically, the annual net growth of biomass of trees and carbon in trees) across procured forests based on the level of bioenergy generation; and (3) an evaluation of the potential for maintaining carbon neutrality and sustainability goals while increasing biopower generation under selected policy interventions. Next, the study introduces a forecasting method for conducting an *ex ante* analysis to project forest attributes and an optimization model to determine the optimal level of biopower generation based on these projected forest attributes under different scenarios. This is followed by results and discussion, providing interpretation and context to the optimization model solutions in light of cost, carbon neutrality, and sustainability considerations.

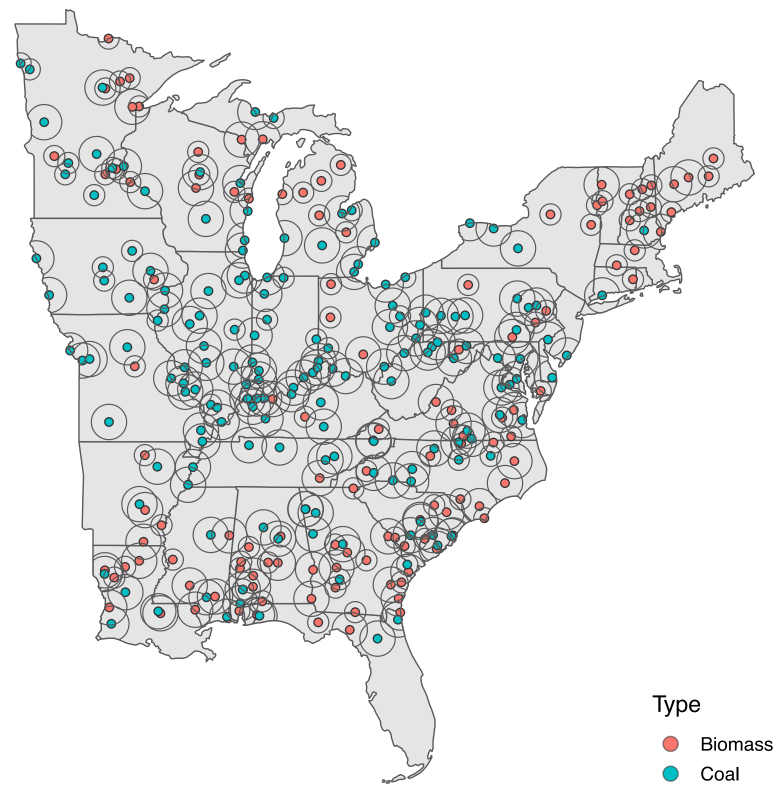

Fig. 2. Consolidated power plants and their procurement areas from 2009 to 2017.

2. Optimization from spatially-explicit biomass and power generation data

2.1. Wood-using and coal-burning power plants

In this analysis, 156 wood-using and 224 coal-burning operational power plants across the eastern US in 2017 were identified (EIA, 2021a,b), shown in Fig. 1. Here, it is assumed that all of the selected coal facilities are eligible for co-firing wood to generate biopower in the short-term. These eligible coal facilities account for 77% of the total US coal fleet in 2017 that had not announced a planned retirement date by 2035 (EIA, 2020a; Picciano et al., 2020). Based on a review of the literature, a circular woody biomass procurement area with a radius of 50 miles (80 km) was assigned to power plants with more than two million MWh of total electricity generation from 2009 to 2017, while a radius of 30 miles (48 km) was assigned to power plants with a lower amount of generation (Aguilar et al., 2020; Goerndt et al., 2013b). To mitigate the complexity of the procurement areas' proximity, power plants located within 20 miles (32 km) of each other were represented by a single notional plant exhibiting the characteristics of the consolidated plants. After these changes, 315 power plants remain across the eastern US as depicted in Fig. 2.

To monitor the sustainability and carbon neutrality of generating bioenergy, two *timberland attributes* around the selected power plants were studied: (1) annual net growth of biomass of trees and (2) annual net growth of carbon in trees. The timberland attributes were collected from Forest Inventory and Analysis (FIA) (USDA, 2021b; Mirzaee, 2021) for all procurement areas from 2009 to 2017. Detailed descriptions about the selected timberland attributes appear in Table 1.

Instead of studying the circular procurement areas directly, each of them was partitioned into a set of mutually exclusive and exhaustive *analysis areas*. This was done to alleviate the inherent dependence in timberland attributes within regions intersecting multiple procurement areas. The method offered by Mirzaee et al. (2022) was applied to estimate levels of the timberland attributes and corresponding bioenergy generation across 932 analysis areas, each comprising at least 20 square miles (50 km^2) in area.

2.2. Biopower policies

Determining the future level of bioenergy generation sourcing from the analysis areas relies on estimates of the expected electricity generation in the future (Burtraw et al., 2003). The projected electricity generations are obtained from the Engineering, Economic, and Environmental Electricity Simulation Tool (E4ST), a detailed model for analysis of power sector policy in US and Canada (Mao et al., 2016; Shawhan et al., 2014; Shawhan and Picciano, 2019). The projected electricity generations under three public policy interventions were collected, as shown in Table 2. Selected policies correspond to those presented by Picciano et al. (2022) which were chosen as viable options for increasing biopower generation to facilitate the decarbonization of the US electricity sector.

In this study, the aim is to evaluate the feasibility of a viable upper bound on the amount of biopower generation in the eastern US. For that reason, it is assumed that the identified coal facilities can utilize woody biomass for 15% of their total generation by 2035. Therefore, the projected biopower generation includes both 100% of the projected generation from biopower plants and 15% of the total projected electricity generation in currently coal-burning plants. Note that under this assumption, policies with more reliance on coal-burning power plants will generate a considerable amount of biopower in the future, independent of the generation by biopower-only plants. As a result, the BAU policy scenario requires higher biopower generation than the CES scenario. E4ST data shows that expected total biopower generation would increase more than three times and reach between 90–115 GWh from 2017 to 2035 under the different policy scenarios in the eastern US.

Fig. 3 shows total historical biopower generation from 2009 to 2017 and projected biopower generation for every three-year from 2026 to 2035 under different policy scenarios as well as expected biopower

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

Attributes	Description
Annual net growth of biomass of trees	Tons of annual net growth of aboveground biomass of trees on timberland[a] (at least 2.54 cm diameter at 1.37 m above the forest floor)
Annual net growth of carbon in trees	Tons of annual net growth of aboveground carbon in trees on timberland[a] (at least 2.54 cm diameter at 1.37 m above the forest floor)

[a] The US Forest Service defines timberland as forest land capable of producing more than 1.4 cubic meters of wood per year and not legally withdrawn from timber production.

Table 2
Selected energy policy scenarios.

Policy scenario	Description
Business as usual (BAU)	US federal and state policies as of August 2019. These include federal renewable energy tax incentives, state CO_2 cap-and-trade programs, and state renewable energy and clean energy standards.
Biopower production tax credit (BIO PTC)	A renewable electricity production tax credit of \$22/MWh in 2025 for biomass co-firing generation at coal facilities, reflecting the PTC historically provided for US wind generation (EPA, 2021)
Clean energy standard (CES)	A federal clean energy standard imposing a national average clean energy requirement of 77%. The requirement reflects an annual linear interpolation from current levels of clean generation to 100% clean in 2050. The standard applies a CO_2 emissions intensity benchmark of 0.82 metric tons/MWh. The benchmark identifies a measure against which partial credit will be awarded. This policy provides linearly interpolated partial credit for resources with a CO_2 emissions intensity between 0.82 and 0.00. For example, a natural gas combined cycle unit with an emissions intensity of 0.41 would receive 0.5 partial credit per MWh, carbon-free source would receive 1 full credit per MWh. Biomass co-firing receives 0.5 partial credit per MWh of biomass generation (Picciano et al., 2020, 2022).

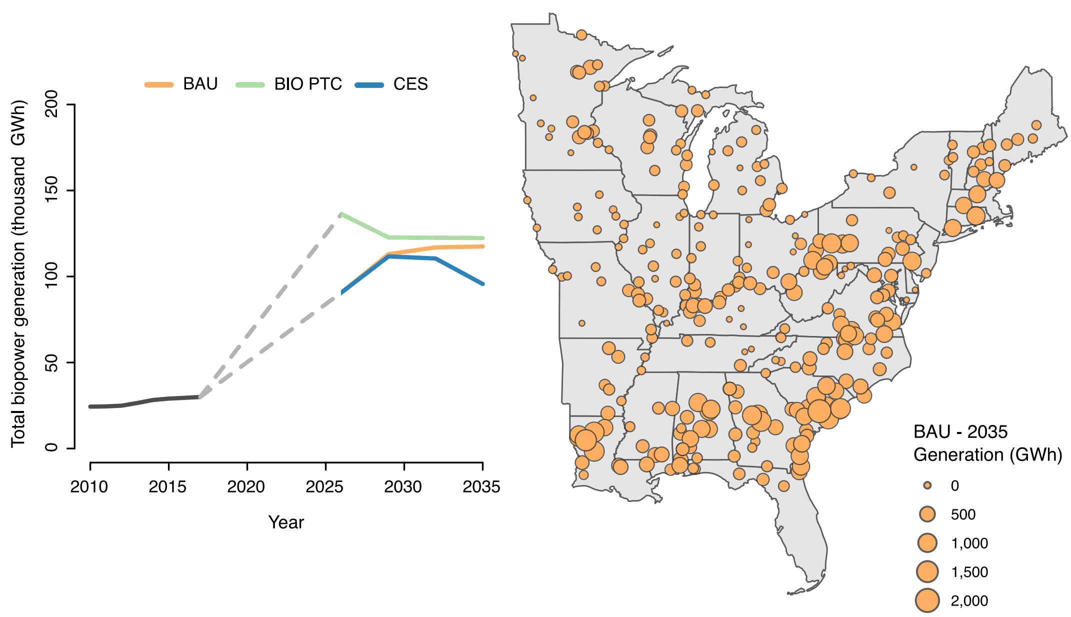

Fig. 3. Total historical (2009–2017) and projected (2026–2035) biopower generations under different policy scenarios (left) and projected generation in 2035 under the BAU scenario (right).

generation from studied power plants in 2035 under the BAU scenario. Observe that total biopower generation decreases starting in the year 2026 for BIO PTC, and also decreases starting in the year 2029 for CES. This occurs because under these policies the total amount of generation from coal resources will decline which will reduce the amount of biopower generation from co-firing in coal-burning power plants.

2.3. Forecasting timberland attributes

The level of biopower generation relies on the biomass resources available within an analysis area. A forecasting model was developed to estimate the annual net growth of both biomass of trees and carbon in trees within the analysis areas across three-year increments from 2026 to 2035, utilizing historical data for every year from 2009 to 2017. The forecasting model incorporates significant factors related to changes in timberland attributes, including those induced by power plants, human interventions, competition from wood industries, and natural disasters. The model's explanatory variables and their descriptions are listed in Table 3. Fig. 4 illustrates the analysis areas and forest regions, along with wood industries, as well as the areas affected by drought in one year (2012).

The forecasting model was constructed by applying a lagged linear mixed model (LMM) to fit the timberland attributes in each analysis area. Let y_i^t denote the level of the timberland attribute in analysis area i at time t, where $i \in \{1, \ldots, 932\}$ and $t \in \{2010, \ldots, 2017\}$, then:

$$\ln(y_i^t) = \beta_0 + \sum_k \beta_k v_{ki}^{t-1} + \sum_u \alpha_u h_{ui} + \epsilon_i^t \quad (1)$$

and

$$\epsilon_i^t = b_i + \varepsilon_i^t \quad (2)$$

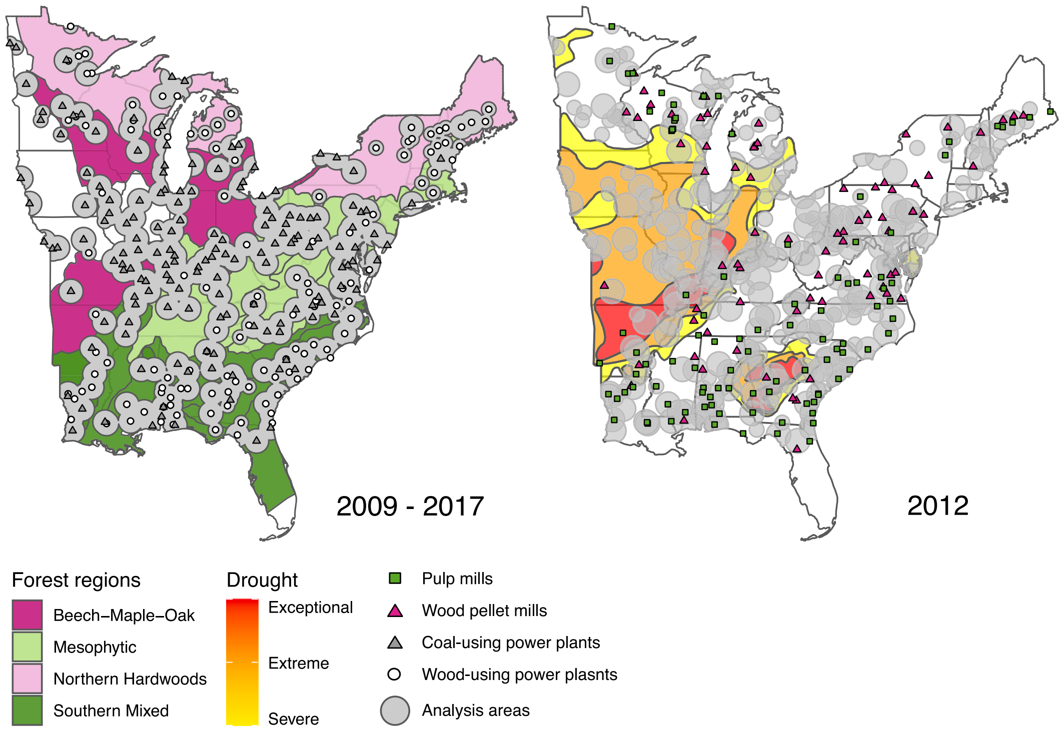

Fig. 4. Forest regions and power plants from 2009 to 2017 (left), along with location of wood pellet mills, pulp mills, and areas of reported extreme weather conditions in 2012 (right).

Here, β_0 represents a fixed intercept, while k and u denote indices for time-variant ($v_{k.}$) and time-invariant variables ($h_{u.}$), respectively, each associated with corresponding coefficients β_k and α_u. Additionally, b_i stands for random intercepts, and $\epsilon_i^t \sim N(0, \sigma_t^2)$ represents error terms. A logarithmic transformation is applied to reduce the impact of high variation among the responses on the normality assumption of the error term. To project the timberland attributes in the future, we made the following assumptions regarding the projection of the explanatory variables by the year 2035:

1. Forest ecological regions will not change.
2. No new wood pellet mill, pulp mill, or port for exporting wood products will be added to the selected facilities.
3. No new dedicated biopower plant will be added to the selected plants.
4. None of the selected power plants or related wood industry mills will be retired.
5. Population of analysis areas will grow by 12.75% (Vespa et al., 2018) with a flat 0.75% annual increase rate.
6. Croplands in analysis areas will decline by 2.5% (USDA, 2021d) with a flat 0.15% annual decrease rate.
7. Drought will impact 10% more of each analysis area (Peters and Iverson, 2019) with a flat 0.6% increase in annual area impacted by drought.

Given the LMM regression coefficients (derived from historical data) and the projected future levels of the explanatory variables (based on the above assumptions), Eq. (1) can be rewritten to project the timberland attributes for every area i and time $t \in \{2026, 2029, \dots, 2035\}$ as a function of biopower generation in power plant j, x_{ij}:

$$\begin{aligned}\ln(y_i^t) &= \beta_0 + \sum_k \beta_k v_{ki}^{t-1} + \sum_u \alpha_u h_{ui} + b_i + \epsilon_i^t \\ &= \beta_0 + \beta_1 v_{1i}^{t-1} + \sum_{k>1} \beta_k v_{ki}^{t-1} + \sum_u \alpha_u h_{ui} + b_i + \epsilon_i^t \\ &= \beta_0 + \beta_1 \sum_{j\in J_i} x_{ij}^{t-1} + \sum_{k>1} \beta_k v_{ki}^{t-1} + \sum_u \alpha_u h_{ui} + b_i + \epsilon_i^t\end{aligned} \tag{3}$$

which implies (Wooldridge, 2020):

$$\begin{aligned}\hat{y}_i^t &= \exp(\beta_0 + \beta_1 \sum_{j\in J_i} x_{ij}^{t-1} + \sum_{k>1} \beta_k v_{ki}^{t-1} + \sum_u \alpha_u h_{ui} + b_i + \frac{\hat{\sigma}^2}{2}) \\ &= \exp(O_i^{t-1} + \beta_1 \sum_{j\in J_i} x_{ij}^{t-1})\end{aligned} \tag{4}$$

where $\hat{\sigma}$ is the standard error of the regression, and $\sum_{j\in J_i} x_{ij}^{t-1}$ is total level of biopower generation sourcing from area i across the associated power plants, J_i, at year $t-1$. O_i^{t-1} is determined a *priori* by adding half of the squared regression standard error, fixed and random intercept values, and the inner product of the projected variable values for all variables excluding biopower generation, along with their corresponding coefficients, for each area i and time $t-1$. In the given context, functions of the annual net growth of biomass of trees per thousand ton ($B(x_{ij}^t)$) and annual net growth of carbon in trees per thousand ton ($C(x_{ij}^t)$) can be written as:

$$B(x_{ij}^t) = \exp(B_i^{t-1} + \beta_b \sum_{j\in J_i} x_{ij}^{t-1}) \tag{5}$$

$$C(x_{ij}^t) = \exp(C_i^{t-1} + \beta_c \sum_{j\in J_i} x_{ij}^{t-1}) \tag{6}$$

where B_i^{t-1} and C_i^{t-1} represent the expected values for annual net growth of biomass of trees and carbon of trees excluding biopower generations effects with β_b and β_c coefficients, respectively.

The proposed LMM was evaluated by comparing it with two other modified forms of the model. The first model (OLS) is a simplified version where the random effects are removed, resulting in a more traditional linear model fitted with ordinary least squares. The second model (GLS) incorporates the first-order autoregressive correlation structure and is fitted using generalized least squares. Both the LMM and GLS models demonstrate significantly better performance in terms of AIC and BIC compared to the OLS model. However, the LMM achieves a lower sum of squared errors of the test set and lower sum of squared residuals.

Table 3
Descriptions and descriptive statistics for model's explanatory variables ($n = 7,456$).

Variables	Description	Min	Mean	Max	SD
Biopower generation (v_1)	Estimated bioenergy generation in the analysis area; per GWh (EIA, 2021a,b)	0.00	28.28	882.53	66.94
Years of operation (v_2)	Average years of operation of power plants contained in the analysis area; since 1990 (EIA, 2021b)	0.00	22.87	27.00	3.65
Number of power plants (v_3)	Number of power plants' procurement area contained in the analysis area (EIA, 2021b)	1.00	2.36	7.00	1.19
Wood pellet mills intersection (v_4)	Total percentage[a] of the analysis area covered by wood pellet mill procurement zones[b] (FORISK, 2018)	0.00	0.19	3.20	0.42
Pulp mills intersection (v_5)	Total percentage[a] of the analysis area covered by pulp mill procurement zones[b] (Johnson and Steppleton, 2007; Johnson et al., 2010; Piva et al., 2014; Bentley and Steppleton, 2013; Gray et al., 2014, 2016)	0.00	1.40	6.52	1.59
Drought level (v_6)	Percentage of the analysis area affected by a severe, extreme, or exceptional drought in August preceding a given year (USDA, 2021c; U.S. Drought Monitor, 2021)	0.00	0.07	1.00	0.24
Population density (v_7)	Summation of county populations (U.S. Census Bureau, 2020b,a) that lie inside the analysis area; per ten thousand	1.14	52.29	1746.12	104.93
Cropland ratio (v_8)	Summation of county's crop acreage (USDA, 2021a) ratios that lie inside the analysis area	0.00	0.13	1.00	0.13
Nearest port distance (h_1)	Euclidian distance from centroid of the analysis area to the nearest port that exports forest products; per mile (USDOT, 2019)	0.50	83.20	360.20	56.10
Forest ecological regions (FR) (h_{2-4})	Categorical variable including four major ecological regions (Dyer, 2006) (fig4]Fig. 4); the forest region covering the maximum amount of the analysis area is selected as forest region of the analysis area	South. Mixed: 33%	Beech–Maple–Oak: 28%	Meso-phytic: 31%	North. Hardwoods: 8%

[a] Can be greater than 1 if area intersects with more than one zone.
[b] Procurement zones, with radii of 50 and 75 miles, respectively, were assigned to wood pellet and pulp mills.

2.4. Optimal level of biopower generation

A multi-objective mathematical model was developed to determine the optimal level of biopower generation sourced from each analysis area. This model generates the required woody biomass energy while considering a set of environmental constraints. It is worth noting that the procurement areas used in the LMM were determined assuming a radius of 30 or 50 miles (48 or 80 km) centered around each power plant, depending on the level of electricity generation. However, in the optimization model, power plants potentially can access more distant analysis areas. This allowance is made because some power plants, particularly those with higher projected biopower generation, may require more biomass fuel than can be found within their 30 (or 50) mile procurement area to satisfy the projected future demands. Therefore, providing a larger sourcing distance allows the model to obtain the required biomass at minimal cost, subject to sustainability conditions. Next, the indices, parameters, decision variables, and constraints used in this model are described.

Indices and parameters

$\boldsymbol{i}$: analysis areas index, $i \in \{1, \ldots, 932\}$

$\boldsymbol{j}$: power plants index, $j \in \{1, \ldots, 282\}$

$\boldsymbol{t}$: year index, $t \in \{2026, 2029, \ldots, 2035\}$, where $t+1$ refers to a three-year increment

$\boldsymbol{\delta}$: a threshold distance, $\delta \in \{150, 200, 250\}$ miles

$\boldsymbol{J_i}$: set of power plants within δ distance from centroid of area i

$\boldsymbol{b_j^t}$: level of projected biopower generation at plant j at time t (GWh)

$\boldsymbol{c_{ij}}$: Transportation cost of generating biopower at power plant j sourcing from area i (\$/GWh)

$\boldsymbol{d_{ij}}$: Euclidean distance between power plant j and centroid of area i (mile)

$\boldsymbol{\varphi_i}$: annual net growth of carbon in trees in area i in year 2010 (thousand ton)

$\boldsymbol{\theta}$: a multiplier for annual net growth of biomass of trees in each area

$\boldsymbol{\rho}$: energy content of burning wood (GWh/thousand ton)

f: freight cost (\$/thousand ton × mile)

The energy content of wood burned in power plants depends on factors such as the wood's water content and the efficiency of the power plant. Typically, one ton of dry wood contains about 4.8 MWh of energy (NREL, 2008). However, wood chips can have a water content ranging from 25% to 45% (Pedišius et al., 2021; Krajnc, 2015), were assumed to have a 30% water content and 70% wood content in this study. Additionally, the power plant's efficiency can affect the electricity generation from wood resources. Combined Heat and Power (CHP) systems, the predominant technology among wood-burning power plants, generally operate with an efficiency of 65%–85% (DOE, 2017). For this analysis, a 75% efficiency was considered for the studied power plants. Therefore, an energy content of $\rho = 4.8 \times 0.7 \times 0.75 = 2.5$ MWh/ton (or GWh/thousand ton) is utilized. Furthermore, a freight cost of $f = \$240$ per thousand ton per mile was considered (Goerndt et al., 2013b).

Decision variable

x_{ij}^t: level of biopower generation at power plant j sourcing from area i at time t (GWh)

Environmental impact functions

$B(x_{ij}^t)$: expected annual net growth of biomass of trees in area i at time t for x level of biopower generation at power plant j (thousand ton)

$C(x_{ij}^t)$: expected annual net growth of carbon in trees in area i at time t for x level of biopower generation at power plant j (thousand ton)

Objective function

The objective function aims to minimize the variable cost of transporting biomass resources to the power plants from each analysis area. It is important to note that E4ST has already optimized the generation amounts at each power plant under each of the considered policies, thereby minimizing the costs of generation. The biomass sourcing decision being optimized here is not modeled within the E4ST framework. The objective function is defined as follows:

$$\min \sum_i \sum_{j \in J_i} \sum_t c_{ij} x_{ij}^t \tag{7}$$

where c_{ij} is computed by:

$$c_{ij} = (f \times d_{ij})/\rho \tag{8}$$

A uniform distribution of biomass resources across each analysis area was assumed due to a lack of information on the biomass sourcing locations for each power plant. Subsequently, transportation costs were computed based on the Euclidean distance from power plants to the centroid of each analysis area (d_{ij}).

Carbon neutrality of biopower generated from woody biomass

To maintain the carbon neutrality of electricity generation from woody biomass, the estimated total annual net growth of carbon stocks in trees across the eastern US in future years should be no less than the historical total annual net growth of carbon pools in that area. In this study, the level of future carbon pools is compared with the 2010 level, predating the intensive bioenergy policy period in the US (Aguilar et al., 2020). The constraint is defined such that the sum total annual net growth of carbon in trees across analysis areas in the eastern US at the end of each year (i.e., 2029, 2032, and 2035) remains greater than or equal to the 2010 level. The corresponding mathematical equation is expressed as:

$$\sum_i C(x_{ij}^{t+1}) \geq \sum_i \varphi_i \quad \forall t \tag{9}$$

which by using Eq. (6), can be represented by:

$$\sum_i \left(\exp(C_i^t + \beta_c \sum_{j \in J_i} x_{ij}^t) \right) \geq \sum_i \varphi_i \quad \forall t \tag{10}$$

Resource sustainability of woody biomass procured from local forests

To sustain timberland resources, the total amount of woody biomass harvested by power plants from each analysis area must not exceed the annual net growth of biomass of trees in that area. Unlike the carbon neutrality constraint, which aggregates effects across geographic regions, this forest sustainability constraint is enforced for each individual analysis area at each time period. This constraint is presented as:

$$\sum_{j \in J_i} x_{ij}^{t+1} \leq \rho \times B(x_{ij}^{t+1}) \quad \forall i, t \tag{11}$$

which after applying Eq. (5) can be written as:

$$\begin{aligned} &\sum_{j \in J_i} x_{ij}^{t+1} \leq \rho \times \exp(B_i^t + \beta_b \sum_{j \in J_i} x_{ij}^t) \\ &\ln(\sum_{j \in J_i} x_{ij}^{t+1}) \leq \ln(\rho) + B_i^t + \beta_b \sum_{j \in J_i} x_{ij}^t \quad \forall i, t \end{aligned} \tag{12}$$

To impose a restrictive assumption regarding forest sustainability, the following constraint is added: the total level of biopower generation sourced from an area throughout the year $t+1$ must not exceed the annual net growth of biomass of trees available at the end of year t, regardless of the level of biopower generation in that year. This constraint is presented as:

$$\ln(\sum_{j \in J_i} x_{ij}^{t+1}) \leq \theta \times (\ln(\rho) + B_i^t) \quad \forall i, t \tag{13}$$

where $0 < \theta \leq 1$ is a multiplier to specify an upper limit for using woody biomass. Note that any θ multiplier less than or equal to 1 can satisfy the biopower sustainability requirement. For instance, a $\theta = 1$ means that power plants can use no more than the amount of annual net growth of biomass which is available at the beginning of the year in each analysis area. Depending on the values of β_b and θ, note that one of Eq. (12) or Eq. (13) becomes a redundant constraint (e.g., when $\theta = 1$ and $\beta_b > 0$, Eq. (12) is redundant).

Biopower demand

Lastly, at each power plant, the total amount of biopower generation sourced from surrounding analysis areas should be equal to the projected biopower generation requirement for that plant as identified by E4ST:

$$\sum_i x_{ij}^t = b_j^t \quad \forall j \in J_i, t \tag{14}$$

To enhance the computational performance of the nonlinear model, the following initialization was applied for the decision variable values based on the available biomass at each area:

$$\hat{x}_{ij}^t = 0.1 \times B_i^t \tag{15}$$

Furthermore, to assess the impact of the optimal solutions on the analysis areas, the *bioenergy ratio* was defined as:

$$R_i^t = \frac{\sum_{j \in J_i} x_{ij}^{*t}}{B(x_{ij}^{*t}) \times \rho} \quad \forall i, t \tag{16}$$

where the numerator is the total optimal level of bioenergy generation sourcing from area i (as determined by the model) and the denominator is the maximum obtainable bioenergy (from the annual growth) within that area.

3. Results and discussion

The defined linear mixed model (LMM) was employed to estimate the corresponding regression parameters (β_b and β_c) in Eqs. (5) and (6). The regression parameters were estimated using restricted maximum likelihood (Harville, 1977) by utilizing the *lme* function from the *nlme* package in R (R, 2021; Pinheiro et al., 2014). Estimated coefficients along with the corresponding *p-values* and standard errors for both timberland attributes, are listed under Table 4. Next, our optimization

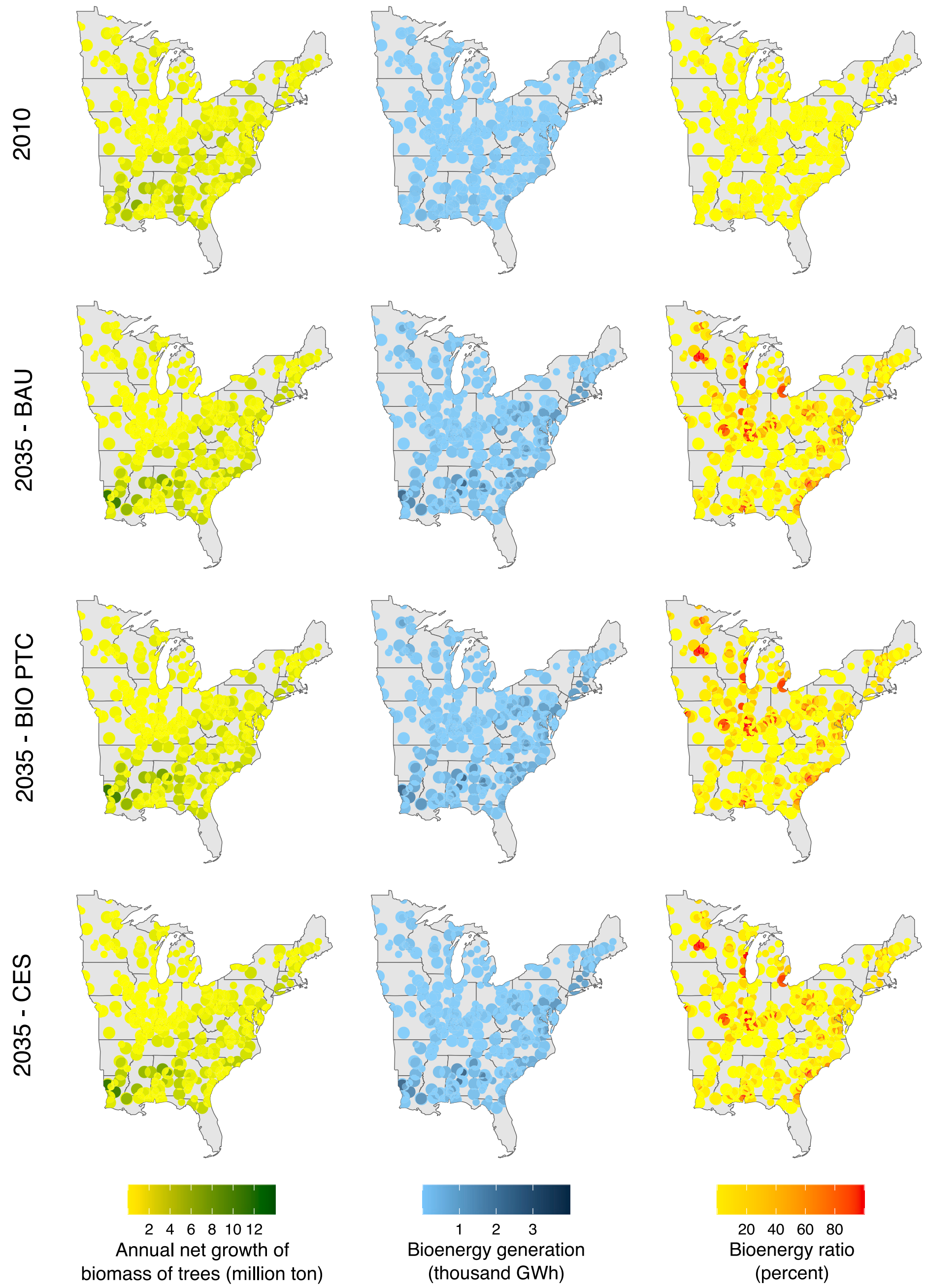

Fig. 5. Annual net growth of biomass (left), bioenergy generations (middle), and bioenergy ratios (right) in 2010 and 2035 under different policy scenarios at $\theta = 1$.

model was constructed using the estimated regression parameters and projected explanatory variables.

The optimization model was solved for two sustainability regimes. First, power plants potentially have access to the entire annual net growth of biomass of trees within the analysis areas. Second, power plants can access up to 80% of the annual biomass net growth. Our results indicate that for each sustainability level, optimal solutions exist that satisfy the sustainability constraints and projected demands under different policy scenarios in the eastern US. Subsequently, these optimal solutions are discussed along with the processes associated with obtaining them. The optimization problems were solved using the CONOPT nonlinear solver in GAMS. All optimization instances were executed on a Linux HPC cluster (Cluster, 2020) using 10 Intel Xeon Gold 2.00 GHz cores with 64 GB memory.

3.1. Sustainable solutions

Harvesting from the annual net growth of woody biomass in an area can be considered a sustainable approach that would maintain forest resources at the same level over time. In our optimization model, this approach can be achieved by setting the multiplier $\theta = 1$ in Eq. (13). By solving the optimization model under this assumption, an optimal solution is found that can sustainably satisfy projected future bioenergy demands as well as the minimum required level for carbon stocks in trees across the eastern US. These optimal solutions exist when the

Table 4
Regression coefficients (log-transformed) along with standard errors and *p-values* ($n = 7,456$).

	Annual net growth of biomass of trees (*thousand ton*) *AIC*: −830.357 $\hat{\sigma}$: 0.152 *RMSE* = 0.044		Annual net growth of carbon in trees (*thousand ton*) *AIC*: −830.354 $\hat{\sigma}$: 0.152 *RMSE* = 0.044	
	Coef. [std. error]	*p-value*	Coef. [std. error]	*p-value*
Intercept	7.296 [0.149]	<.001	6.603 [0.149]	<.001
Biopower generation	0.001 [0.000]	<.001	0.001 [0.000]	<.001
Years of operation	−0.007 [0.001]	<.001	−0.007 [0.001]	<.001
Number of power plants	−0.719 [0.038]	<.001	−0.719 [0.038]	<.001
Wood pellet mills intersection	0.031 [0.009]	0.001	0.031 [0.009]	0.001
Pulp mills intersection	−0.022 [0.010]	0.029	−0.022 [0.010]	0.029
Drought level	−0.049 [0.008]	<.001	−0.049 [0.008]	<.001
Population density	−0.001 [0.000]	0.022	−0.001 [0.000]	0.022
Cropland ratio	0.048 [0.068]	0.482	0.048 [0.068]	0.482
Nearest port distance	0.001 [0.001]	0.028	0.001 [0.001]	0.028
FR: Beech–Maple–Oak	−1.496 [0.115]	<.001	−1.496 [0.115]	<.001
FR: Mesophytic	−0.601 [0.111]	<.001	−0.601 [0.111]	<.001
FR: Northern Hardwoods	−0.586 [0.175]	<.001	−0.586 [0.175]	<.001

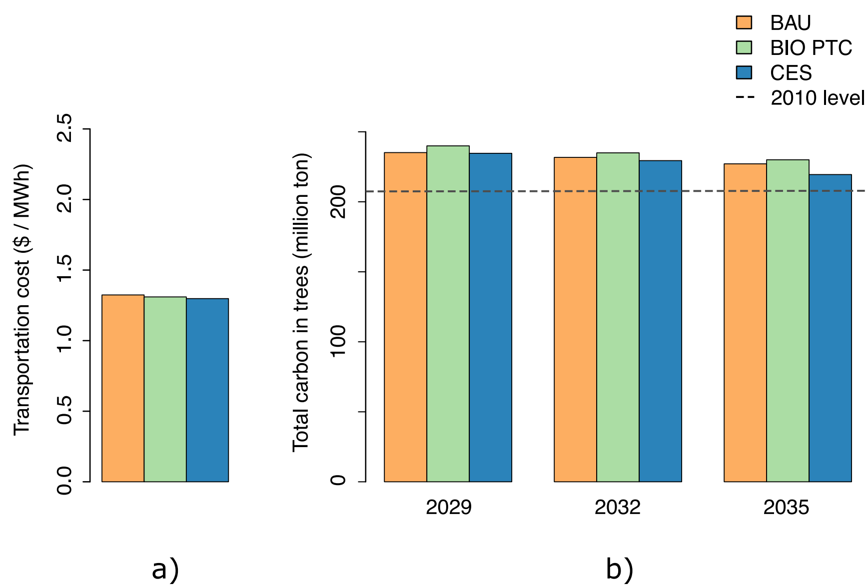

Fig. 6. Transportation cost per MWh biopower generation (a) and total annual growth of carbon in trees under different policies scenarios (b) in the eastern US.

annual net growth of woody biomass in the analysis areas can be accessed by power plants within a maximum range of δ = 150 miles (241 km).

Upon reviewing the optimal levels of biopower generation, significant increases are observed across the analysis areas in Southeastern states, including Louisiana, Alabama, Georgia, and South Carolina (Fig. 5). Furthermore, in our *ex post* statistical analysis, a positive trend was associated with the amount of biopower generation and the annual net growth of biomass of trees ($\beta_b = 0.001$), as shown in Table 4. This positive coefficient indicates that for any GWh of biopower generation sourced from an analysis area in time $t + 1$, there must have been no decrease in the annual net growth of biomass of trees due to the biopower generation in that analysis area in time t. Therefore, as observed, the analysis areas with the highest projected bioenergy generation are expected to have the highest annual net biomass growth to address the projected demands (Fig. 5).

The total annual net growth of woody biomass across the analysis areas in 2035 is expected to be 10.5%, 9%, and 5.5% more than the 2010 level under BIO PTC, BAU, and CES policies, respectively. Moreover, the bioenergy ratios were computed to evaluate the intensity of using biomass resources for biopower generation using Eq. (16). The ratios reveal that most analysis areas would require less than 40% of their biomass annual net growth. However, it was observed that areas near metropolitan regions would require significantly higher woody biomass utilization to fulfill the projected biopower demands. For instance, in 2035, more than 80% of the annual net biomass growth near Detroit, MI, Chicago, IL, Madison, WI, and Saint Louis, MO would be required to fulfill the expected biopower demands (Fig. 5).

Regarding the carbon neutrality assumption of generating biopower, it was found that the estimated total annual net growth of carbon stocks in trees across the eastern US in 2035 is expected to be 5% to 10% more than in 2010 under all of the different policy scenarios (Fig. 6b). Among the policies considered, BIO PTC has the highest total variable cost over each three-year period. This can be explained by the fact that BIO PTC has the highest projected bioenergy generation and relies on supplying more wood resources, thus increasing the total transportation cost of biopower generation. Comparing the cost of transporting woody biomass per MWh of bioenergy generation shows little difference between the policy scenarios (Fig. 6a).

It is important to note that in conducting sensitivity analysis with road distances instead of Euclidean distances for calculating total transportation costs, a tortuosity factor ranging from 1.2 to 1.5, as suggested in the literature (Goerndt et al., 2013b; Perez-Verdin et al., 2009), was incorporated. The sensitivity analysis indicates that increasing the

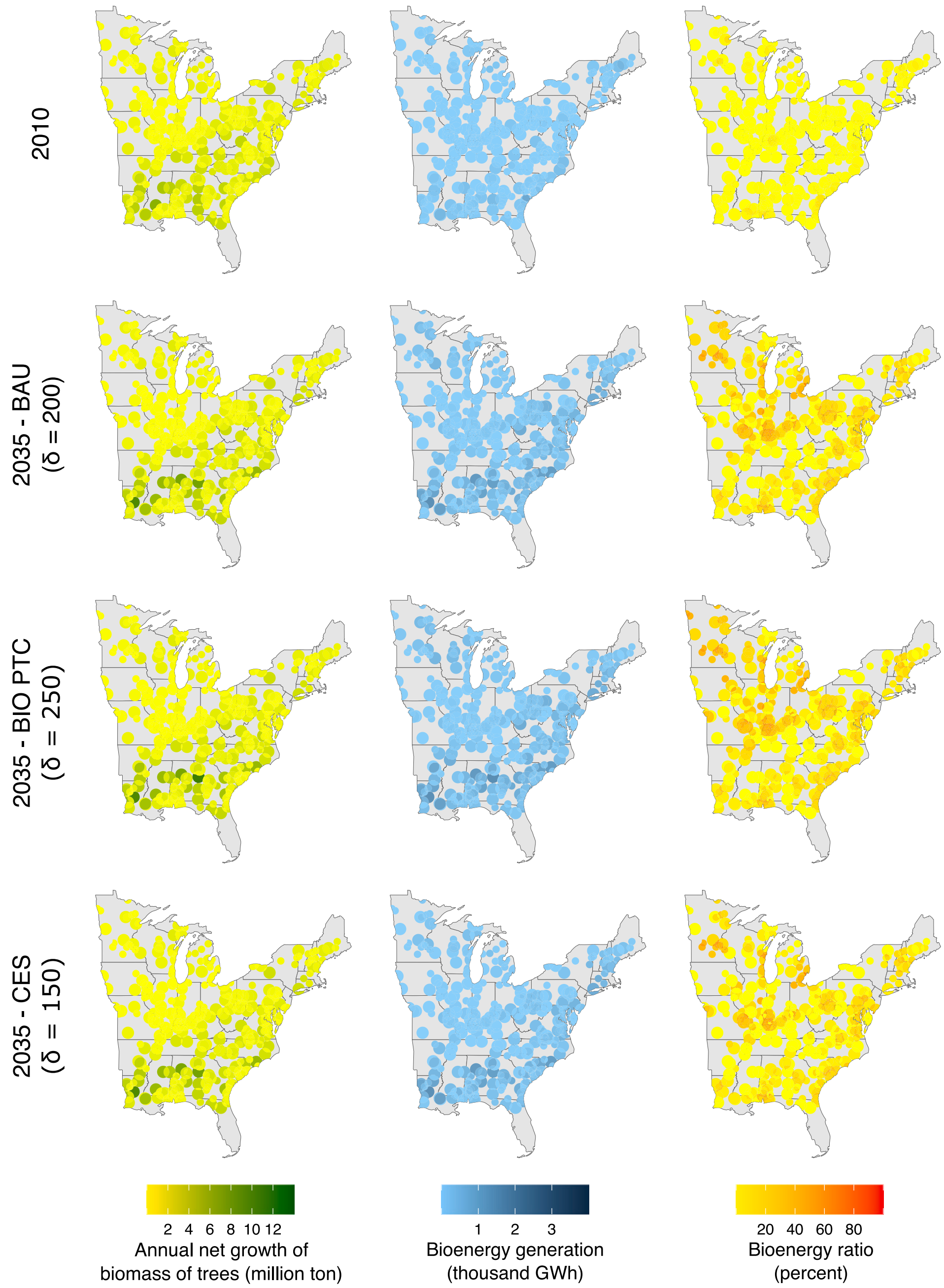

Fig. 7. Annual net growth of biomass (left), bioenergy generations (middle), and bioenergy ratios (right) in 2010 and 2035 under different policy scenarios at $\theta = 0.8$.

distance by a factor ranging between 20% to 50% would lead to approximately a 35% increase in total costs. Nevertheless, the other findings presented in this paper remain consistent despite this adjustment.

3.2. Biomass-cap solutions

Utilizing the entire annual net growth of woody biomass resources in an area for biopower generation would present challenges in implementation. To find a more sustainable approach, the amount of woody biomass that can be used by power plants was limited. A multiplier $\theta = 0.8$ was applied in Eq. (13) to restrict the available woody biomass for electricity generation to 80% of the annual net biomass growth within each analysis area.

By limiting the maximum harvestable biomass for energy generation, power plants would require accessing more distant supplies to satisfy their projected demands. Three threshold distances were considered for $\delta = 150$, 200, and 250 miles to find feasible solutions under each policy scenario. For the BIO PTC policy – the policy with the highest projected biopower generation – a distance of $\delta = 250$ miles (402 km) provides sufficient resources to satisfy both projected demands and environmental constraints. For BAU and CES policy scenarios, $\delta =$ 200 and 150 miles (322 and 241 km), respectively, were found to be the minimum feasible distances. Fig. 7 shows the annual net growth of biomass, the amount of biopower generation, and the bioenergy ratios within the analysis areas, as determined by the optimization model.

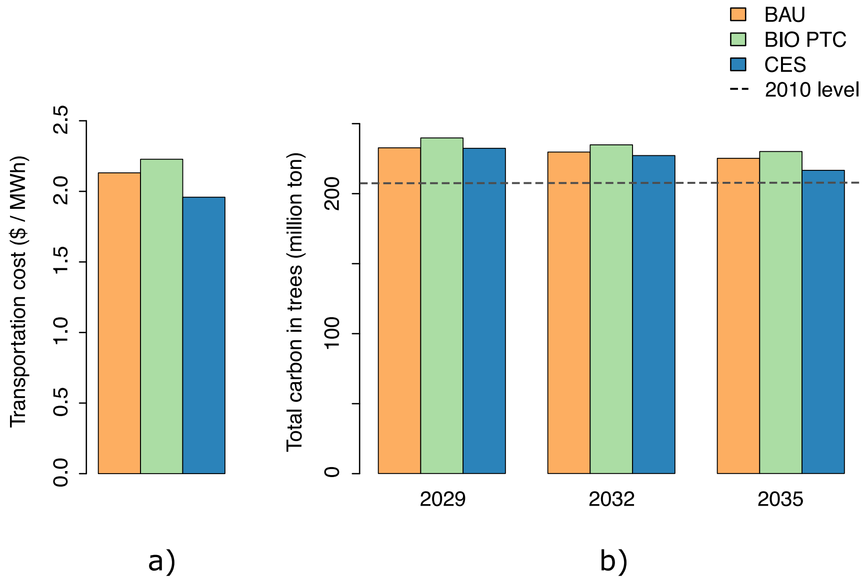

Fig. 8. Transportation cost per MWh biopower generation (a) and total annual growth of carbon in trees under different policies scenarios (b) in the eastern US using an upper limit to harvest-able woody biomass resources.

By reviewing these optimal solutions, it was found that applying an 80% biomass-cap policy can significantly decrease pressure on areas with a high woody biomass utilization ratio (Fig. 7). However, this upper limit would increase the total transportation cost of generating bioenergy by more than 50% in comparison to the $\theta = 1$ regime (Fig. 8a). Among the studied policies, BIO PTC and CES would be expected to have the highest and the lowest total transportation cost per MWh, respectively. Across these solutions, the total annual net growth of biomass of trees and their carbon pools in 2035 is expected to be 5% to 10% more than the 2010 level, similar to the expected biomass of trees and carbon pools obtained under the alternative assumption $\theta = 1$ (Fig. 8b).

3.3. Policy implications

Reviewing the optimal solutions for the discussed policy scenarios, it is observed that increasing the use of woody biomass for electricity generation while still satisfying the environmental constraints in the analysis areas is feasible. Under the BIO PTC, BAU, and CES scenarios, the projected bioenergy generation would increase from 30 GWh in 2017 to 115, 110, and 90 GWh in 2035, respectively. Policies supporting more biopower generation can reduce the dependence on coal resources and decrease the power sector's carbon footprint. However, increased bioenergy generation can also raise demand for wood resources and potentially impact timberland areas.

In terms of employing different suitability regimes, limiting maximum harvestable woody biomass to 80% of the annual net biomass growth prevents overly high woody biomass utilization and preserves a greater amount of resource in each area. However, the biomass-cap policy would not change the total amount of woody biomass consumption by power plants. Rather, it shifts the distribution of biomass usage in the analysis areas in such a way that it creates more areas with moderate utilization (10%–50%) and fewer areas with high (or low) utilization ratios (Fig. 9). This would create a safeguard for the sustainability of timberland resources, especially in areas where other wood industries – like wood pellet or pulp mills – are located.

Meanwhile, limiting harvestable resources requires accessing more distant timberland areas to address the power plants' biomass demands, which necessitates more transportation and, as a result, more carbon emissions from transportation. Our findings indicate that implementing the biomass-cap regime would result in a transportation increase of over 50% across the eastern US from 2026 to 2035 compared to the sustainable regime. However, the potential increase in transportation-related CO_2 impact might be offset by future transportation technologies, such as the adoption of electric trucks.

4. Conclusions

In this study, we examined the impacts of increasing the use of woody biomass for electricity generation on timberland areas across the eastern US through the year 2035. Our findings suggest that timberland areas within 150 miles (241 km) of the studied power plants would provide adequate sustainable woody biomass resources to support a more than three-fold increase in the total biopower generation across these US states, compared to the 2017 level. Such increases would require growth in the level of biomass resources for GWh biopower generation, consistent with historical experience. Using woody biomass for energy generation can potentially reduce the electric sector's carbon footprint (Böhringer and Rosendahl, 2022). Moreover, providing a market for low-value timberland resources can empower local economies and improve forest health, diversity, and resilience (Mirzaee et al., 2022; Susaeta et al., 2011; Soliño et al., 2018). However, a biomass-cap solution that limits biomass harvesting for electricity generation to no more than 80% of the annual net biomass growth in a region would come with a significant transportation cost trade-off.

Our analysis identifies sourcing decisions that support the optimized level of biopower electricity generation with minimal resource impacts, ensuring satisfaction of carbon neutrality and forest sustainability constraints. Our findings suggest the potential to maintain carbon neutrality and sustainability goals while increasing biopower generation under multiple policy interventions supporting increased biopower generation. This analysis provides evidence of the potential for increased use of biomass resources for bioenergy generation in the next decade. However, such increases would come with possible challenges that need to be considered by policymakers to ensure a sustainable future for bioenergy production.

CRediT authorship contribution statement

Ashkan Mirzaee: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ronald G. McGarvey:** Writing

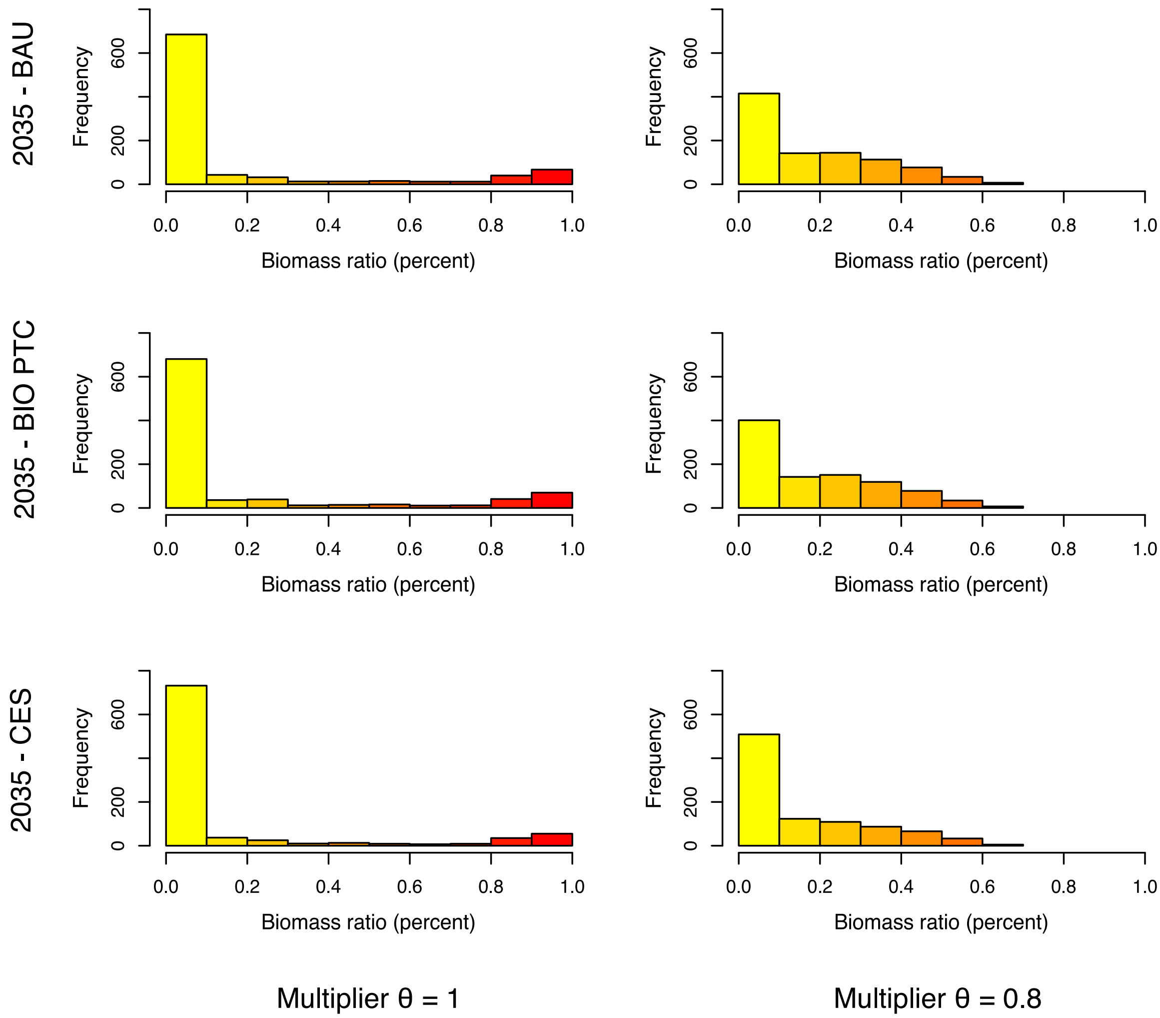

Fig. 9. Analysis areas' biomass ratio frequency under the different scenarios in 2035.

– review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Francisco X. Aguilar:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Code and data availability

Data, results, and graphics that support 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.

Acknowledgments

We thank Dr. Erin Schliep at the University of Missouri's Department of Statistics for her comments and insights throughout the project. We also thank Paul Picciano of Resources for the Future for sharing the E4ST model results with us. This research was partly funded under US Department of Agriculture's National Institute of Food and Agriculture Project Number MO-C00055871, and US Department of Agriculture McIntire-Stennis Project Number MO-NRSL0893. The computation for this work was performed on the high-performance computing infrastructure provided by Research Computing Support Services which is partly funded by the National Science Foundation under Grant number CNS-1429294 at the University of Missouri, Columbia, MO. This publication is not intended to reflect the opinions of these institutions or individuals. Any errors remain the responsibility of the authors.

References

Abt, K.L., Abt, R.C., Galik, C.S., Skog, K.E., 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, vol. 202, U.S. Department of Agriculture Forest Service, Southern Research Station, p. 33. http://dx.doi.org/10.2737/SRS-GTR-202.

Aguilar, F.X., Goerndt, M.E., Song, N., Shifley, S., 2012. Internal, external and location factors influencing cofiring of biomass with coal in the US northern region. Energy Econ. 34 (6), 1790–1798. http://dx.doi.org/10.1016/j.eneco.2012.07.005.

Aguilar, F.X., Mirzaee, A., McGarvey, R.G., Shifley, S.R., Burtraw, D., 2020. Expansion of US wood pellet industry points to positive trends but the need for continued monitoring. Sci. Rep. 10 (1), 18607. http://dx.doi.org/10.1038/s41598-020-75403-z.

Aguilar, F.X., Sudekum, H., McGarvey, R., Knapp, B., Domke, G., Brandeis, C., 2022. Impacts of the US southeast wood pellet industry on local forest carbon stocks. Sci. Rep. 12 (1), 19449. http://dx.doi.org/10.1038/s41598-022-23870-x.

Álvarez-Miranda, E., Garcia-Gonzalo, J., Ulloa-Fierro, F., Weintraub, A., Barreiro, S., 2018. A multicriteria optimization model for sustainable forest management under climate change uncertainty: An application in Portugal. European J. Oper. Res. 269 (1), 79–98. http://dx.doi.org/10.1016/j.ejor.2017.04.052.

Amigues, J.P., Moreaux, M., 2019. Competing land uses and fossil fuel, and optimal energy conversion rates during the transition toward a green economy under a pollution stock constraint. J. Environ. Econ. Manage. 97, 92–115. http://dx.doi.org/10.1016/j.jeem.2019.03.006.

Ansari, J., Davis, M.P., Anderson, S.H., Eivazi, F., Bardhan, S., 2023. Greenhouse gas emissions from row crop, agroforestry, and forested land use systems in floodplain soils. Water Air Soil Pollut. 234 (4), 227. http://dx.doi.org/10.1007/s11270-023-06227-6.

Bentley, J.W., Steppleton, C.D., 2013. Southern Pulpwood Production, 2011. U.S. Department of Agriculture Forest Service, Southern Research Station, p. 38, URL: https://www.fs.usda.gov/treesearch/pubs/43626.

Bentsen, N.S., Jack, M.W., Felby, C., Thorsen, B.J., 2014. Allocation of biomass resources for minimising energy system greenhouse gas emissions. Energy 69, 506–515. http://dx.doi.org/10.1016/j.energy.2014.03.045.

Böhringer, C., Rosendahl, K.E., 2022. Europe beyond coal–an economic and climate impact assessment. J. Environ. Econ. Manage. 113, 102658. http://dx.doi.org/10.1016/j.jeem.2022.102658.

Burtraw, D., Krupnick, A., Palmer, K., Paul, A., Toman, M., Bloyd, C., 2003. Ancillary benefits of reduced air pollution in the US from moderate greenhouse gas mitigation policies in the electricity sector. J. Environ. Econ. Manage. 45 (3), 650–673. http://dx.doi.org/10.1016/S0095-0696(02)00022-0.

Chen, Y.H., Lu, S.Y., Chang, Y.R., Lee, T.T., Hu, M.C., 2013. Economic analysis and optimal energy management models for microgrid systems: A case study in Taiwan. Appl. Energy 103, 145–154. http://dx.doi.org/10.1016/j.apenergy.2012.09.023.

Chinese, D., Meneghetti, A., 2005. Optimisation models for decision support in the development of biomass-based industrial district-heating networks in Italy. Appl. Energy 82 (3), 228–254. http://dx.doi.org/10.1016/j.apenergy.2004.10.010.

Cluster, L.H., 2020. University of missouri-columbia. http://dx.doi.org/10.32469/10355/69802.

Dahal, R.P., Aguilar, F.X., McGarvey, R., Becker, D., Abt, K.L., 2020. Localized economic contributions of renewable wood-based biopower generation. Energy Econ. 91, 104913. http://dx.doi.org/10.1016/j.eneco.2020.104913.

De Meyer, A., Cattrysse, D., Van Orshoven, J., 2015. A generic mathematical model to optimise strategic and tactical decisions in biomass-based supply chains (OPTIMASS). European J. Oper. Res. 245 (1), 247–264. http://dx.doi.org/10.1016/j.ejor.2015.02.045.

Dechezleprêtre, A., Nachtigall, D., Venmans, F., 2023. The joint impact of the European union emissions trading system on carbon emissions and economic performance. J. Environ. Econ. Manage. 118, 102758. http://dx.doi.org/10.1016/j.jeem.2022.102758.

Dincer, I., 1999. Environmental impacts of energy. Energy policy 27 (14), 845–854. http://dx.doi.org/10.1016/S0301-4215(99)00068-3.

DOE, 2017. Combined Heat and Power Technology. U.S. Department of Energy, URL: https://www.energy.gov/sites/default/files/2017/12/f46/CHP%20Overview-120817_compliant_0.pdf.

Dundar, B., McGarvey, R.G., Aguilar, F.X., 2016. Identifying optimal multi-state collaborations for reducing CO2 emissions by co-firing biomass in coal-burning power plants. Comput. Ind. Eng. 101, 403–415. http://dx.doi.org/10.1016/j.cie.2016.09.028.

Dundar, B., McGarvey, R.G., Aguilar, F.X., 2021. Optimal multi-state partnerships for woody biomass co-firing incorporating a demand-response function for biomass procurement. Optim. Lett. 16 (3), 821–844. http://dx.doi.org/10.1007/s11590-021-01747-8.

Dwivedi, P., Bailis, R., Bush, T.G., Marinescu, M., 2011. Quantifying GWI of wood pellet production in the southern United States and its subsequent utilization for electricity production in the netherlands/florida. Bioenergy Research 4, 180–192. http://dx.doi.org/10.1007/s12155-010-9111-5.

Dyer, J.M., 2006. Revisiting the deciduous forests of eastern north america. BioScience 56, 341–352. http://dx.doi.org/10.1641/0006-3568(2006)56[341:RTDFOE]2.0.CO;2.

EIA, 2019. The United States Consumed a Record Amount of Renewable Energy in 2019. U.S. Energy Information Administration, URL: https://www.eia.gov/todayinenergy/detail.php?id=45516.

EIA, 2020a. Annual Energy Outlook 2020. U.S. Energy Information Administration, URL: www.eia.gov/aeo.

EIA, 2020b. U.S. energy facts explained. U.S. Energy Information Administration, URL: https://www.eia.gov/energyexplained/us-energy-facts.

EIA, 2021a. Form EIA-923 Detailed Data with Previous Form Data (EIA-906/920). U.S. Energy Information Administration, URL: https://www.eia.gov/electricity/data/eia923.

EIA, 2021b. From EIA-860 Detailed Data with Previous Form Data (EIA-860A/860B). U.S. Energy Information Administration, URL: https://www.eia.gov/electricity/data/eia860.

Ekşioğlu, S.D., Acharya, A., Leightley, L.E., Arora, S., 2009. Analyzing the design and management of biomass-to-biorefinery supply chain. Comput. Ind. Eng. 57 (4), 1342–1352. http://dx.doi.org/10.1016/j.cie.2009.07.003.

EPA, 2021. Renewable Electricity Production Tax Credit Information. U.S. Environmental Protection Agency, URL: https://www.epa.gov/lmop/renewable-electricity-production-tax-credit-information.

FORISK, 2018. U.S. wood bioenergy database: Q1 2018. URL: http://forisk.com.

Goerndt, M.E., Aguilar, F.X., Skog, K., 2013a. Drivers of biomass co-firing in U.S. coal-fired power plants. Biomass Bioenergy 58, 158–167. http://dx.doi.org/10.1016/j.biombioe.2013.09.012.

Goerndt, M.E., Aguilar, F.X., Skog, K., 2013b. Resource potential for renewable energy generation from co-firing of woody biomass with coal in the Northern U.S.. Biomass Bioenergy 59, 348–361. http://dx.doi.org/10.1016/j.biombioe.2013.08.032.

Gray, J.A., Bentley, J.W., Cooper, J.A., Wall, D.J., 2014. United States Department of Agriculture Southern Pulpwood Production, 2014. U.S. Department of Agriculture Forest Service, Southern Research Station, p. 15, URL: https://www.fs.usda.gov/treesearch/pubs/56235.

Gray, J.A., Bentley, J.W., Cooper, J.A., Wall, D.J., 2016. United States Department of Agriculture Southern Pulpwood Production, 2016. U.S. Department of Agriculture Forest Service, Southern Research Station, p. 15, URL: https://www.fs.usda.gov/treesearch/pubs/56531.

Gugler, K., Haxhimusa, A., Liebensteiner, M., 2021. Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables. J. Environ. Econ. Manage. 106, 102405. http://dx.doi.org/10.1016/j.jeem.2020.102405.

Harville, D.A., 1977. Maximum likelihood approaches to variance component estimation and to related problems. J. Am. Stat. Assoc. 72, http://dx.doi.org/10.1080/01621459.1977.10480998.

Hashim, H., Douglas, P., Elkamel, A., Croiset, E., 2005. Optimization model for energy planning with CO2 emission considerations. Ind. Eng. Chem. Res. 44 (4), 879–890. http://dx.doi.org/10.1021/ie049766o.

He, L., English, B.C., Menard, R.J., Lambert, D.M., 2016. Regional woody biomass supply and economic impacts from harvesting in the southern US. Energy Econ. 60, 151–161. http://dx.doi.org/10.1016/j.eneco.2016.09.007.

Henning, D., Amiri, S., Holmgren, K., 2006. Modelling and optimisation of electricity, steam and district heating production for a local Swedish utility. Eur. J. Oper. Res. 175 (2), 1224–1247. http://dx.doi.org/10.1016/j.ejor.2005.06.026.

Hu, M.C., Lin, C.H., Chou, C.A., Hsu, S.Y., Wen, T.H., 2011. Analysis of biomass co-firing systems in Taiwan power markets using linear complementarity models. Energy Policy 39 (8), 4594–4600. http://dx.doi.org/10.1016/j.enpol.2011.04.062.

Johnson, T.G., Steppleton, C.D., 2007. United States Department of Agriculture Southern Pulpwood Production, 2005. U.S. Department of Agriculture Forest Service, Southern Research Station, p. 42, URL: https://www.fs.usda.gov/treesearch/pubs/27728.

Johnson, T.G., Steppleton, C.D., Bentley, J.W., 2010. United States Department of Agriculture Southern Pulpwood Production, 2008. U.S. Department of Agriculture Forest Service, Southern Research Station, p. 42, URL: https://www.fs.usda.gov/treesearch/pubs/34565.

Kang, J., Ng, T.S., Su, B., 2020. Optimizing electricity mix for CO2 emissions reduction: A robust input-output linear programming model. European J. Oper. Res. 287 (1), 280–292. http://dx.doi.org/10.1016/j.ejor.2020.04.026.

Kim, J., Realff, M.J., Lee, J.H., Whittaker, C., Furtner, L., 2011. Design of biomass processing network for biofuel production using an MILP model. Biomass Bioenergy 35 (2), 853–871. http://dx.doi.org/10.1016/j.biombioe.2010.11.008.

Krajnc, N., 2015. Wood Fuels Handbook. FAO, URL: http://large.stanford.edu/courses/2017/ph240/timcheck1/docs/fao-krajnc-2015.pdf.

Liu, Z., Altman, I., Johnson, T.G., 2014. The feasibility of co-firing biomass for electricity in Missouri. Biomass Bioenergy 69, 12–20. http://dx.doi.org/10.1016/j.biombioe.2014.06.020.

Mao, B., Shawhan, D., Zimmerman, R., Yan, J., Zhu, Y., Schulze, W., Schuler, R., Tylavsky, D., 2016. The engineering, economic and environmental electricity simulation tool (E4ST): Description and an illustration of its capability and use as a planning/policy analysis tool. In: 2016 49th Hawaii International Conference on System Sciences. HICSS, IEEE, pp. 2317–2325. http://dx.doi.org/10.1109/HICSS.2016.290.

Mirzaee, A., 2021. A python API for accessing forest inventory and analysis (FIA) database in parallel. http://dx.doi.org/10.6084/m9.figshare.14687547.

Mirzaee, A., McGarvey, R.G., Aguilar, F.X., Schliep, E.M., 2022. Impact of biopower generation on eastern US forests. Environ. Dev. Sustain. 1–19. http://dx.doi.org/10.1007/s10668-022-02235-4.

NREL, 2008. Strategies for Heating with Woody Biomass. URL: https://www.nrel.gov/docs/gen/fy09/42857.pdf,

Omu, A., Choudhary, R., Boies, A., 2013. Distributed energy resource system optimisation using mixed integer linear programming. Energy Policy 61, 249–266. http://dx.doi.org/10.1016/j.enpol.2013.05.009.

Pedišius, N., Praspaliauskas, M., Pedišius, J., Dzenajavičienė, E.F., 2021. Analysis of wood chip characteristics for energy production in Lithuania. Energies 14 (13), 3931. http://dx.doi.org/10.3390/en14133931.

Perez-Verdin, G., Grebner, D.L., Sun, C., Munn, I.A., Schultz, E.B., Matney, T.G., 2009. Woody biomass availability for bioethanol conversion in Mississippi. Biomass Bioenergy 33 (3), 492–503. http://dx.doi.org/10.1016/j.biombioe.2008.08.021.

Peters, M.P., Iverson, L.R., 2019. Projected Drought for the Conterminous United States in the 21st Century. U.S. Department of Agriculture, URL: https://www.fs.usda.gov/research/treesearch/59161.

Picciano, P., Aguilar, F.X., Burtraw, D., Mirzaee, A., 2022. Environmental and socio-economic implications of woody biomass co-firing at coal-fired power plants. Resour. Energy Econ. 101296. http://dx.doi.org/10.1016/j.reseneeco.2022.101296.

Picciano, P., Rennert, K., Shawhan, D., 2020. Two key design parameters in clean electricity standards. URL: https://media.rff.org/documents/IB_20-03.pdf.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., Team, R.C., 2014. nlme: Linear and nonlinear mixed effects models. 3, p. 117, R package version. URL: https://cran.r-project.org/web/packages/nlme/nlme.pdf.

Piva, R.J., Bentley, J.W., Hayes, S.W., 2014. National Pulpwood Production, 2010. U.S. Department of Agriculture, Forest Service, Northern Research Station, p. 74. http://dx.doi.org/10.2737/NRS-RB-89.

R, 2021. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL: https://www.r-project.org.

Röder, M., Whittaker, C., Thornley, P., 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. http://dx.doi.org/10.1016/j.biombioe.2015.03.030.

Saunders, A.M., Aguilar, F.X., Dwyer, J.P., Stelzer, H.E., 2012. Cost structure of integrated harvesting for woody biomass and solid hardwood products in southeastern Missouri. J. Forestry 110 (1), 7–15. http://dx.doi.org/10.5849/jof.10-072.

Shawhan, D.L., Picciano, P.D., 2019. Costs and benefits of saving unprofitable generators: A simulation case study for US coal and nuclear power plants. Energy Policy 124, 383–400. http://dx.doi.org/10.1016/j.enpol.2018.07.040.

Shawhan, D.L., Taber, J.T., Shi, D., Zimmerman, R.D., Yan, J., Marquet, C.M., Qi, Y., Mao, B., Schuler, R.E., Schulze, W.D., et al., 2014. Does a detailed model of the electricity grid matter? Estimating the impacts of the Regional Greenhouse Gas Initiative. Resour. Energy Econ. 36 (1), 191–207. http://dx.doi.org/10.1016/j.reseneeco.2013.11.015.

Soliño, M., Oviedo, J.L., Caparrós, A., 2018. Are forest landowners ready for woody energy crops? Preferences for afforestation programs in Southern Spain. Energy Econ. 73, 239–247. http://dx.doi.org/10.1016/j.eneco.2018.05.026.

Susaeta, A., Lal, P., Alavalapati, J., Mercer, E., 2011. Random preferences towards bioenergy environmental externalities: A case study of woody biomass based electricity in the Southern United States. Energy Econ. 33 (6), 1111–1118. http://dx.doi.org/10.1016/j.eneco.2011.05.015.

U.S. Census Bureau, 2020a. Cartographic boundary files. URL: https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.

U.S. Census Bureau, 2020b. County population totals. URL: https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-total.html.

U.S. Drought Monitor, 2021. GIS data files. URL: https://droughtmonitor.unl.edu.

USDA, 2021a. Crop Acreage Data. U.S. Department of Agriculture, URL: https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data.

USDA, 2021b. Forest Inventory and Analysis National Program. U.S. Department of Agriculture, URL: https://www.fia.fs.usda.gov/tools-data.

USDA, 2021c. U.S. forest change assessment viewer (ForWarn). U.S. Department of Agriculture, URL: https://forwarn.forestthreats.org/fcav2.

USDA, 2021d. USDA Agricultural Projections to 2030. U.S. Department of Agriculture, URL: https://www.ers.usda.gov/webdocs/outlooks/100526/oce-2021-1.pdf.

USDOT, 2019. Major Ports. U.S. Department of Transportation, URL: https://data-usdot.opendata.arcgis.com/datasets/major-ports.

Vespa, J., Armstrong, D.M., Medina, L., 2018. Demographic Turning Points for the United States: Population Projections for 2020 to 2060. U.S. Department of Commerce, Economics and Statistics Administration, URL: https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf.

Wooldridge, J.M., 2020. Introductory Econometrics: A Modern Approach, seventh ed.