Optimal Scale of Carbon-negative Energy Facilities

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Abstract

Bioenergy with Carbon Capture and Storage (BECCS) may be one of the few cost-effective carbon-negative electricity technologies, but little work has focused on design of such systems. BECCS, like other bioenergy facilities, will likely exhibit economies of scale in capital costs, but diseconomies of scale in biomass transportation and supply costs. In this paper we develop a spatially explicit optimization framework to characterize the drivers of optimal sizing for potential BECCS facilities in Illinois. The approach leverages county-level biomass supply data, detailed road transportation networks,

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1 existing technology cost estimates, and previous geologic characterizations of long-term
2 CO₂ storage. Optimal scales are an order of magnitude larger than proposed scales found
3 in existing literature. Biomass supply, scaling exponents, and technology costs are large
4 drivers of optimal scale, while facility location, pretreatment options, and transportation
5 costs are less important. When choosing between multiple facility locations, economies
6 of scale support a centralized BECCS infrastructure. Deviations from optimal scaled size
7 have little effect on overall systems costs – suggesting that other factors, including
8 regulatory, political, or logistical considerations, may ultimately have a greater influence
9 on plant size than the techno-economic factors we consider here.

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12 **Keywords:** Bioenergy with Carbon Capture and Storage (BECCS), Carbon dioxide
13 removal (CDR), Optimization, Optimal Scale, Carbon-negative energy
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1. Introduction

The urgency of climate change has led to societal pressure not only for technologies that reduce CO₂ emissions, but also those that can reduce the net amount of CO₂ in the atmosphere [1] [2] [3][4]. These technologies, collectively referred to as Carbon Dioxide Removal (CDR) options, include direct air capture of CO₂, biochar, afforestation, soil carbon sequestration, ocean fertilization, and bioenergy with carbon capture and sequestration (BECCS) [5][6]. Deploying BECCS results in a net reduction in atmospheric carbon, and may be an important technology for dealing with abrupt climate change [7]. Currently, BECCS is being deployed at commercial scale in ethanol production and waste incineration facilities [8][9]. Previous work, primarily using Integrated Assessment Models (IAMs), has identified the critical role of BECCS in long-term climate change mitigation, particularly should carbon-negative technologies be required [3][4] [10][11]. Additionally, recent work exploring BECCS deployment in low-carbon power systems indicates that BECCS could be a key technology for aggressive decarbonization in pre-2050 timeframes [12][13]. This work, however, has not focused on practical design issues for BECCS facilities, including systems scale.

Bioenergy facilities, including BECCS facilities, likely exhibit economies of scale in capital costs, but diseconomies of scale in biomass transportation and supply costs [14]. The intuition behind capital cost economies of scale is that the capacity of different plant components (e.g., boilers) is a function of volume, while the cost of these components is a function of the material involved, which will scale at a rate closer to the component surface area. For a perfect sphere, volume grows as a cubic function of radius while surface area grows quadratically, so facility capital costs exhibit economies of scale. In

1 contrast, transport costs exhibit diseconomies of scale because as plant capacity
2 increases, feedstock must be hauled from longer distances. Profit-maximizing or cost-
3 minimizing producers must also buy more expensive sources of biomass to satisfy plant
4 demand. Probing these tradeoffs results in an optimal scale for BECCS facilities, which
5 minimize average costs for a single facility, or total costs for a portfolio of facilities.
6 Previous high-resolution modeling of BECCS deployment has treated BECCS capital
7 costs as linear, despite the likelihood of non-linear costs [12].

8 Two key factors affecting optimal scale are biomass availability and cost. Estimates
9 of lignocellulosic feedstock supply for bioenergy production are influenced by
10 assumptions about available land, diet, population, and yield increases [15]. Additional
11 constraints include water availability and competing demands for land [16][17]. The
12 spatial distribution and cost of bioenergy resources have been estimated via a variety of
13 methods, resulting in detailed inventories in the continental United States [18]. These
14 publicly available biomass inventories can promote transparency and consistency in
15 biomass and bioenergy analysis.

16 Biomass is less energy-dense and more spatially distributed than fossil fuels or other
17 forms of renewable energy such as solar and wind, increasing the importance of
18 management and logistics in cost-effective bioenergy supply. Optimization via linear
19 programming, non-linear programming, and mixed-integer linear programming can help
20 design bioenergy supply chains subject to constraints on supply and sustainability [19]. In
21 this paper we use large spatial datasets to characterize the drivers of optimal sizing, both
22 for a single facility and multiple facilities. This framework can be applied to a broad
23 range of bioenergy technologies, including BECCS, and to diverse geographic areas.

1 We then apply this framework to optimally size BECCS facilities in Illinois,
2 leveraging county-level biomass supply data, detailed road transportation networks,
3 existing technology cost estimates, and previous geologic characterizations for long-term
4 CO₂ storage. Illinois contains relatively plentiful low-carbon biomass resources from
5 corn stover and other crop residues, as well as excellent geologic sequestration potential
6 for CO₂ in the Illinois Basin [20]. For example, the Illinois Industrial Carbon Capture and
7 Storage Project in Decatur, IL is one of the first commercial applications of BECCS in
8 the world [21]. Several other commercial-scale CCS projects, such as the FutureGen Coal
9 CCS facility in Meredosia, IL, are being planned around the state [22]. As of 2010,
10 Illinois contained six paper mills, presenting further options for bioenergy integration
11 [23].

12 Our study is novel in several respects. First, we focus on BECCS, an emerging
13 bioenergy technology for climate change mitigation, which has not been subject to
14 detailed examination of practical design issues. Second, we develop a spatially-explicit
15 model for optimal scale, which leverages publicly available biomass supply and
16 transportation databases. Relatively few studies have studied economies-of-scale in a
17 spatially-explicit context. Those that have rely on self-generated, rather than publicly
18 available, biomass availability and cost estimates, and have studied conventional, rather
19 than emerging, biomass facilities [24][25].

20 We focus on BECCS systems for electricity production. Biomass can be converted to
21 electricity via two methods: 1) direct combustion, and 2) gasification [26]. Different
22 conversion methods have varying degrees of permanence, CO₂ fixation efficiency, and
23 technical potential, with important implications for climate change mitigation [27].

BECCS for electricity can proceed via post-combustion capture, pre-combustion capture, or oxycombustion processes [28]. BECCS can also proceed via ethanol, gasoline, diesel, or biogas production [17][29][30][31]. BECCS for fuel or chemicals production can occur on biochemical or thermochemical conversion processes [32].

Using Illinois as a case study, we find optimal scale for several BECCS technologies, biomass availability scenarios, locations, capital cost scaling parameters, and transportation cost scenarios. We characterize the sensitivity of cost to scale. We also find the optimal scales of multiple facilities across Illinois. Our results highlight the importance of economies of scale for BECCS system design, with implications for entrepreneurs, power plant designers, policymakers, and power system planners.

2. Materials and Methods

2.1. Problem Statement

2.1.1. Multiple facility case

Our first formulation of the optimization problem minimizes the net present value (NPV) of the total cost (\$) of operating a set of BECCS facilities over the entire project lifetime (Table 1a). Costs include capital, variable operations and maintenance (O+M), fixed O+M, biomass purchase, fixed transportation, and variable transportation costs. Our problem is constrained by county-level biomass availability, and a constraint ensuring that sufficient biomass is delivered to meet expected electricity demand at the facility (Table 1b). We also enforce a constraint on the minimum size of the sum of the portfolio of BECCS facilities; this constraint can be interpreted as a total size goal, or portfolio standard, for a set of facilities throughout the study area.

1 This optimization problem chooses the size (S) of a set of potential facilities at
2 several different locations, as well as biomass supplied from each county to each location
3 (A), that minimizes total costs, subject to constraints. Decision variables include the size,
4 S, of each facility, and amount of biomass supplied, A, from each county to each facility
5 to satisfy demand. Capital costs are determined using a scaling parameter, $\alpha \leq 1$, which
6 represents economies of scale. Biomass price, P, is a function of biomass supplied (A).
7 Our sets include counties with available biomass, c, and a set of facility locations, l.

8 (a)

Objective function: minimize total cost (\$2014)			
Generation	Capital	$\sum_l \left(\frac{S_l}{S_0}\right)^\alpha S_0 * C_{cap}$	Capital costs incurred for installing capacity at location l are calculated as the ratio of generator size in S_l to the base size, S_0 , raised to a scaling exponent, α , and multiplied by the base capital cost of generation, $S_0 * C_{cap}$. Costs are annualized over the plant lifetime.
	Fixed	$+ \sum_l S_l * C_{fixed\ o+m}$	Fixed operation and maintenance costs paid for plant in location l are calculated as the total generation capacity of the plant, multiplied by the recurring fixed costs $C_{fixed\ o+m}$.
	Variable	$+ \sum_l S_l * C_{var\ o+m} * t_{op}$	The variable costs paid for operating plant in location l are calculated from the power output in MWh, $S_l * t_{op}$, multiplied by the variable costs associated with the generator, $C_{var\ o+m}$.
Biomass	Feedstock	$+ \sum_c A_c * P_c(A)$	The cost of biomass feedstock in each county c is calculated as the product of the amount of biomass sourced from each county, A_c , and the county-level price for biomass, P_c . Price is represented as a one- or two-stage exponential function of biomass sourced in each county (Eqs. 1 and 2). Sufficient biomass must be sourced to satisfy demand for input energy at each location.
	Fixed	$+ \sum_{c,l} A_{c,l} * T_{fixed}$	Fixed biomass transportation costs are calculated as the product of the total amount of biomass transported from each county c to each location l , $A_{c,l}$, and the fixed transportation cost T_{fixed} .
	Variable	$+ \sum_{c,l} A_{c,l} * T_{c,l\ var}$	Variable biomass transportation costs are calculated as the product of the amount of biomass transported from each county c to each location l , $A_{c,l}$, and the variable transportation cost $T_{c,l\ var}$. Variable transportation costs are found using road transportation distances.

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1 (b)

Constraints	
$\sum_l A_{c,l} \leq A_{c,max}$	Biomass availability. The amount of biomass delivered from each county c to each location l , $A_{c,l}$, must be less than or equal to the maximum amount of biomass available in each county, $A_{c,max}$.
$\sum_c A_{c,l} * (1 - storage\ loss) \geq S_l * \frac{t_{op} * heat\ rate * availability}{energy\ content\ per\ ton}$	Demand for biomass. The amount of biomass delivered from each county c to each location l , $A_{c,l}$, must be greater than or equal to the amount of biomass demanded at each location. Biomass demand is derived from the scaled size, S_l , time in operation, heat rate, and energy content of biomass.
$\sum_l S_l \geq S_{min}$	Scaled size goal. The sum of scaled sizes at all locations, S_l , must be greater than or equal to a specified scaled size goal, S_{min} .

2 Table 1. (a) Objective function and (b) constraints for total cost problem (multiple facility case).
 3 Objective for average cost problem can be found by dividing by the scaled size, S_l . Constraints for average
 4 cost problem are identical, except there is no scaled size goal.

5 2.1.2. Single facility case.

6 Our second optimization problem minimizes the NPV of the average cost (\$/W) of
 7 operating a BECCS facility at a given location over the entire project lifetime. For a fixed
 8 capacity factor, minimizing capacity and energy are equivalent. This “average cost”
 9 minimization problem determines the optimal scale of a single BECCS facility. This
 10 framework is similar to prior studies of optimal scale for bioenergy facilities that are not
 11 spatially explicit [33] [34] [14]. Constraints are identical to the multiple facility case,
 12 except no scaled size goal is enforced. We restrict our set of facility locations, l , to a
 13 single facility. Decision variables and parameters are identical between the two
 14 optimization problems.

15 2.2. Data Sources and Parameters

1 We leverage advances in public spatial databases to obtain model inputs, focusing on
2 the State of Illinois. County-level biomass price and availability has been documented for
3 several lignocellulosic feedstocks in the continental United States as part of the 2011
4 Billion Ton Study Update (BTS) [18]. The BTS represents economically recoverable
5 biomass resources from agricultural residues, wastes, forest residues, and dedicated
6 energy crops. BTS data includes price and quantity of available biomass by feedstock
7 type at different price points, which can form the basis of county-level biomass supply
8 curves. In particular, the BTS estimates the costs of harvesting, collection, and
9 transportation to the roadside or farmgate. It does not estimate additional handling,
10 processing, transportation, or storage costs. We characterize biomass availability for 102
11 Illinois counties, disregarding available biomass supply in neighboring states. Biomass in
12 neighboring states might be reserved for other facilities or applications.

13 We develop three biomass availability scenarios: a base supply case, an expanded
14 supply case, and a high price case. Our base supply case includes biomass from
15 agricultural residues and waste streams, including corn stover, wheat straw, unused
16 primary mill residues, and urban wood wastes. Total available supply for our base case is
17 sufficient for 3112 MW in capacity (electricity output, throughout this paper) under
18 assumed energy content, losses, and heat rates for an integrated gasification combined
19 cycle facility with carbon capture and sequestration (IGCC-CCS). Maximum county-
20 level availability is shown in Fig. 1. Our base supply case does not account for biomass
21 competition from lignocellulosic biorefineries, or other other uses of available biomass
22 [35]. We assume that biomass is dried prior to transport to the facility in our base case.

Figure 1. County supply limit (10^5 bone dry ton biomass), and potential facility locations in Illinois for base case scenario.

Our expanded supply case also includes woody biomass from forests, annual energy crops, perennial grasses, and logging residues. These feedstocks, especially energy crops used on primary agricultural land, may entail higher sustainability risks [16] [18]. Our high price case, used for sensitivity analysis, doubles the price of available biomass from the base supply case. This case may represent increased competition for biomass, or higher costs for biomass production, harvesting, and collection.

To ensure differentiability of our objective function, we fit county-level biomass availability using a single-term (Eq. 1) or two-term (Eq. 2) exponential model. We employ MATLAB Curve Fitting Toolbox, and chose the exponential form for each county that maximizes the coefficient of determination (r^2). Biomass price is well-

1 represented by this functional form; most counties have $r^2 \geq .85$. We assume that all
2 biomass consumed in each county sells for a uniform price determined by the marginal
3 cost of biomass. This is consistent with a horizontal integration structure, where plant
4 operators purchase biomass from producers in each county.

$$P_c(A) = C_1 e^{C_2 A} \quad (\text{Eq. 1})$$

6 or

$$P_c(A) = C_1 e^{C_2 A} + C_3 e^{C_4 A} \quad (\text{Eq. 2})$$

8 We choose candidate locations for BECCS facilities in identical locations to
9 existing or planned CO₂ injection locations in Illinois (Fig. 1). Much of the state of
10 Illinois is located on the Illinois Basin, a geological basin with large potential for long-
11 term CO₂ storage, which also underlies western Indiana and western Kentucky. For the
12 (single site) average cost optimization problem and most of our sensitivity analyses, we
13 use Decatur, IL. Decatur is the location of the Illinois Industrial Carbon Capture and
14 Storage Project, an existing BECCS facility producing ethanol, and is close to the
15 geographic center of the State [21]. This project is storing biogenic CO₂, a byproduct of
16 industrial fermentation, in the Mt. Simon Formation, a deep saline aquifer.

17 For the total cost optimization problem (which allows for more than one site) we
18 use four additional facility locations: Meredosia, Taylorville, Loudon, and Tanquary.
19 Meredosia, IL is the site of the proposed FutureGen Coal oxycombustion CCS facility
20 located in Morgan County [22]. Taylorville was the location of a proposed IGCC-CCS
21 facility in Christian County, with CO₂ storage in the Mt. Simon Formation [36]. Loudon
22 Field is located Fayette County, has been tested for enhanced oil recovery (EOR)
23 potential by the Midwest Geological Sequestration Consortium (MGSC) [37]. Tanquary

1 Farms, located in Wabash County in Southwestern, IL, has been tested for enhanced coal
2 bed methane recovery via CO₂ injection by the MGSC. MGSC has also overseen
3 injection for the Decatur Illinois Industrial Carbon Capture and Storage Project. Projects
4 in these locations should be able to leverage geologic characterization and monitoring
5 planned for these injections, while minimizing transportation distance for CO₂. Pulp and
6 paper mills are also strong candidates for BECCS facilities, as they can increase scale.
7 However, mill capacities are not publicly available. This data limitation hinders our
8 ability to consider co-location of existing paper mills and BECCS.

9 We consider three scenarios for transportation costs: a base, low-cost, and high-
10 cost scenario. Fixed and variable biomass transportation costs are drawn from existing
11 literature [38] [39] [14]. We employ the Google Maps API to find optimal transportation
12 distances between the geographic center of each of Illinois' 102 counties and our project
13 facility locations, minimizing transport time. These distances are used to calculate
14 variable transportation costs in our objective function.

15 We also consider several variations in biomass pretreatment. As mentioned
16 previously, we assume that biomass is dried prior to transport to the facility in our base
17 case. For sensitivity, we consider two variations. First, we assume that biomass is dried at
18 the final facility location, and is transported prior to drying. Here, we assume a moisture
19 content of 20%, a central estimate for biomass in [39]. Second, we consider pelletization
20 technology, which can reduce biomass transportation costs. We derive shipping cost
21 reductions based on changes in density, and calculate pelletization costs for a stationary
22 pelletization facility. Specifically, we assume that pelletization incurs a variable cost of
23 \$43/ton-yr, based on [40].

1 We identify base costs, heat rates, and base sizes for several BECCS technology
2 configurations, including pre-combustion capture (IGCC-CCS), oxycombustion, and
3 post-combustion capture [41] [42] [28]. Our base scenario, upon which sensitivity
4 analysis is performed, assumes IGCC-CCS technology with a capital cost of 5,795 \$/kW
5 (2014\$) and base size of 262.46 MW. These costs, along for those for oxycombustion
6 and post-combustion capture, and derived from the National Energy Technology
7 Laboratory (NETL) [27] [28]. We also consider a low-cost IGCC scenario, with a capital
8 cost of 2,089 \$/kW and base size of 123 MW, based on estimates from Carnegie Mellon
9 University [19]. We assume that heat rate does not vary with scale.

10 We vary the capital cost scaling exponent parametrically across values found in
11 existing literature. Chemical industry scaling exponents demonstrate a central tendency
12 around .6, which we treat as our lower bound in study [33]. Such an estimate, however,
13 may not hold for BECCS facilities. Gallagher et al., for example, reports a capital cost
14 scaling factor of 0.86 for the U.S. dry mill ethanol industry, while others report values
15 between .7-.9 [43] [44]. Scaling exponents for coal-fired power plants and nuclear plants
16 in the United States have been found to be as high as .93-.94 [45] [34]. We set our base
17 capital cost scaling exponent as .8, and vary this parameter between .6 and .95 for single
18 site sensitivity analysis.

19 Several other parameters are fixed for the purposes of this study. We assume a
20 plant life of 20 years, a discount rate of .1, and set 2014 as the base year for our study. All
21 plants operate with a capacity factor of .85, a typical value for baseload plants. Carbon
22 prices may need to rise to sufficient levels to justify baseload operation for BECCS

plants. We assume a mean biomass energy content of 18 MMBtu / BDT [46]. We set biomass storage losses at 5%, based on existing literature [47].

We calculate implied carbon abatement cost and levelized cost of electricity (LCOE) for our facilities. LCOE is calculated over the entire plant lifetime assuming no revenues from carbon prices. For our base abatement costs, we define the carbon abatement cost as the necessary carbon price (\$/tCO₂) to compensate for the difference between current average marginal prices in central Illinois, and plant LCOE (Eq. 3).² We assume that BECCS displaces electricity from a modern coal steam turbine with emissions intensity of .86 tCO₂/MWh. BECCS facilities are compensated both from electricity displacement (which we reason would come from an increased marginal electricity price) and geologic sequestration of CO₂.

Implied Carbon Abatement Cost =

$$\frac{\text{Plant LCOE} - \text{Average Marginal Price}}{\text{Carbon Intensity}_{\text{Displaced Electricity}} + \text{Carbon Stored}_{\text{Produced Electricity}}} \quad (\text{Eq. 3})$$

We also consider several sensitivity cases for our implied carbon abatement costs. First, we calculate long-run abatement costs from displacement of electricity from coal IGCC-CCS facilities in Illinois. Costs and performance for these facilities are estimated by NETL [42]. Second, we evaluate carbon abatement costs for displacement of combined cycle gas turbines (CCGTs), with emissions intensity of .36 tCO₂/MWh, at current average marginal prices. Finally, we calculate abatement costs assuming non-zero lifecycle emissions from biomass. Here, we assign a lifecycle emissions penalty from biomass at 10% of its biogenic carbon content, as in [12].

² Data obtained from Midcontinent Independent Storage Operator (MISO), at: <https://www.misoenergy.org/Library/MarketReports/Pages/MarketReports.aspx>. For our implied cost of carbon calculations, we use the mean locational marginal price (LMP) between July and September, 2014, in Central Illinois, \$29.74/MWh.

Finally, we perform a partial lifecycle analysis (LCA), focusing on transportation emissions. We assume a transportation emissions factor of 161.8 gCO₂/ton-mi, as in [48]. Our supply curves contain several classes of biomass feedstock, which limits our ability to include other sources of emissions, including land use change, below-ground sequestration, growth, or harvest.

2.3. Solution Method

This problem is non-convex. The objective function includes a number of terms that are linear in facility size but also a concave term (capital cost of capacity scales to the power $\alpha < 1$) and a summation of convex terms (biomass feedstock costs increase exponentially with quantity). In general, it is not possible to ensure global optima from non-convex problems [49]. To identify optima, we apply gradient-based methods for inequality-constrained, differentiable, non-linear programs from starting points across the feasible region [50]. Starting points include a range of facility sizes, between 0 and 3100 MW, and county-level feedstock allocations sufficient to meet demand. By comparing several different local optima, we are able to approach global optimality. Novel algorithms for non-convex optimization are currently under research, and can be applied to this problem in the future [51]. We use the NEOS server, a free internet-based service for solving numerical optimization problems, to find solutions [52] [53] [54]. Our problem is written in AMPL, an algebraic modeling language for optimization [55].

3. Results and Discussion

3.1. Single facility case.

Optimal scales are an order of magnitude larger than proposed scales found existing literature. We identify an optimal scale of 2713 MW (electricity) for the single IGCC-

CCS facility case (Decatur, IL), for our base inputs. The facility produces carbon-negative electricity at a price of \$142/MWh, with an implied carbon abatement cost of \$59/tCO₂. This scale is about ten times larger than the proposed base facility size reported by NETL [42]. This suggests that BECCS facilities could be larger than previously assumed.

This BECCS facility consumes 87% of available biomass in the base case from all counties in the State. Highest levels of normalized consumption (the ratio of consumed biomass to available biomass) occur near the facility location in Decatur (Fig. 2a). Normalized consumption has considerable range, between 40-100% of available biomass. Consumption tends to be lowest in counties farthest from the facility, where transportation costs are highest. We observe similar trends in county-level biomass market prices (Fig. 2b). The highest biomass prices occur immediately adjacent to the plant, to its Southeast. Biomass prices tend to be higher in counties near the facility. This is likely due to higher amounts of biomass consumption in those areas, and lower variable transportation costs from these counties, which lowers average costs. Biomass market prices range from \$19-87/BDT across the state. Lowest prices occur in the northeast of the state.

(a)

1

2

(b)

Figure 2. (a) Normalized biomass consumption (values between 0 and 1), and (b) biomass market clearing price (\$/BDT) for Illinois counties for base case in Decatur (scale = 2713 MW).

Deviations from optimal scaled size have little effect on overall systems costs. To test the sensitivity of costs to scale, we fix scale at several values and allow the average cost optimization to determine biomass allocation (Fig. 3). While costs at optimal scale are roughly 24% lower than base costs, reducing LCOE from \$177/MWh to \$143/MWh, costs are relatively insensitive to scale at larger sizes. For example, a plant that is 60% smaller than optimal is only 5% more expensive than optimal. This suggests that non-techno-economic considerations – including investor availability, regulatory institutions, political processes, and public relations issues may ultimately have a strong impact on plant size. Power plant designers may instead wish to focus on practical limitations rather than optimal scale [33].

Figure 3. Difference in cost (% difference from optimal objective) and implied cost of carbon (\$/tCO₂) for different fixed scale sizes in Decatur (base case). Optimal scale is denoted by a star, while base scale is denoted by a circle.

Biomass supply, scaling exponents, and technology costs are large drivers of optimal scale, while facility location, pretreatment, and transportation costs are less important (Fig. 4). Increasing biomass availability (expanded supply case) increases optimal scale to nearly 3500 MW (29% increase), while high biomass prices (high price case) lower scale to 2317 MW (15% decrease). Scale is similarly sensitive to scaling exponents and technology types. Scale exhibits a non-linear response to changes in scaling parameter; increasing the parameter to .95 from .8 decreases scale to 1150 MW (58% decrease), while decreasing the parameter to .6 leads to scale of 2900 MW (7% increase). All other facility types considered in this study—oxycombustion, post-combustion capture, and low-cost IGCC—have lower optimal scale than our base scenario. The low-cost IGCC facility, which is able to capture fewer economies of scale due to its lower cost, has the smallest scale, at 1245 MW. Varying transportation costs from the base scenario affect scale, between 2260-2848MW, but have a smaller effect than other parameters. Similarly, drying at the facility decreases the optimal scale to 2584 MW, while pelletization increases it to 2843 MW. Finally, scale is relatively insensitive to the location of the facility.

Figure 4. Sensitivity of base case to biomass availability, transportation costs, pretreatment options, capital cost scaling parameters, location, and technology type.

Across sensitivity scenarios, LCOE ranges between \$88-176/MWh, while implied carbon abatement cost ranges between \$44-76/tCO₂. Alternative base facility assumptions, including oxycombustion or low-cost IGCC, tend to have the lower carbon abatement costs than our base IGCC-CCS case. Scaling exponents also have a large affect of carbon abatement costs over the range of values tested in this analysis.

Implied carbon abatement costs depend on assumptions about electricity displacement. Long-run abatement costs from displacement of coal IGCC-CCS electricity (LCOE = \$122.5/MWh, emissions intensity = .19 tCO₂/MWh), is only \$16/tCO₂ at optimal scale. However, NETL employs different design considerations and operating cost estimates. For example, NETL identifies minimum biomass costs as \$85/BDT, while

1 we identify biomass prices between \$19-87/BDT in our base case [42]. In contrast, the
2 implied cost of carbon for their base-case BECCS facility (262 MW, \$257/MWh) is
3 \$108/tCO₂, while ours is \$43/tCO₂.

4 Implied carbon abatement costs are also dependent on assumptions of carbon
5 emissions intensity. Non-zero emissions from biomass, as a result of direct and indirect
6 emissions from biomass cultivation, increase abatement costs from coal displacement
7 from \$59 to \$65/tCO₂ at optimal scale, assuming a 10% biogenic emissions penalty.
8 Assuming that BECCS displaces a CCGT instead of coal increases abatement costs to
9 \$80/tCO₂. Future evolution of the electricity sector will have a large effect on abatement
10 costs from BECCS.

11 We find that levelized transportation CO₂ emissions double between our base and
12 optimal scale facilities. Biomass must be transported longer distances as scale increases:
13 as a result, the volume of CO₂ emitted from each ton of delivered biomass increases.
14 Total transportation emissions, however, are relatively small—on the order of 1% of
15 biogenic carbon contained in the biomass.

16 Transportation logistics may present an additional barrier to scale. At our assumed
17 heat rate, a BECCS facility at optimal scale would require nearly 40,000 dry tons/day of
18 biomass. Assuming a truckload of 15 dry tons, this would require the delivery and
19 unloading of nearly 110 trucks each hour. In contrast, NETL limits biomass delivery to
20 5,000 dry tons/day, citing traffic congestion and other barriers to large-scale biomass
21 logistics [42]. At this 5,000 ton limit, facility scale in our analysis would be limited to
22 354 MW. In contrast, advanced transportation logistics, including high-volume biomass

1 railcars, would reduce railcar deliveries to 23 each hour [56]. Pelletization, which we
 2 investigate here, improves transportation logistics for large-scale BECCS facilities.

3 **3.2. Multiple facility case.**

4 When choosing between multiple facility locations, economies of scale lead to a
 5 centralized BECCS infrastructure. That is, across a range of scaled size goals and scaling
 6 parameters, the optimal solution is still a single facility. Here, the total cost minimization
 7 chooses to build facilities in Decatur equal to the scaled size goal. We did not observe
 8 solutions with more than one facility until we increased the capital cost scaling
 9 parameter, α , to greater than .96 (Fig. 5). This result indicates that economies of scale for
 10 BECCS facilities have a larger effect than transportation or biomass costs in the context
 11 of promoting a decentralized BECCS infrastructure. Policymakers considering mandates
 12 for BECCS or other carbon dioxide removal (CDR) technologies should consider this
 13 result in policy design, especially as lower-cost CDR facilities benefit ratepayers.
 14 Similarly, entrepreneurs or power plant designers should consider the benefits of
 15 integration and scale when deploying BECCS.

17 **Figure 5. Scaled size results among potential facility locations at different scaling exponents, α , for a**
 18 **scaled size goal of 2500. A single facility is built in all cases where $\alpha \leq .96$.**

One model enhancement, which we do not attempt here, is to allow for variable, rather than constant, cost scaling, as in Jenkins [34]. Under variable cost scaling, a scaling parameter might increase asymptotically towards 1 with increasing capacity, to reflect increasing constraints or risks with scale. Jenkins, in applying this framework to conventional biopower facilities, finds that variable cost scaling decreases optimal scale 76%, from 1252 MW to 305 MW, under his reference cost and biomass availability assumptions. Given uncertainty about scaling, those implementing BECCS facilities may want to proceed with caution during industry scale up.

Our analysis may underestimate other benefits of decentralized BECCS infrastructure. These include decreased risk, ease of coordination, and impacts on the broader power system. Our results are consistent with other studies of optimal scale for bioenergy facilities, which tend to find optimal scales an order of magnitude larger than existing facilities [33][14].

4. Conclusions

This work has application to entrepreneurs, power plant designers, and power system planners interested in building BECCS facilities. In general, we find that economies of scale support centralized BECCS infrastructure, both when considering a single facility and a portfolio of facilities. This result derives from the fact that, at optimal scales, transportation cost, pretreatment, and location have a small influence on costs. However if biomass supply is constrained due to competition with other uses, such as cellulosic biorefineries, optimal scales will decrease and levelized costs will increase.

Illinois, while an ideal case study for this exercise, contains many characteristics that will lead to larger optimal scales than in other locations. Corn stover is relatively plentiful

1 in the state, and available at lower cost than dedicated feedstocks and some forest
2 products that can be used for BECCS [18]. Illinois roads have low tortuosity, leading to
3 low transportation distances and variable transportation costs, an important diseconomy
4 of scale. Illinois also has plentiful geologic storage capacity, lessening CO₂ transportation
5 costs. While we find that optimal scale is insensitive to location in Illinois, this may not
6 be the case in areas with limited road infrastructure, or where biomass supply and
7 geologic storage are not co-located.

8 Those wishing to implement policy to promote BECCS infrastructure, such as a
9 portfolio standard, should consider large optimal scales in policy design. Mandates for
10 distributed BECCS infrastructure, which may mimic mandates for distributed solar
11 energy or feed-in-tariffs for small bioenergy facilities in the State of California, may
12 sacrifice important economic efficiencies and ratepayer benefits [57][58]. However, there
13 are declining economic returns to increased scale (Fig. 3). Additionally, we find
14 relatively little variation in implied cost of carbon between different facility scales. This
15 is due both to relatively small variation in LCOE, and the large carbon benefit of BECCS
16 over other low-carbon generation options from negative emissions.

17 Though we find that biomass supply, technology cost and cost scaling do have a
18 strong effect on optimal size, we also find that levelized cost and the implied carbon
19 abatement cost are relatively insensitive to deviations from the scaled size. This suggests
20 that regulatory and political factors, transportation logistics, issues of public perception,
21 and financing may ultimately drive what size facilities are built – rather than the techno-
22 economic factors we consider here.

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