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How negative can biofuels with CCS take us and at what cost? Refining the economic potential of biofuel production with CCS using spatially-explicit modeling

Nils Johnson[a,]*, Nathan Parker[b], and Joan Ogden[b]

[a]International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, Laxenburg A-2361, Austria
[b]Institute of Transportation Studies, University of California, Davis, One Shields Avenue, Davis, CA 95616, USA

Abstract

Global integrated assessment models indicate the importance of technologies that can achieve negative emissions in scenarios that limit warming to 2˚C over pre-industrial levels. One of the most promising options for achieving negative emissions is the production of electricity or fuels using biomass coupled with carbon capture and storage (BECCS). Given that the transport sector is relatively difficult to decarbonize, BECCS can be particularly valuable for reducing the carbon intensity of transport fuels. This paper combines spatially-explicit biorefinery siting and CCS infrastructure models to examine the potential for biofuels with CCS in the United States. The outputs provide insight into the optimal deployment of biorefineries with CCS from 2020 to 2050, including an assessment of the magnitude of the required infrastructure and identification of regional storage constraints. Furthermore, the model identifies the average biofuel production cost at each site and develops geospatial supply curves, abatement cost curves, and negative emission potentials for biofuels with CCS over time.

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Keywords: Biofuels; carbon capture and storage (CCS); spatial optimization; geographic information systems (GIS); United States

1. Introduction

To limit global warming to 2˚C over pre-industrial levels, the majority of global integrated assessment models indicate that net anthropogenic CO_2 emissions in the latter part of the 21st century will need to be negative,

* Corresponding author. Tel.: +43-2236-807-490; fax: +43-2236-71313.
E-mail address: johnsonn@iiasa.ac.at

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particularly if stringent climate action is delayed [1-4]. One of the most promising options for achieving negative emissions is the production of electricity or fuels using biomass coupled with carbon capture and storage (BECCS) [5, 6]. Given the importance of this option for achieving the 2˚C target, it is critical that we understand how much BECCS can contribute to negative emissions and at what cost. Although there has been excellent research illustrating the importance of BECCS and quantifying its regional potential at a coarse scale, the opportunity exists to further refine regional potentials and supply curves using spatially-explicit modeling [7].

Given the relative difficulty of mitigating CO_2 emissions in the transport sector, *biofuel* production with CCS is expected to play a significant role in reducing the carbon intensity of liquid transport fuels in 2˚C scenarios. For example, three integrated assessment models in the AMPERE model inter-comparison project indicate that 1-9 EJ and 10-24 EJ of biofuel with CCS will need to be produced in the United States in 2050 and 2100, respectively, if an optimal mitigation pathway is followed to limit warming to 2˚C by 2100 (Fig. 1) [1, 8]. However, questions remain as to whether these biofuel quantities can be produced and what they will cost when the spatial proximity of biomass feedstock, biofuel production, and CO_2 storage is considered. We examine this question by combining a spatially-explicit biorefinery siting model with a spatially-explicit CO_2 transport and disposal model to conduct a case study of the deployment of *biofuel* production with CCS in the United States.

The outputs of the coupled model provide insight into the optimal deployment of biorefineries with CCS in the United States, including an assessment of the magnitude of the required infrastructure and identification of regional storage constraints. Furthermore, the model identifies the average biofuel production cost at each site and, thus, can develop geospatial supply curves and abatement cost curves for biofuels with CCS over time. Using the supply curves, we can then refine the economic potential of biofuels with CCS and identify the potential for negative emissions.

2. Methods

We employ spatially-explicit optimization models for biorefinery siting and CCS infrastructure to study the possible development of biofuel supply with CCS in the US to 2050. Several scenarios are analysed to explore different strategies for implementing biofuels with CCS. The deployment of biofuel with CCS is optimized in 5-year time steps from 2020 to 2050, assuming that all new biofuel production must include CCS starting in 2020. In each time step, deployment is optimized for an exogenously-defined biofuel demand, but is constrained by the infrastructure built in previous time steps, including biorefineries built without CCS prior to 2020[1]. The biofuel demand follows the projection for the U.S. made by the IEA for the 2˚C scenario (2DS) in *Energy Technology Perspectives 2012* (ETP) [9]. The portion of the ETP demand that requires CCS is calculated by subtracting the demand met by plants without CCS, assuming a plant lifetime of 20 years (Fig. 1). This portion of the demand is the biofuel with CCS target in each time step (Table 1).

Table 1: Biofuel with CCS target in each time step

Time Step	Target (EJ/yr)
2020	0.5
2025	1.6
2030	2.3
2035	3.7
2040	5.0
2045	5.8
2050	5.4

[1] In this project, CCS infrastructure is designed to serve biorefineries only and, thus, the transport and storage costs represent an upper estimate given that biorefineries will most likely link into CO_2 storage networks that also serve fossil-based power plants, which could generate significant economies-of-scale. We hope to model all CO_2 sources in subsequent work.

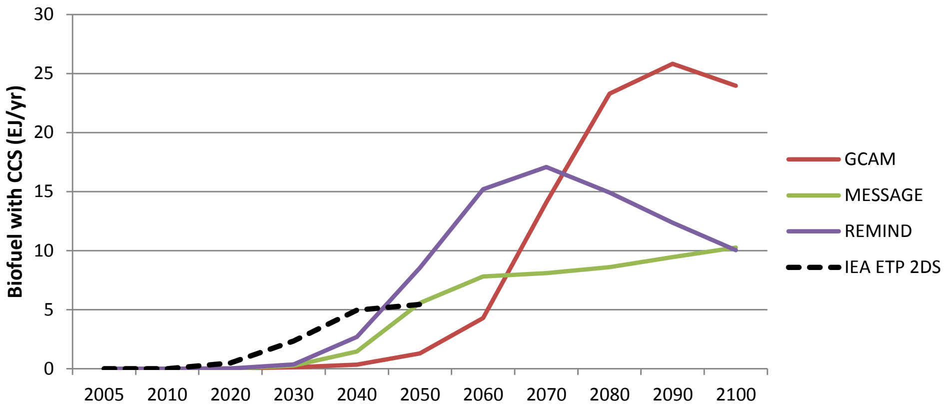

Fig. 1. Biofuel with CCS projections in the United States in a scenario in which an optimal mitigation pathway for limiting warming to 2˚C is achieved (AMPERE2-450-FullTech-OPT). The three models are GCAM (Joint Global Change Research Institute), MESSAGE (International Institute for Applied Systems Analysis), and REMIND (Potsdam Institute for Climate Impact Research). Note that MESSAGE results are for North America while GCAM and REMIND results are for the United States. The IEA ETP values have been adjusted to reflect the portion of biofuel demand that would require CCS under the assumption that all plants built in 2020 and beyond are mandated to include CCS.

Given the biofuel targets from ETP, two distinct scenarios are conducted. The first scenario, entitled "MinCO2", requires *only* that the biofuel with CCS target is met and mimics the case in which policy-makers mandate the addition of CCS to all new biofuel plants, but without providing any incentive for maximizing the CO_2 captured (i.e., no carbon price). As a result, we expect the model to prefer biofuel production technologies that minimize the CO_2 captured per unit of fuel (e.g., ethanol production) since less investment into CCS infrastructure is required. The second scenario, entitled "MaxCO2", requires that the biofuel target is met while maximizing the CO_2 captured per unit of fuel. Consequently, we expect this scenario to prefer Fischer-Tropsch (FT) diesel production since more CO_2 per unit of fuel can be captured. Essentially, this scenario mimics the case in which the carbon price exceeds the levelized cost of CCS (i.e., once producers can make money from each unit of CO_2 captured, they will try to maximize the CO_2 captured per unit of fuel). Thus, for a given biofuel with CCS target, these two scenarios represent the two extremes of CCS infrastructure investment. The first scenario effectively minimizes CO_2 capture, and thus CCS investment, while the second scenario maximizes these parameters. For example, the MaxCO2 scenario captures ~650 Mt CO_2/year in 2050 while the MinCO2 scenario captures ~540 Mt CO_2/year. Consequently, these scenarios provide insight into the types of technologies deployed, the potential for negative emissions, and the cost of mitigating emissions under these extremes.

To optimize the deployment of biofuel production with CCS in each time step, the *Geospatial Bioenergy Systems Model* (GBSM) [10] is first run to identify a set of candidate biorefineries for consideration by the *CCS Deployment Model* [11, 12]. The GBSM uses the location and magnitude of fuel demand and the type, cost, and location of biomass resources to identify the type, location and size of potential biorefineries that can produce biofuels below a threshold price (e.g., \$50/GJ). Upon completion, the GBSM passes the set of candidate biorefineries along with specific attributes (e.g., biofuel and CO_2 capture costs and quantities of biofuel produced and CO_2 captured) to the *CCS Deployment Model*, which then selects the optimal subset of sites that minimize the total system cost, including CCS, while meeting the biofuel and CO_2 capture targets, as applicable. Upon completion, the *CCS Deployment Model* passes files describing the built infrastructure to the next time step to constrain the next round of deployment. The next three sections describe the details of each model and the assumptions used in calculating the biofuel supply, abatement cost, and negative emission curves. All costs are in 2009 U.S. dollars and assume a real discount rate of 10%.

2.1. Geospatial Bioenergy Systems Model (GBSM)

The Geospatial Bioenergy Systems Model uses the spatial variation in feedstock supply, performance of conversion technologies and the logistics of both the feedstock and the product fuel to find configurations of biorefineries across the United States that maximize the total industry profit [10]. The GBSM is formulated as a mixed integer linear programming (MILP) optimization model that is formulated in the General Algebraic Modeling System (GAMS) and solved using CPLEX [13].

2.1.1 Biomass resource assessment

The assessment of biomass resources is a critical input for GBSM. For this study, the biomass resource assessment was drawn from the U.S. Department of Energy's *Billion Ton Update,* which projects biomass supplies at a county-level resolution from 2012 through 2030 [14]. Energy crops and agricultural residues were assessed using an economic model of the U.S. agricultural sector. Some key assumptions in the assessment include yield growth of 1% per year for cellulosic energy crops and residue removal restricted to prevent soil degradation. Biomass from forestry and municipal streams were estimated based on expected activity in those sectors and the cost of accessing the resources generated. The *Billion Ton* assessment was modified to provide continuous monotonic supply curves for each county and each feedstock type. For years beyond the 2030 timeframe, the biomass resource is held constant.

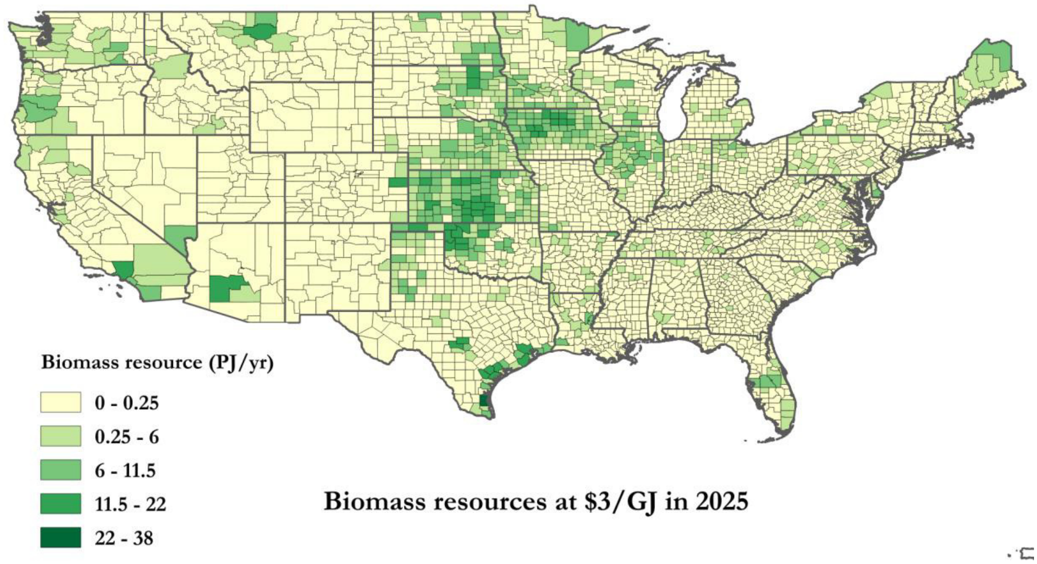

Fig. 2. Biomass resources at $3/GJ in 2025

2.1.2 Biofuel conversion technology performance

The focus of the model is on cellulosic biofuel resources and technologies. Conventional biofuel resources and technologies are included in the analysis to track the contribution of existing facilities to meeting the biofuel targets until they are retired. Cellulosic biofuels offer both the potential for CCS and a large potential resource base. Two cellulosic technologies are considered, lignocellulosic ethanol (LCE) and Fischer-Tropsch diesel (FT-diesel). Pyrolysis technologies were not considered as clean CO_2 streams are not produced in the process.

Table 2: Performance of cellulosic biofuel technologies

Technology	Conversion efficiency	CO_2 capture efficiency
Cellulosic ethanol [15]	33 – 40%*	14%
Fischer-Tropsch diesel [16]	44%	56%

*Cellulosic ethanol conversion efficiency depends on the composition of the biomass

2.2. CCS Deployment Model

The *CCS Deployment Model* is a mixed integer linear programming (MILP) optimization model that is formulated in the General Algebraic Modeling System (GAMS) and solved using CPLEX [13]. It determines the least-cost biofuel and CCS infrastructure that meets the CO_2 capture target (Mt CO_2/year) and/or biofuel with CCS target (EJ/year) [12]. In addition to the candidate biorefineries from the GBSM, the *CCS Deployment Model* requires a candidate CO_2 pipeline network and the locations and capacities of potential storage sites (*NATCARB v.1204*) to optimize the biofuel and CCS infrastructure [17]. The outputs include the number and location of biorefineries, the location, length, and diameter of CO_2 pipelines, and the location, number, and size of injection sites.

2.2.1 Spatial Inputs

The location and characteristics of the 913 candidate biorefineries in the U.S. are provided by the GBSM and include the CO_2 capture potential, biofuel production potential, biofuel production cost, and CO_2 capture cost (Fig. 3). The location and capacity of potential CO_2 injection sites are derived from version 1204 of the national carbon sequestration database and geographic information system (NATCARB) [17]. Potential sites are limited to saline aquifers for this analysis. In the original dataset, storage capacity is identified for each 10 km by 10 km (i.e., 100 km^2) grid cell within each saline aquifer. To make the model tractable, the number of potential injection sites is reduced by aggregating the 100 km^2 grid cells to 100 km by 100 km (i.e., 10,000 km^2) grid cells. The centroids of the 10,000 km^2 grid cells represent the potential injection sites and are assigned the aggregated storage capacity of all 100 km^2 grid cells that they contain. In addition, all centroids within 10 km of urbanized areas and within national parks are moved and all offshore sites in the Gulf of Mexico are deleted because of sufficient onshore potential in the region. In total, 439 potential injection sites are distributed across the U.S. For this study, storage at each injection site is limited to the low storage capacity estimate from NATCARB.

The candidate pipeline network provides the potential linkages between the locations of CO_2 sources (i.e., biorefineries) and sinks (i.e., injection sites). In this project, it is assumed that CO_2 pipelines will follow existing pipeline rights-of-way (ROWs) as defined by the National Pipeline Mapping System (NPMS) dataset [18]. However, this dataset includes all pipelines in the United States and is overly complex for modeling purposes. The candidate pipeline network was developed by removing redundancies and manually simplifying the NPMS dataset so that only ROWs that connect the source and sink locations are retained. In cases where existing pipeline ROWs do not connect to the source or sink nodes, a spur was manually added following major roads. The candidate pipeline network was also modified to reflect the increased cost of pipeline construction in mountainous, offshore, and urban areas. Assuming that construction costs double in these areas and that the construction cost is ~50% of total pipeline installation cost, this additional cost can be included as a 50% increase in pipeline length where a pipeline travels through high cost terrain. Urban terrain is defined by the U.S. Census Bureau's urbanized areas dataset [19] and mountainous terrain is defined as areas with slopes greater than 8% as derived from the U.S. Geological Survey's National Elevation Dataset (NED) [20]. The candidate pipeline length is over 140,000 km in length and includes about 3,900 individual segments.

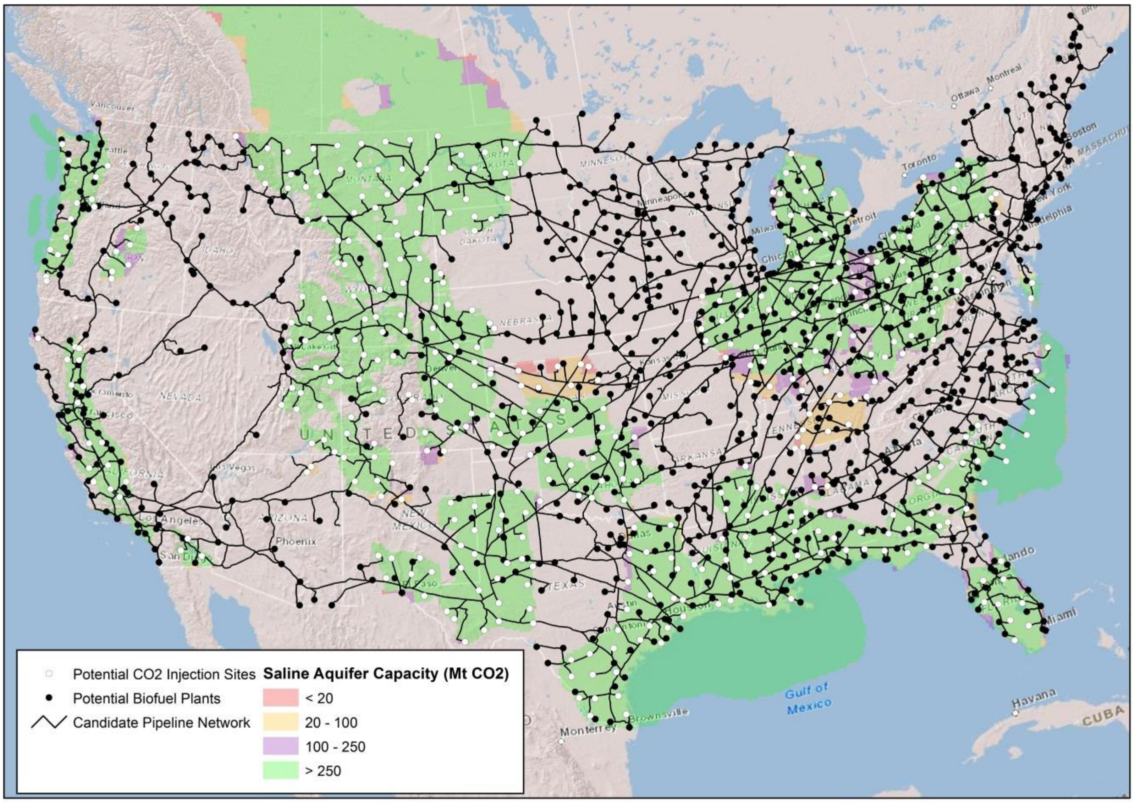

Fig. 3. Candidate CCS network, including potential injection sites, biorefineries, and pipeline ROWs

2.2.2 Techno-economic Inputs

The model also requires inputs defining the costs of biofuel production and CO_2 capture, transport and injection. Biofuel production, CO_2 capture and injection costs are provided to the model exogenously in units of thousand $ per Mt CO_2 captured. Site-specific biofuel production costs and CO_2 capture quantities are provided for each potential biorefinery, as calculated by the GBSM. Only high purity CO_2 streams are considered for capture and thus CO_2 capture costs are limited to those associated with compression and drying. Site-specific capture costs are calculated based on McCollum et al. [21] and are \$10-45/tCO_2 captured, depending on the amount of CO_2 captured per year. By incorporating unique capture costs, the model can account for important site-specific factors that influence the cost of capture (e.g., facility type and size). In contrast, the cost of CO_2 injection is assumed to be \$5/tCO_2 captured at all sites. The model can be modified to incorporate site-specific injection costs if sufficient data is available. However, current characterizations of potential CO_2 sinks are too general to develop accurate cost models for individual injection sites or even reservoirs. A fixed site characterization cost of \$27 million per injection site is also included, which encourages (though does not require) the model to utilize existing injection sites before building new sites.

The *CCS Deployment Model* considers onshore and offshore CO_2 pipelines and uses as inputs the capacities and capital costs of several pipeline diameter classes, or nominal pipe sizes. In this case study, the capital costs and pipeline capacities are provided by the Interstate Natural Gas Association of America (INGAA) [22] (Table 3). The reported pipeline capacity assumes a 90% capacity factor and a 250-km pipeline with a design pressure of 150 bar and an available pressure drop of 35 bar.

Table 3: Capacities and base installed costs of pipelines for several nominal pipe sizes

Nominal pipe size (inches)	Capacity ($MtCO_2$/year)	Capital Cost (thousand$/km)	$/$tCO_2$ (250-km, level, onshore, 90% capacity)
12.75	1.5	594	18.6
16	3	777	12.2
24	8	1,255	7.4
30	17	1,611	4.5
36	24	1,984	3.9
42	35	2,374	3.2

Booster compressors are not explicitly modeled in this study, but the cost of booster compression is included in the annual O&M cost, which is assumed to be 2.5% of capital expenditure. The levelized cost of CO_2 for a 250-km onshore pipeline on level terrain that is operating at 90% capacity is also given in Table 3. The base pipeline costs in Table 3 are for pipelines in rural areas with level terrain. In mountainous, offshore, and populated areas, it is assumed that construction costs are doubled with construction being 50% of the total installed pipeline cost (i.e., total installed cost is 1.5 times larger). Since CO_2 transport, compression, and injection are established technologies, learning is not expected to result in cost reductions over time (i.e., no learning rate is applied).

2.3. Derivation of Supply Curves and Negative Emissions

In each time step, the *CCS Deployment Model* provides the infrastructure required to meet a particular biofuel target. At each biorefinery, the biofuel production cost, CO_2 captured, biofuel produced, and CO_2 capture cost are known. Thus, derivation of the biofuel with CCS and CO_2 abatement costs at each biorefinery only requires that the costs of CO_2 injection and transport are identified for each plant. The contribution of injection is simple since it is a fixed \$5/tCO_2 captured. However, the transport cost is a bit more complicated since a plant may be one of many on a large integrated regional network. To identify biorefinery-specific transport costs, we make two assumptions: 1) all plants are responsible for the cost of their own connection to the network (i.e., non-shared pipelines) and 2) the cost of all shared pipelines are distributed over the biorefineries on each network. In other words, all plants on a network pay a fixed rate per tonne CO_2 to cover the cost of the shared network. Given the cost of transport for each biorefinery, biofuel supply and abatement cost curves can be generated at each time step. However, these supply curves assume no carbon price and thus do not account for carbon credits that could be accrued for negative emissions.

The quantity of negative emissions that can be achieved at each plant is the difference between the CO_2 captured and the indirect upstream emissions from the biofuel supply chain. For herbaceous feedstock, 7 kg CO_2-equiv/GJ of primary biomass is assumed, which is the average of the indirect emissions associated with switchgrass and corn stover in Wang et al. [23], including fertilizer production, fertilizer N_2O, transmission and distribution, and farming. For woody feedstock, 8 kg CO_2-equiv/GJ of primary biomass is assumed [24].

Given the negative emissions associated with each biorefinery, additional biofuel supply curves are generated that account for carbon credits accrued under different CO_2 price trajectories from the Reference, GHG10, and GHG25 scenarios of the EIA Annual Energy Outlook 2014 [25] (Fig. 4). In addition, gasoline and diesel price projections from these scenarios (including only wholesale price and carbon tax) are used to identify whether biofuels with CCS become competitive with conventional fuels in each scenario (Table 4).

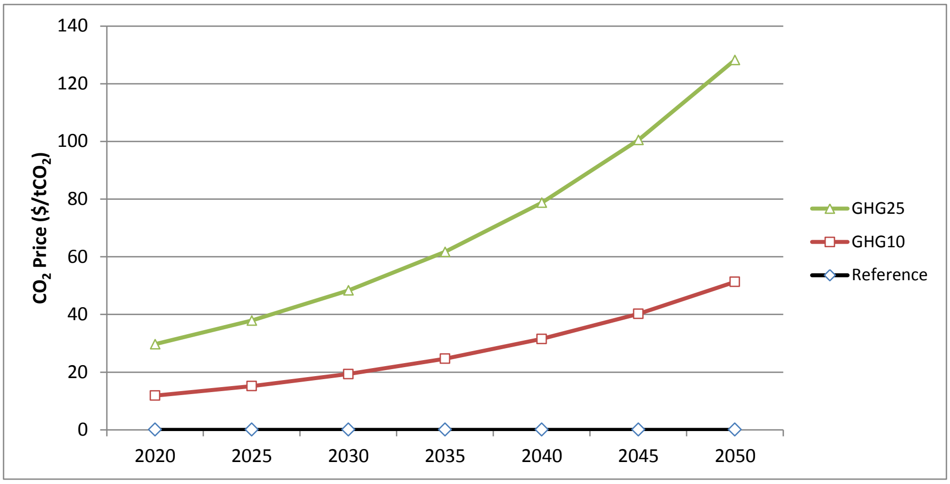

Fig. 4. CO_2 price trajectories from EIA Reference, GHG10, and GHG25 scenarios (2009$)

Table 4: CO_2, gasoline, and diesel prices from EIA Reference, GHG10, and GHG25 scenarios (2009$). Gasoline and diesel prices include only the wholesale price and carbon tax.

Price	EIA Scenario	2020	2030	2040	2050
CO_2 ($/t$CO_2$)	Reference	0	0	0	0
	GHG10	12	19	31	51
	GHG25	30	48	79	128
Gasoline ($/GJ)	Reference	19.39	22.28	26.13	27.19
	GHG10	20.28	23.60	27.97	30.13
	GHG25	21.38	25.53	30.94	34.93
Diesel ($/GJ)	Reference	18.77	22.68	26.55	29.04
	GHG10	19.55	24.01	28.48	32.38
	GHG25	20.71	25.92	31.58	37.37

3. Results

This section summarizes the main findings of this project, including the optimal infrastructure design, biofuel supply curves, negative emission curves, abatement cost curves, and regional CO_2 storage constraints found in each optimization scenario (MinCO2 and MaxCO2).

3.1. Infrastructure Design

Before examining the optimal location of biorefineries with CCS, it is important to note that existing biorefineries without CCS exist primarily in the Corn Belt of the Midwestern United States (Fig. 5). Much of this region is notably distant from CO_2 storage reservoirs, suggesting that the location of biorefineries with CCS may be distinctly different from those without CCS. In fact, with the requirement to include CCS in 2020, biorefinery locations shift to be in closer proximity to CO_2 storage sites, particularly in the MaxCO2 scenario in which only FT-diesel plants are built and CCS contributes significantly to the total cost of biofuel (Fig. 6). For this reason, almost all plants maintain CCS costs below $25/t$CO_2$ captured in the MaxCO2 scenario. However, in the MinCO2 case, CCS has a smaller impact on biofuel costs and, consequently, many biorefineries remain in the Corn Belt where feedstock costs are low (Fig. 7). Yet all of these plants participate in a shared CO_2 pipeline network to reduce the cost of CO_2 transport. Without the ability to share pipelines, it is doubtful that these plants would remain economical with CCS. Nonetheless, CCS costs for the biorefineries in the Corn Belt exceed \$50/tCO_2.

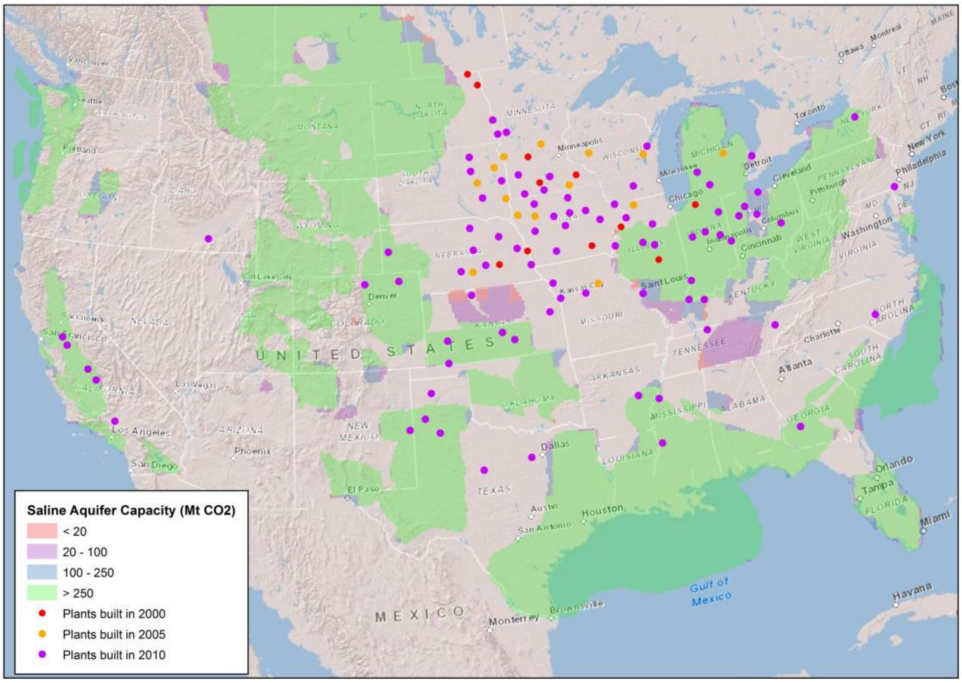

Fig. 5. Location of existing biorefineries

In 2030 and beyond, a large number of biorefineries with CCS are required, which allows for the development of large regional CO_2 pipeline networks throughout the Midwestern U.S. and significant economies-of-scale in CO_2 transport. As a result, biorefineries are built extensively in the Corn Belt in both scenarios and the differences in the locations of biorefineries become less distinct (Fig. 8-11). However, two distinctions remain between the scenarios. First, the much larger quantities of CO_2 captured in the MaxCO2 scenario result in the need for larger pipelines, but only slightly more pipeline investment. For example, in 2050, the cost of the CO_2 pipeline network is ~\$18 billion in the MaxCO2 scenario and ~\$17 billion in the MinCO2 scenario. Second, as a result of these economies-of-scale, the average cost of CCS abatement on a \$/tCO_2 basis remains significantly smaller in the MaxCO2 scenario. Although not shown in the figures, the MaxCO2 scenario builds only FT-diesel plants in all time steps while the MinCO2 scenario builds a mix of FT-diesel and LCE plants.

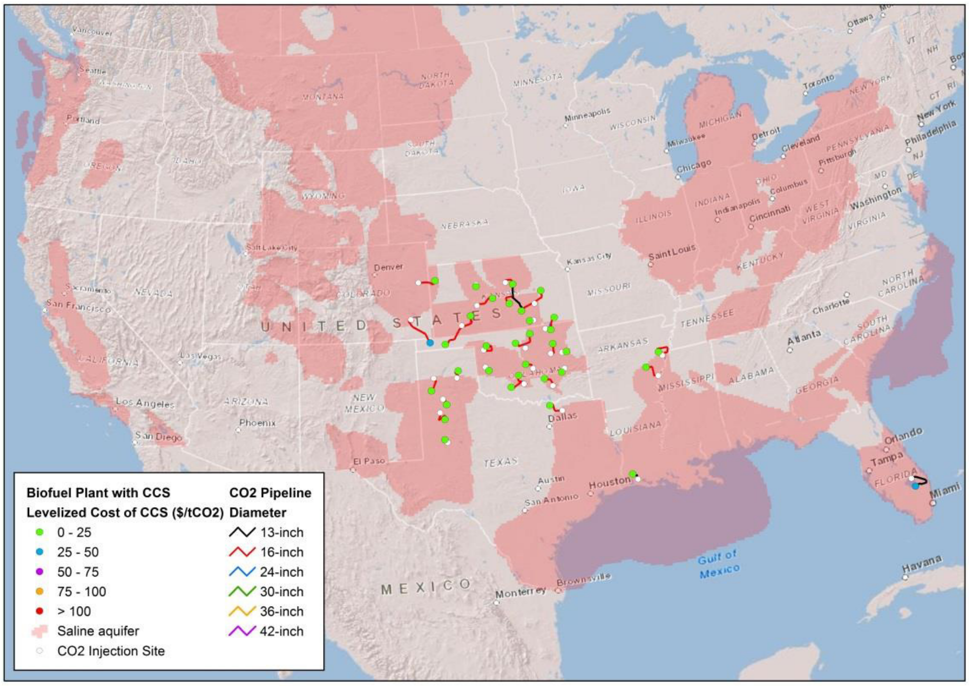

Fig. 6. Optimal biorefinery and CCS infrastructure in 2020 (MaxCO2); 60 Mt CO_2/year captured

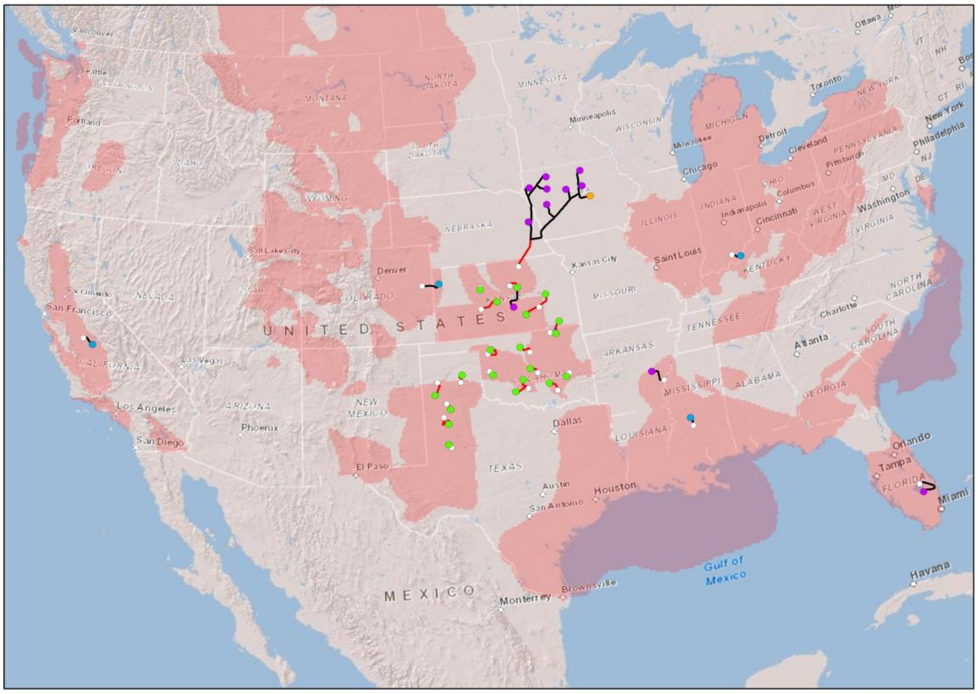

Fig. 7. Optimal biorefinery and CCS infrastructure in 2020 (MinCO2); 40 Mt CO_2/year captured

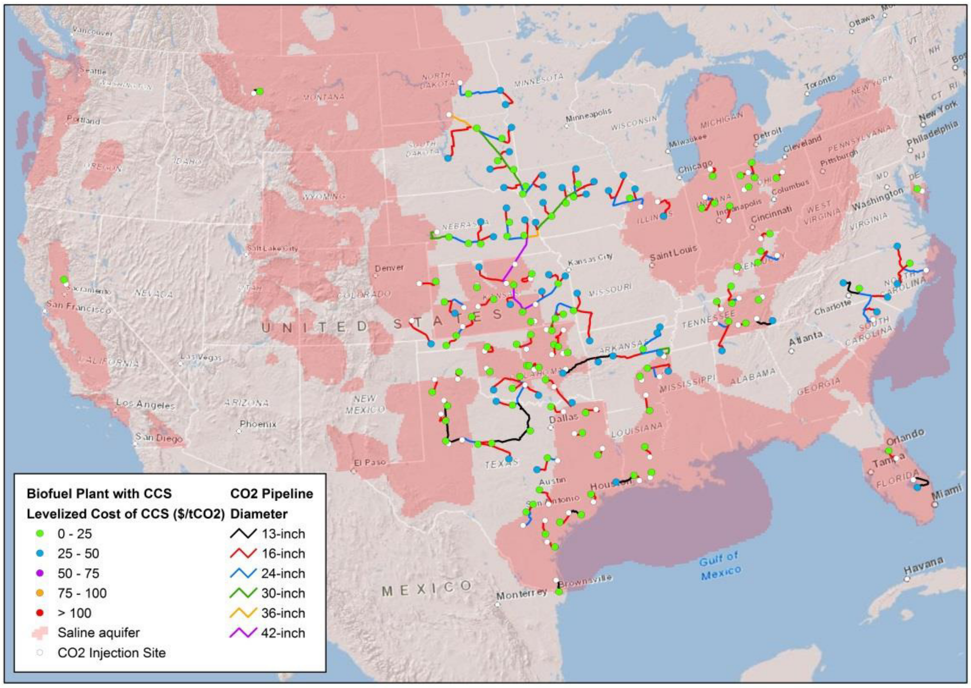

Fig. 8. Optimal biorefinery and CCS infrastructure in 2030 (MaxCO2); 270 Mt CO_2/year captured

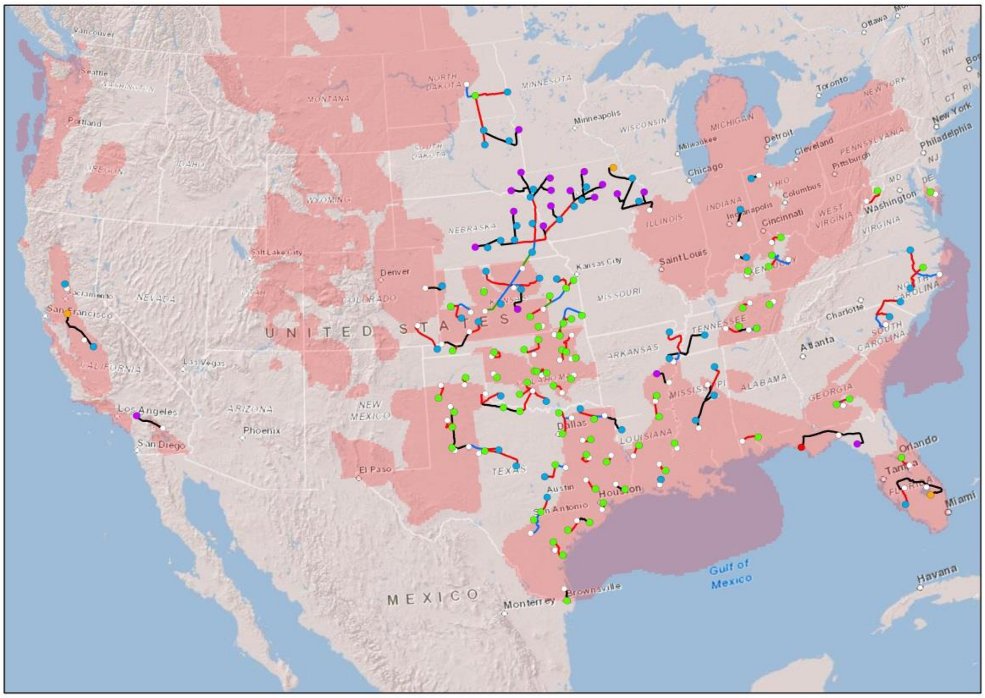

Fig. 9. Optimal biorefinery and CCS infrastructure in 2030 (MinCO2); 200 Mt CO_2/year captured

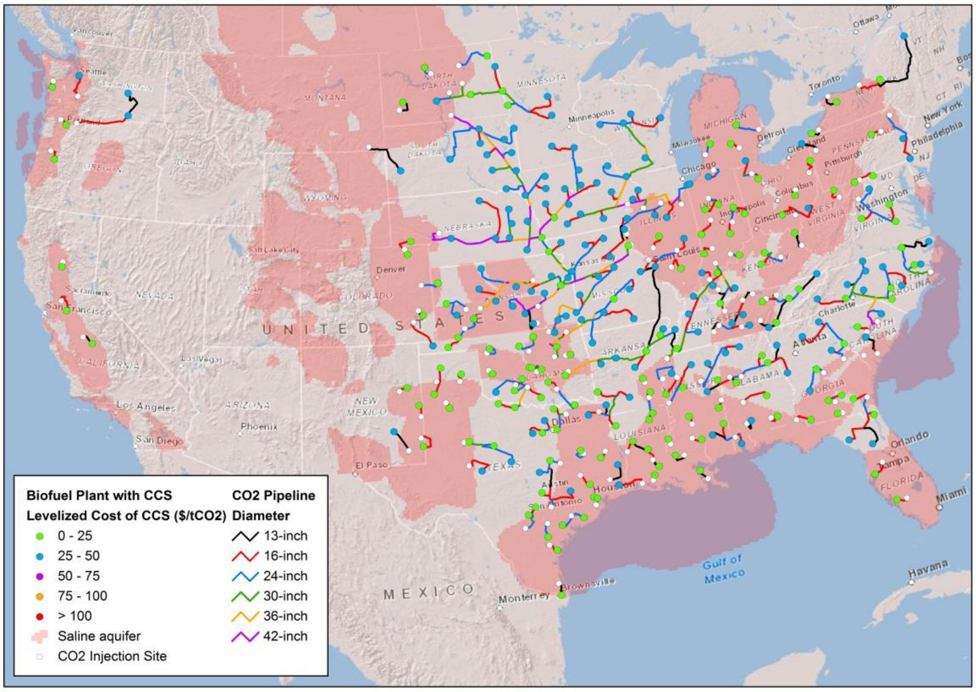

Fig. 10. Optimal biorefinery and CCS infrastructure in 2050 (MaxCO2); 650 Mt CO_2/year captured

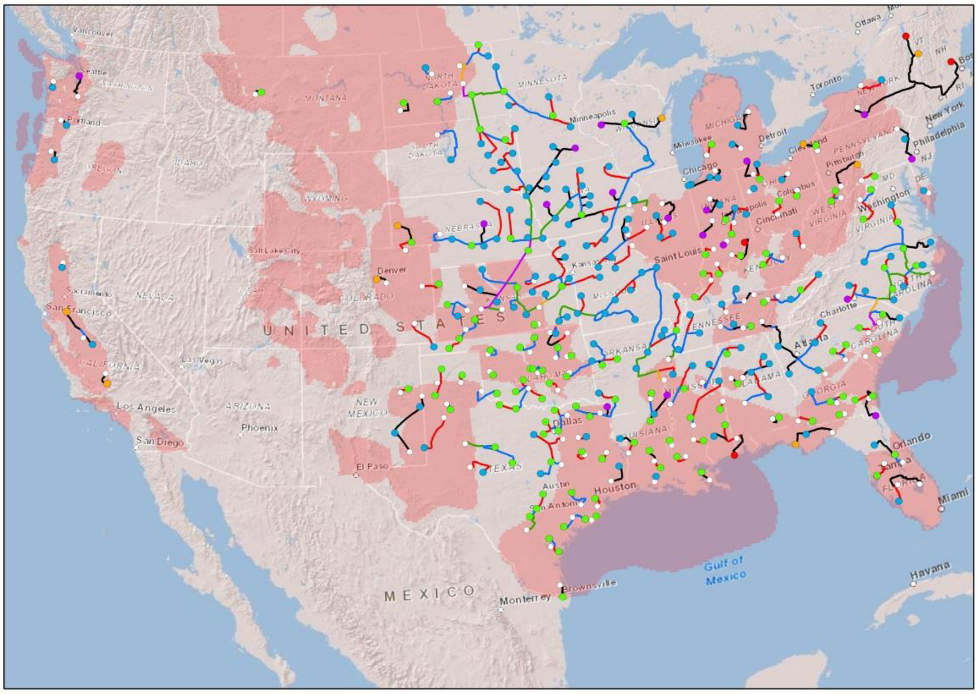

Fig. 11. Optimal biorefinery and CCS infrastructure in 2050 (MinCO2); 540 Mt CO_2/year captured

3.2. Biofuel Supply Curves

Biofuel supply curves are presented in ten-year time steps between 2020 and 2050 and are provided for all three CO_2 price trajectories (Fig 4) for the MaxCO2 scenario. For the MinCO2 scenario, only the case with no CO_2 price (i.e., Reference) is provided since CO_2 prices are not consistent with a scenario in which the CO_2 captured per unit of fuel is minimized[2]. The decline in biofuel costs between 2020 and 2030 is the result of increasing feedstock yields and reduced feedstock prices. In the scenarios with no CO_2 price, biofuels with CCS are not competitive with conventional fuels in 2020 or 2030 (Fig 12 and 13). Although a small portion of the supply curve in 2030 is below the conventional fuel prices (< 0.1 EJ of supply), the supply curve includes the benefits of shared pipeline networks. Thus, if all plants that lie above the fuel price were not built, it is likely that the cost of CO_2 transport would increase for the lower cost plants. Consequently, it is unclear whether this small amount of supply would remain competitive. Incidentally, the biorefineries sited in 2020 would not be competitive even without CCS. However, most of the biofuel production would be competitive in 2030 without CCS. In 2040 and 2050, most of the biofuel supply with CCS is competitive with conventional fuels even without a CO_2 price. However, slightly more supply is competitive in the MaxCO2 scenario since diesel prices are higher than gasoline prices and the MinCO2 scenario builds fewer FT-diesel plants. These figures also indicate that the majority of competitive biofuel is biodiesel in both scenarios.

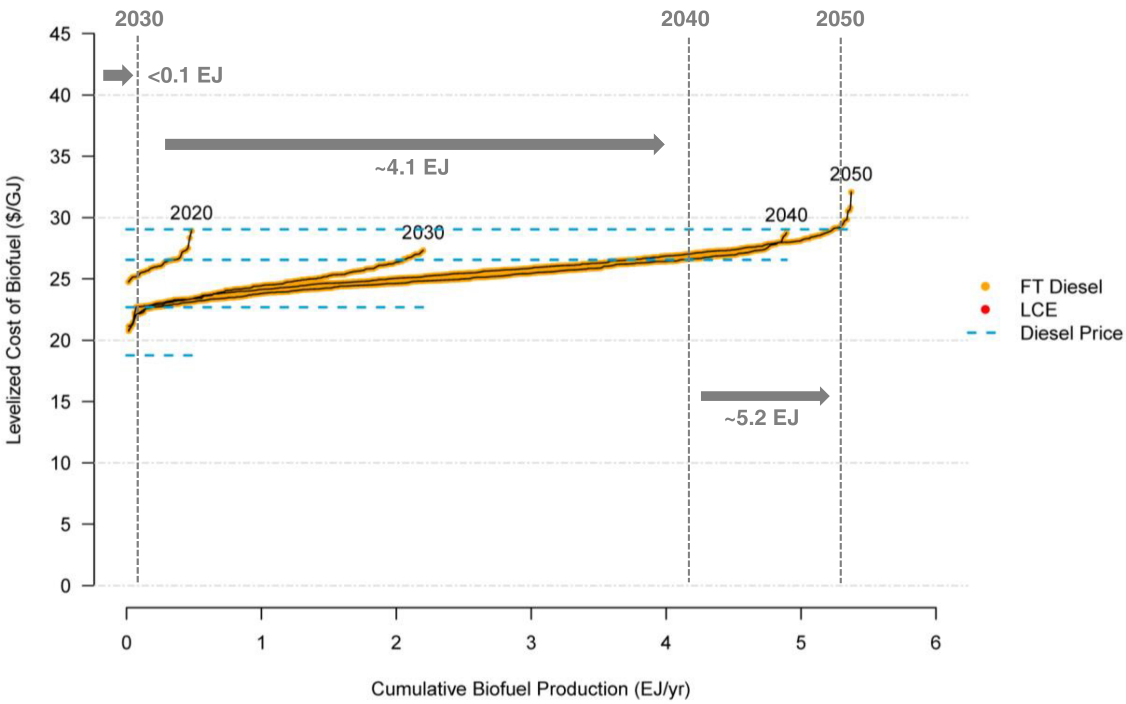

Fig. 12. Biofuel supply curves in the Reference CO_2 price scenario (MaxCO2)

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[2] The horizontal dotted lines indicate the diesel and gasoline prices for each time step (2020, 2030, 2040, 2050). In cases with carbon taxes, the diesel and gasoline prices increase according to EIA projections. For each time step, the vertical dotted lines indicate how much biofuel can be produced at a price that is competitive with diesel (biodiesel) or gasoline (ethanol). Any biofuel available at less than the price of its conventional competitor is considered economical.

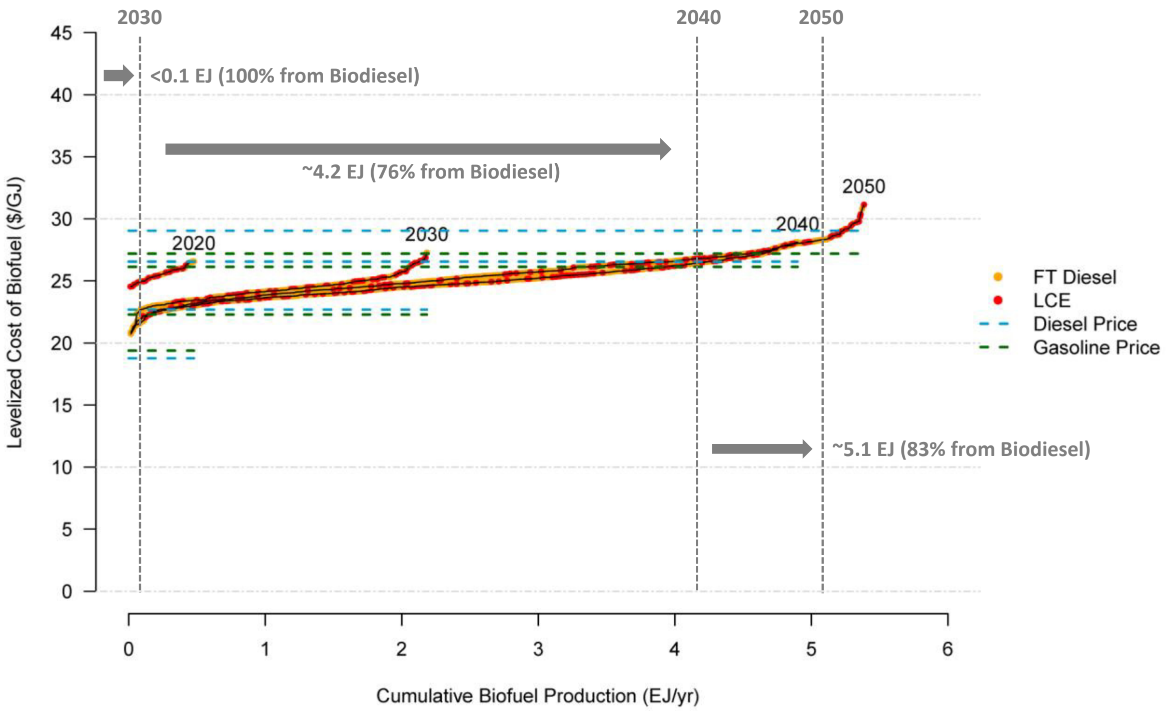

Fig. 13. Biofuel supply curves in the Reference CO_2 price scenario (MinCO2)

In the GHG10 case, biofuel with CCS is still not competitive with conventional fuels in 2020. However, a \$19/tCO_2 price is sufficient to allow approximately 1.8 EJ/year to be economical in 2030 (Fig. 14). Furthermore \$31 and \$51/tCO_2 prices in 2040 and 2050, respectively, make all of the biofuel with CCS required to meet the respective targets competitive with conventional fuels. In the GHG25 case, biofuel with CCS remains uncompetitive in 2020, despite a \$30/tCO_2 price (Fig. 15). However, CO_2 prices are sufficient to yield the entire supply curve competitive in 2030 and beyond. This is largely the result of the impact of the CO_2 price on the cost of conventional fuels.

In summary, biofuels with CCS do not appear competitive with conventional fuels in 2020 when the CO_2 price is as large as \$30/tCO_2. However, at least 5 EJ/year of biofuel with CCS is competitive in 2050 even without a CO_2 price. Thus, increasing the CO_2 price largely impacts the quantity of competitive biofuel with CCS in the intermediate years (2030 and 2040). Moreover, the CO_2 prices in the GHG10 scenario seem sufficient for rendering the majority of biofuel supply with CCS economical in 2030 and beyond. When ignoring the value of carbon credits, the average cost of biofuel production with CCS is relatively stable at \$24-26/GJ in both scenarios. On average, CCS adds 9-14% to the cost of biofuel production.

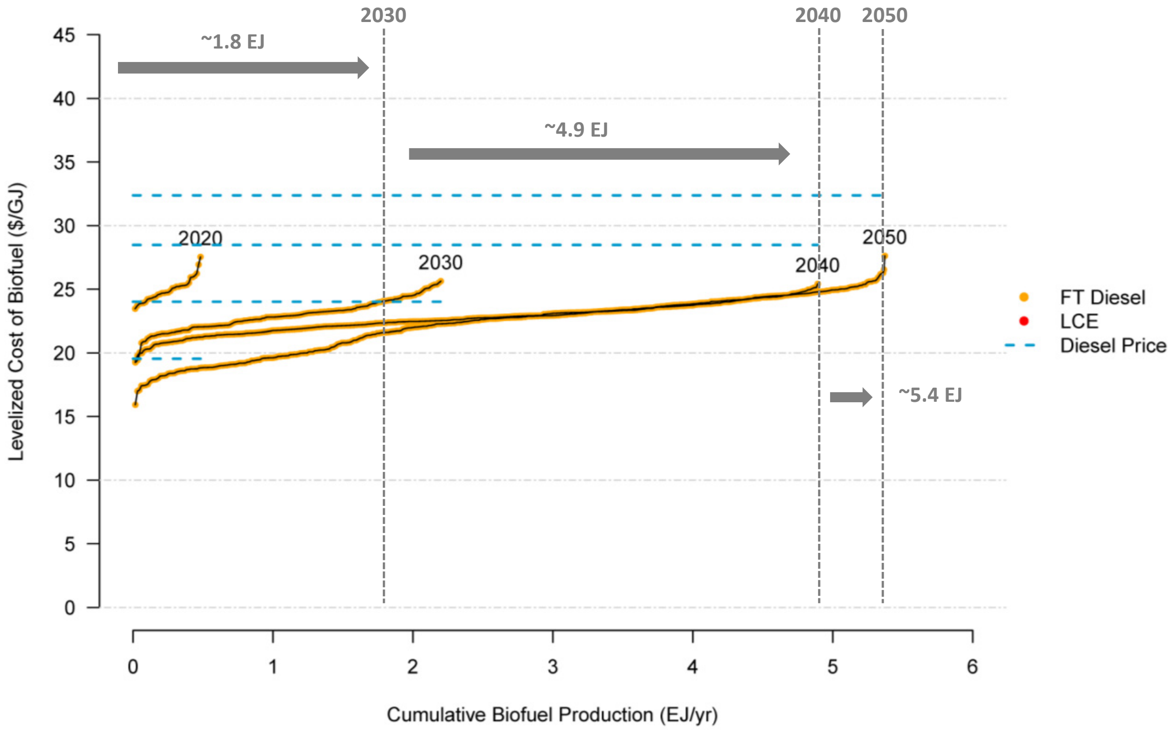

Fig. 14. Biofuel supply curves in the GHG10 CO_2 price scenario (MaxCO2)

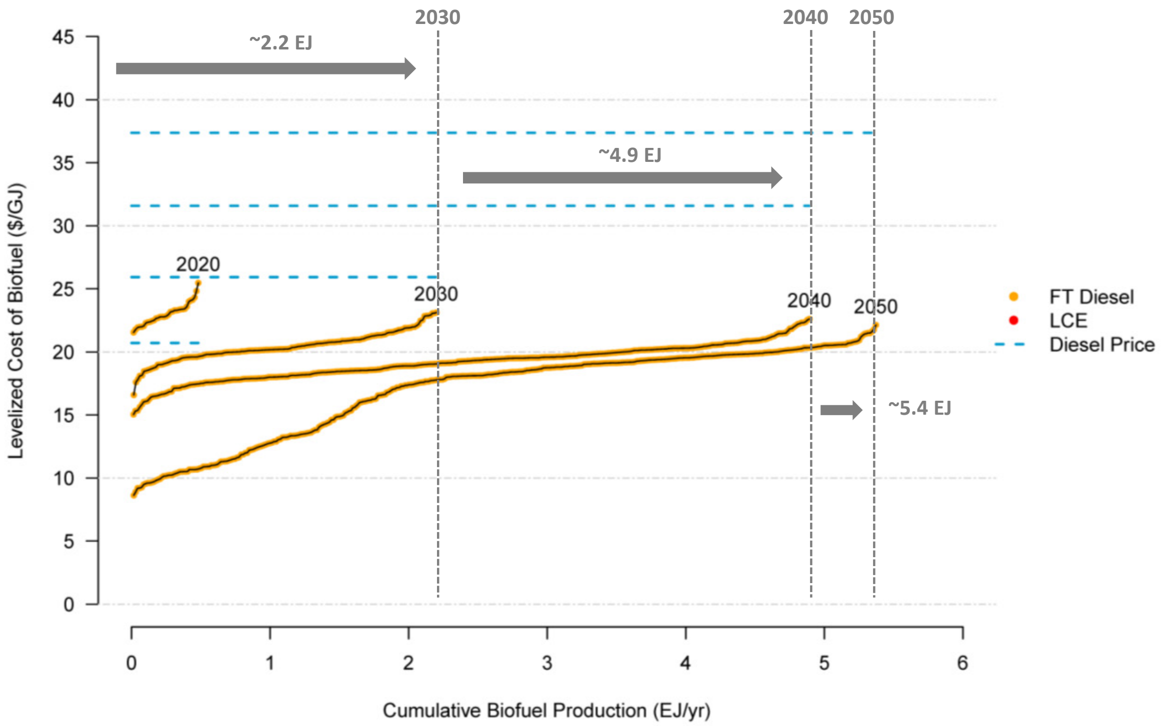

Fig. 15. Biofuel supply curves in the GHG25 CO_2 price scenario (MaxCO2)

3.3. Negative Emission Curves

The negative emission curves for the GHG10 and GHG25 cases are not provided given that they exhibit the same trends as the biofuel supply curves, notably that larger CO_2 prices increase the quantity of negative emissions that can be achieved in the intermediate periods represented by 2030 and 2040. However, figures 16 and 17 illustrate the difference in the negative emission potential between the MaxCO2 and MinCO2 scenarios. Given that MaxCO2 maximizes the CO_2 captured per unit of fuel, the negative emission potential in 2050 is approximately 25% larger even though both scenarios produce the same amount of fuel. In addition, even though biodiesel plants provide ~83% of the biofuel supply in MinCO2, they account for ~99% of the negative emissions. This reinforces the fact that the higher capture efficiency of FT-diesel plants allows them to be much more effective in achieving negative emissions than cellulosic ethanol plants. The biofuel with CCS and negative emission potentials for each scenario and CO_2 price are summarized in Table 5. The maximum negative emissions potential is 560 Mt CO2 per year, which is associated with a biofuel with CCS supply of 5.4 EJ per year.

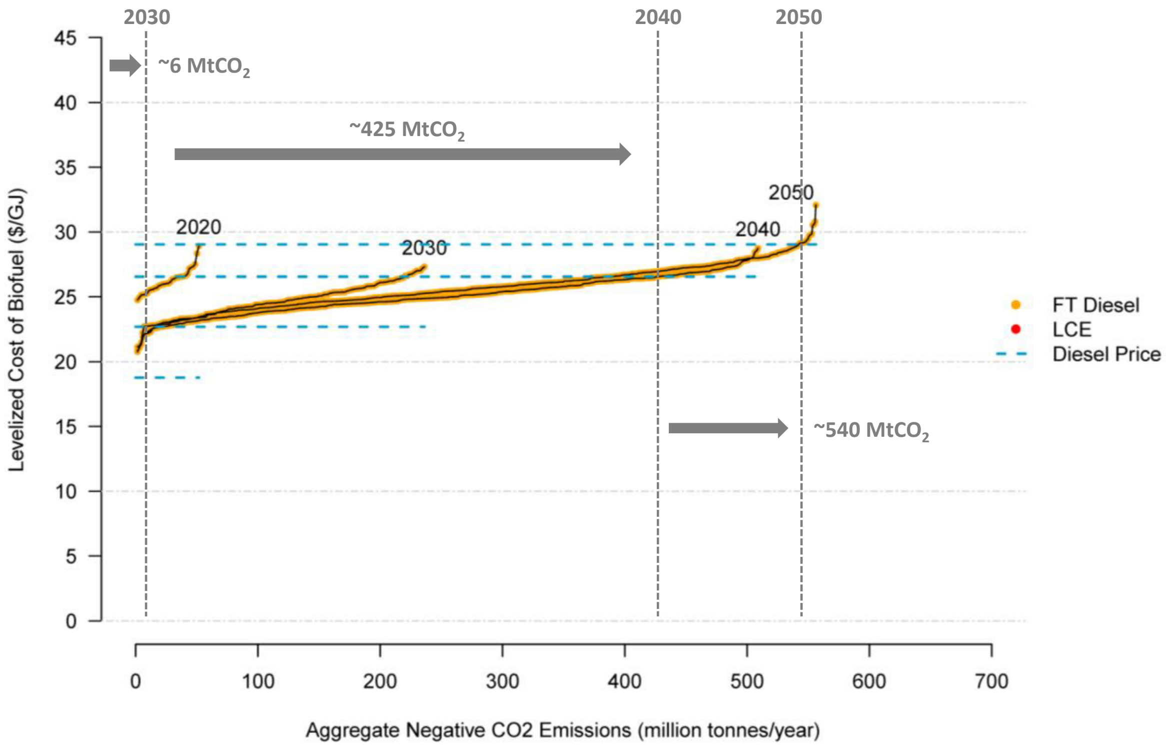

Fig. 16. Negative emission curves in the Reference CO_2 price scenario (MaxCO2)

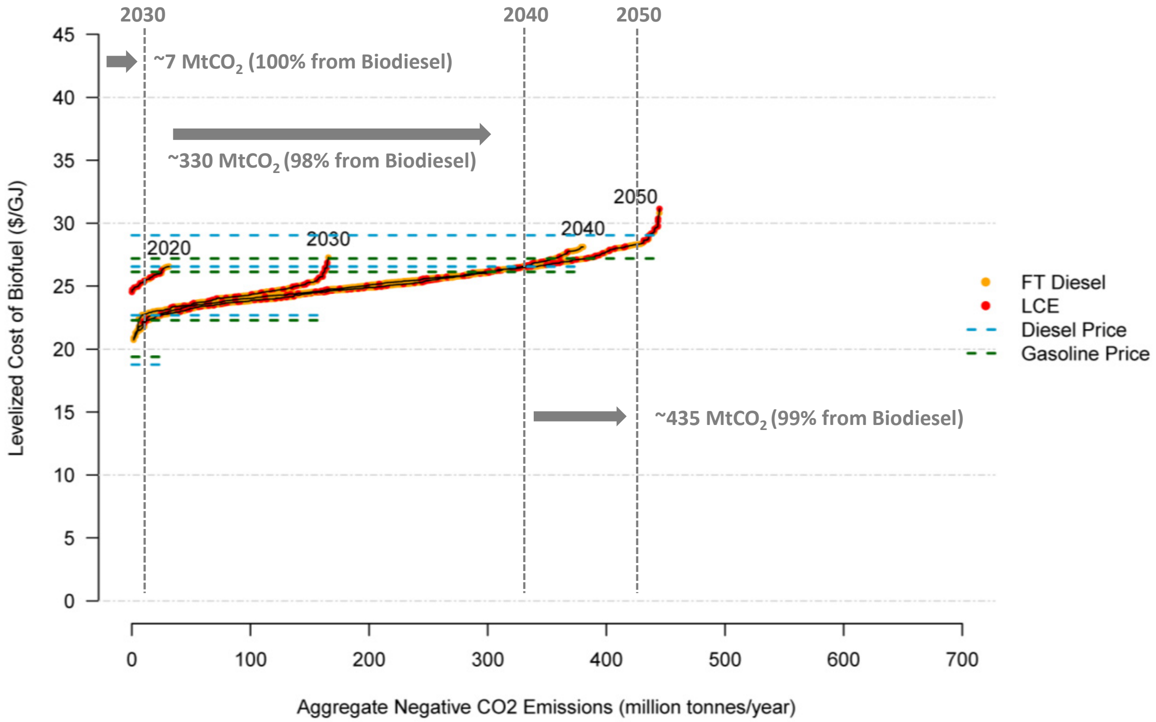

Fig. 17. Negative emission curves in the Reference CO_2 price scenario (MinCO2)

Table 5: Biofuel with CCS and negative emission potentials associated with each scenario and CO_2 price trajectory. Colors indicate whether the biofuel target in each period can be fully (green), partially (orange), or not at all (red) fulfilled by biofuels with CCS that are competitive with conventional fuels. The value in parentheses is the percent of the biofuel target fulfilled.

Scenario	CO_2 Price	2020	2030	2040	2050
MinCO2	Reference	0 EJ (0%) 0 Mt CO_2	0 EJ (0%) 0 Mt CO_2	4.2 EJ (86%) 330 Mt CO_2	5.1 EJ (94%) 435 Mt CO_2
MaxCO2	Reference	0 EJ (0%) 0 Mt CO_2	0 EJ (0%) 0 Mt CO_2	4.1 EJ (84%) 425 Mt CO_2	5.2 EJ (96%) 540 Mt CO_2
	GHG10	0 EJ (0%) 0 Mt CO_2	1.8 EJ (82%) 190 Mt CO_2	4.9 EJ (100%) 510 Mt CO_2	5.4 EJ (100%) 560 Mt CO_2
	GHG25	0 EJ (0%) 0 Mt CO_2	2.2 EJ (100%) 240 Mt CO_2	4.9 EJ (100%) 510 Mt CO_2	5.4 EJ (100%) 560 Mt CO_2

3.4. Abatement Costs

CO_2 abatement curves are generated for each scenario and time period and are provided on a $/t$CO_2$ captured and $/GJ biofuel basis. In the MaxCO2 scenario, the model builds only FT-diesel plants. In this case, the abatement cost in $/t$CO_2$ is relatively stable between $20 and $40/t$CO_2$ captured, with an average abatement cost of $21/t$CO_2$ and $25/t$CO_2$ in 2020 and 2050, respectively (Fig. 18). However, given the large quantity of CO_2 captured at FT-diesel biorefineries, the abatement cost in $/GJ biofuel is relatively large ($2-5/GJ), meaning that CCS has a much larger impact on fuel prices at FT-diesel plants than it does at cellulosic ethanol plants. This finding is confirmed by the MinCO2 scenario in which the cellulosic ethanol plants have much smaller $/GJ abatement costs ($1-2/GJ) than the FT-diesel plants (Fig. 19). However, this scenario also indicates that the $/t$CO_2$ abatement costs are significantly larger and less stable for cellulosic ethanol plants with a range between \$25 and \$175/tCO_2 in later time periods. By sorting plants according to their abatement costs, Fig. 19 also clearly illustrates that cellulosic ethanol plants contribute a small share of the total CO_2 captured in each time period. Given their small contribution to negative emissons and relatively large \$/tCO_2 abatement costs, cellulosic plants will benefit less than FT-diesel plants from increasing CO_2 prices and will become less competitive under more stringent climate policy.

Table 6 summarizes the average levelized cost for CO_2 transport only and for the full CCS supply chain in each scenario. In 2020, when a large portion of the biofuel in MinCO2 is produced by cellulosic ethanol plants and only fledgling pipeline networks are constructed, average costs are significantly larger in the MinCO2 scenario. However, as large regional networks become the norm and FT-diesel dominates production in both scenarios, the average costs become more similar over time. As a rule-of-thumb, the average cost of CO_2 transport is \$7-8/tCO_2 and the average cost of CCS is \$24-26/tCO_2 in most time periods.

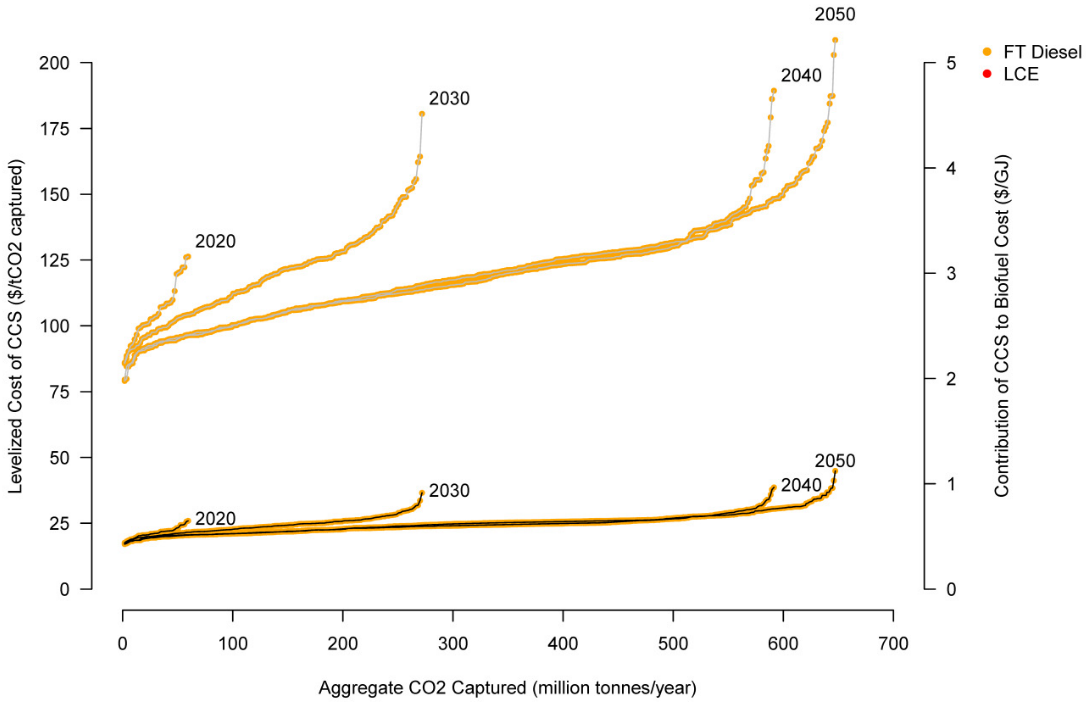

Fig. 18. CO_2 abatement costs in terms of \$/tCO_2 captured and \$/GJ biofuel (MaxCO2)

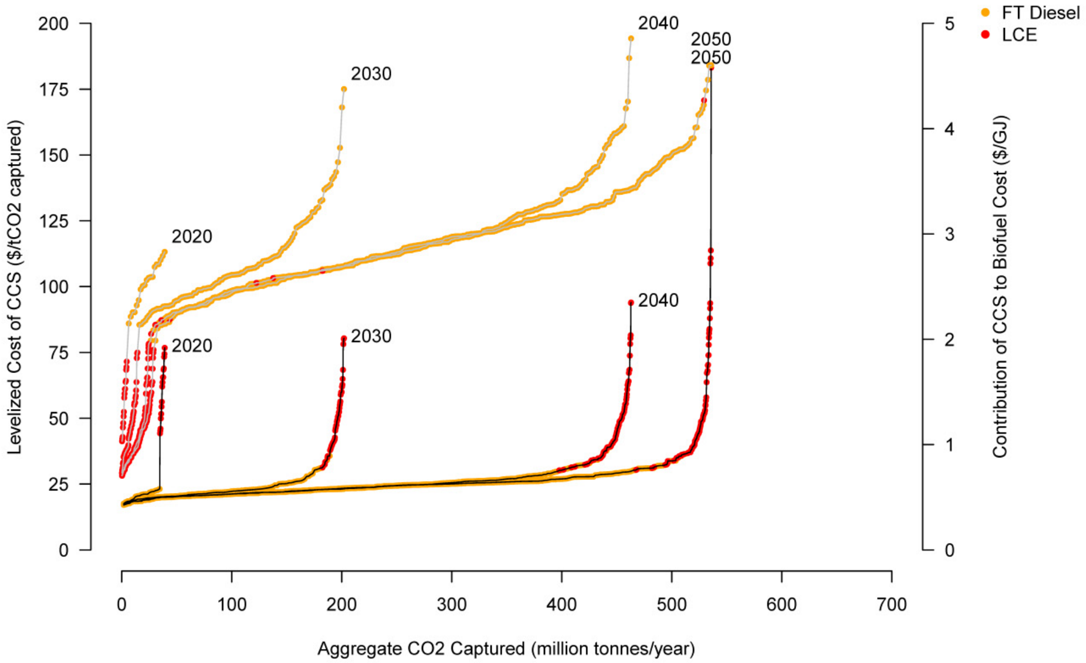

Fig. 19. CO_2 abatement costs in terms of $/t$CO_2$ captured and $/GJ biofuel (MinCO2)

Table 6: Average levelized cost of CCS and CO_2 transport in each time period and scenario ($/t$CO_2$ captured)

Scenario		2020	2030	2040	2050
MinCO2	Transport	$6.9	$7.2	$7.9	$8.1
	Full Supply Chain	$25.0	$25.0	$25.7	$25.8
MaxCO2	Transport	$4.3	$6.9	$6.9	$7.7
	Full Supply Chain	$21.3	$24.0	$24.1	$25.0

3.5. Regional Storage Constraints

This section explores whether there are any regional storage constraints associated with storing the quantity of CO_2 captured over the lifetime of the biorefineries built until 2050. In each scenario, the lifetime storage requirements are tracked for each plant and reservoir capacities are adjusted for the storage used by existing and retired biorefineries. Approximately 14 Gt CO_2 is stored in the MinCO2 scenario and ~18 Gt CO_2 is stored in the MaxCO2 scenario. Both scenarios exhibit some storage limitations along the fringes of the Corn Belt, particularly in reservoirs with relatively low storage capacities (Fig. 20 and 21). The most acute storage constraints appear to be in Kansas and Tennessee and the limitations are more severe in the MaxCO2 scenario as expected. Yet there is substantial capacity remaining throughout the U.S. and additional pipelines should be able to affordably access the reservoirs to the west and east of the Corn Belt. However, this study does not consider competition for storage capacity from electricity production with CCS or storage requirements beyond 2050. Both of these additional demands for storage capacity should be assessed as they may further limit regional storage supply.

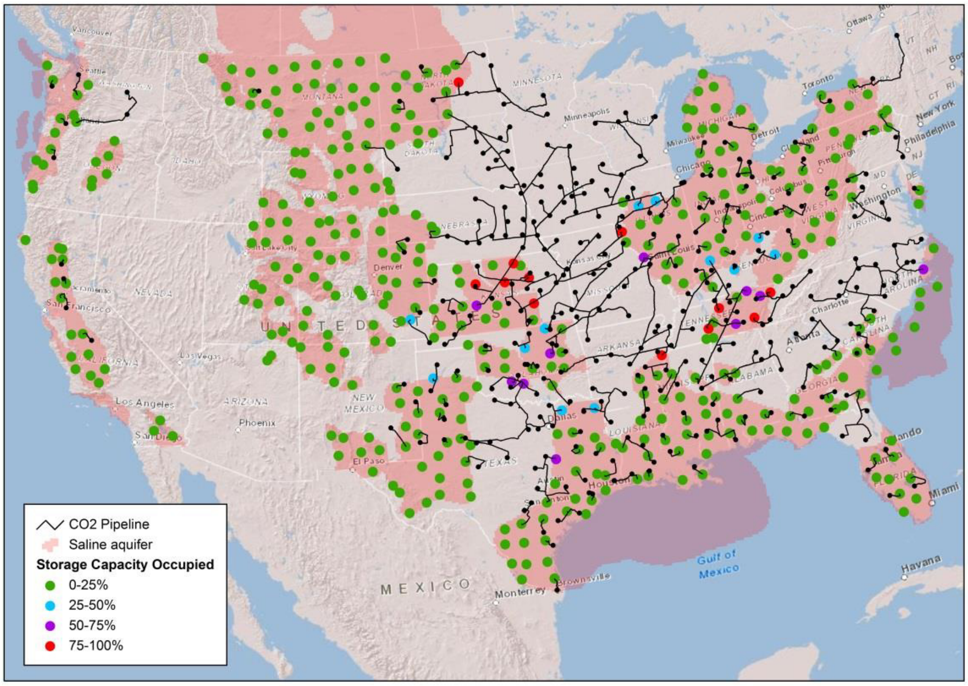

Fig. 20. Storage capacity constraints (MaxCO2)

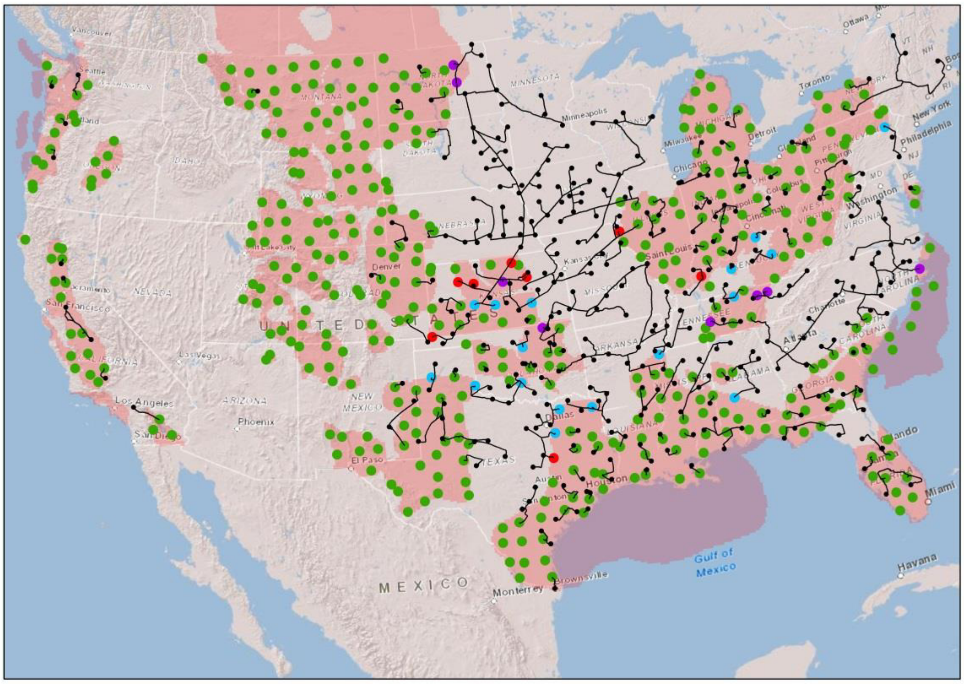

Fig. 21. Storage capacity constraints (MinCO2)

4. Conclusions

A spatially-explicit biorefinery siting model and CCS infrastructure model are coupled to examine whether IEA projections of biofuel use in the United States can be met and at what cost. The use of spatially-explicit models allows for the explicit consideration of the proximity of biomass resources, production locations, and CO_2 storage capacity and provides the opportunity to develop site-specific CCS and biofuel production costs. These site-specific costs are aggregated to develop geospatial supply curves, negative emission potentials, and CO_2 abatement curves. Moreover, the results provide insight into how biofuel with CCS infrastructure might develop in the U.S. The following main insights follow from this work.

1) *Integrated regional networks are valuable for linking CO_2 storage capacity to low-cost biomass resources*

Much of the prime biomass resource resides in a portion of the country that is remote from CO_2 storage capacity. To cost-effectively utilize these resources in conjunction with CCS, large integrated regional networks are developed to allow producers in these remote areas to share the cost of CO_2 transport. This is a valuable service and helps to stabilize the average cost of transport at \$7-8/tCO_2 throughout the timeframe of the project. Despite the relatively long distance of some of these plants from CO_2 storage capacity, integrated networks also help to reduce the average pipeline length per plant to around 80 km in 2050.

2) *Long-term biofuel demand projections from the IEA can be met by biofuels with CCS*

By 2050, increasing conventional fuel prices will render most biofuels with CCS competitive with conventional fuels even with no carbon price. However, biofuels with CCS are not expected to be competitive in 2020 unless carbon prices are larger than \$30/tCO_2. In the intermediate years, carbon prices help to accelerate the transition to biofuels with CCS and carbon prices consistent with the IEA GHG10 scenario (\$19/tCO_2 in 2030 and \$31/tCO_2 in 2040) are sufficient to enable most biofuel production with CCS to be economical in 2030 and 2040. Without a carbon price, the average cost of biofuel production with CCS is \$24-26/GJ and CCS adds about 9-14% to the cost of biofuel production.

3) *Up to 560 Mt CO_2 per year of negative emissions can be achieved by 2050 in the United States*

A maximum of 560 Mt CO_2 per year of negative emissions can be achieved when 5.4 EJ per year of biofuel with CCS is produced. However, the full potential will only be realized with a carbon tax and if all biorefineries are producing biodiesel. Once negative emissions become valued, biodiesel production is preferable to ethanol production because of the larger quantity of high purity CO_2 that can be captured from these plants.

4) *Regional storage constraints occur along the border of the Corn Belt in the Midwestern United States*

Considering only the CO_2 storage requirements of biorefineries built until 2050, storage constraints arise in a few parts of the country, particularly around the Corn Belt. Although there appears to be sufficient remaining storage capacity in nearby areas, connecting to these sites would require additional CO_2 pipeline networks and may result in larger costs if biofuel production with CCS expands through the end of the century. Moreover, CO_2 storage requirements imposed by the power sector would likely put more pressure on constrained regions and these impacts should be studied further.

Although this work provides some good preliminary estimates of biofuel with CCS potential in the United States, the current supply curves are limited in their applicability since each supply curve represents a particular infrastructure design (i.e., the supply curve depends on the integrated networks that have been developed for all plants in the network). Thus, each plant on the supply curve cannot be considered in isolation and the plants in the supply curve may not retain their costs if other plants are removed from the system. As a result, future work will develop independent supply curves for small tranches of biofuel deployment with CCS. In this way, individual systems that are economical on their own can be identified at different supply levels. In addition, carbon prices will be endogenized within the model so that the mix of biodiesel and ethanol plants is optimized given a particular price. Finally, the model will be expanded to include CO_2 sources from the power sector so that the benefits of larger pipeline networks as well as the impacts on CO_2 storage capacity can be explored.

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