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A Spatial Modeling Framework to Evaluate Domestic Biofuel-Induced Potential Land Use Changes and Emissions

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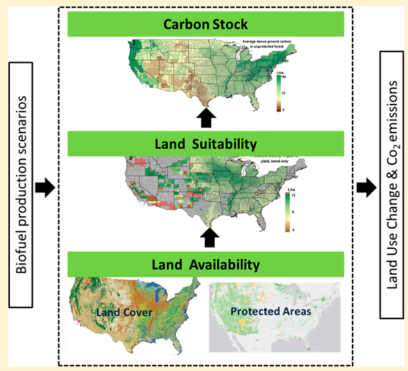
Supporting Information

ABSTRACT: We present a novel bottom-up approach to estimate biofuel-induced land-use change (LUC) and resulting CO_2 emissions in the U.S. from 2010 to 2022, based on a consistent methodology across four essential components: land availability, land suitability, LUC decision-making, and induced CO_2 emissions. Using high-resolution geospatial data and modeling, we construct probabilistic assessments of county-, state-, and national-level LUC and emissions for macroeconomic scenarios. We use the Cropland Data Layer and the Protected Areas Database to characterize availability of land for biofuel crop cultivation, and the CERES-Maize and BioCro biophysical crop growth models to estimate the suitability (yield potential) of available lands for biofuel crops. For LUC decisionmaking, we use a county-level stochastic partial-equilibrium modeling framework and consider five scenarios involving annual ethanol production scaling to 15, 22, and 29 BG, respectively, in 2022, with corn providing feedstock for the first 15 BG and the remainder coming from one of two dedicated energy crops. Finally, we derive high-resolution above-ground carbon factors from the National Biomass and Carbon Data set to estimate emissions from each LUC pathway. Based on these inputs, we obtain estimates for average total LUC emissions of 6.1, 2.2, 1.0, 2.2, and 2.4 gCO2e/MJ for Corn-15 Billion gallons (BG), *Miscanthus* × *giganteus* (MxG)-7 BG, Switchgrass (SG)-7 BG, MxG-14 BG, and SG-14 BG scenarios, respectively.



1. INTRODUCTION

Global energy demand is projected to increase by over one-third by the year 2050, driven predominantly by economic and population growth in developing countries.[1] Fossil fuels remain the major source of energy worldwide, raising concerns about both climate change due to CO_2 emissions and energy security.[2] Biofuels have long been championed for their potential to meet future energy needs in a secure and sustainable way that furthermore supports rural economic development.[3] The Energy Independence and Security Act (EISA) of 2007 mandates through the Renewable Fuel Standard (RFS) an increase in biofuel use to 36 BG of ethanol annually by 2022, of which 16 BG are mandated from "cellulosic biofuel". However, biofuels production to meet these goals requires land for the cultivation of biomass feedstock, which can displace other land uses. Quantifying shifts among land uses and the corresponding change in carbon stocks has become a key focus in the examination of the environmental merits of biofuels.

Despite extensive life-cycle analysis of corn ethanol focused on land-use change (LUC) and technology advancement,[4−6] LUC remains a contentious part of the calculation of net greenhouse gas (GHG) emissions from corn ethanol. As cellulosic ethanol moves toward commercialization, dedicated energy crops like *Miscanthus x gigantus* (MxG) or *Panicum virgatum* (switchgrass: SG) are among the most promising feedstocks.[7] Some studies have suggested that significant amounts of cellulosic biofuels could be produced by dedicated high-yielding grasses planted on marginal, fallow, or abandoned former agricultural lands without causing major environmental or economic consequences.[8−10] Other studies have found that large-scale feedstock production (whether corn or dedicated grasses) will result in repurposing of existing agricultural lands, primarily pasture.[11,12]

Given that LUC is a major source of GHG emissions[13] among other potential environmental issues,[14] various models have been developed for or applied to the analysis of LUC and its environmental impact. These models include (1) global computable general equilibrium (CGE) models such as GTAP[15−18] and CIM-EARTH;[19] (2) partial equilibrium and

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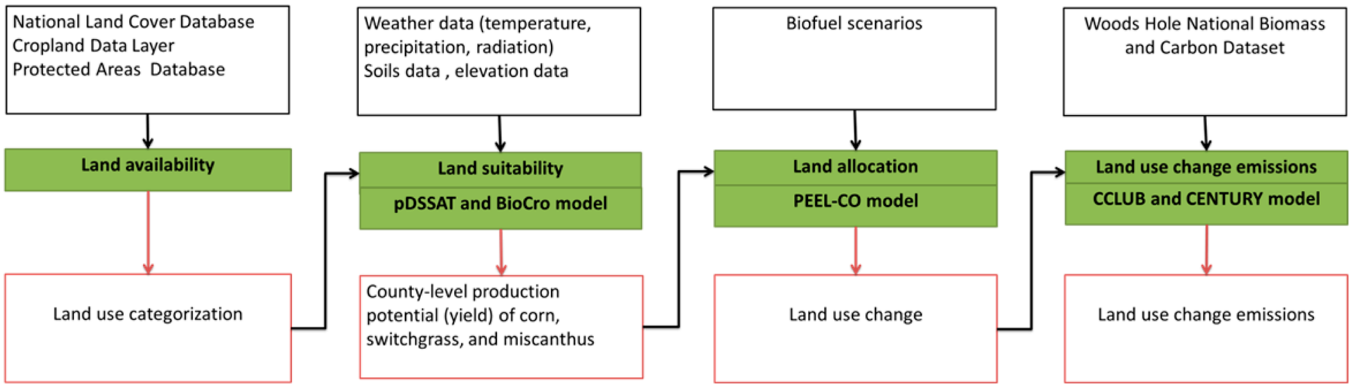

Figure 1. Data flow diagram for LUC and resulting emissions analysis. The black boxes and arrows indicate inputs, the green boxes indicate modeling or processing steps, the red boxes and arrows indicate outputs.

other economic-based models such as the POLYSYS Agricultural Policy Analysis Center[20] and FAPRI;[21] and (3) optimization models such as that developed by Gnansounou and Panichelli.[22] The first complete analysis of LUC emissions, from Searchinger, et al.,[11] estimated that corn ethanol would double GHG emissions over 30 years as compared to the gasoline it displaced. Subsequent studies found biofuel-induced LUC and emissions to be significantly lower (see Table S-1 in the Supporting Information (SI)).

LUC is a local phenomenon driven by large-scale economic conditions. Different modeling approaches provide varying results due to differences in modeling framework, assumptions, input parameters, scenarios considered, and implementation at the local, regional, national, and global level. In general, equilibrium agro-economic models, sometimes also referred to as "top-down" models because the approach uses macro-economic theory with highly aggregate parametrizations, lack the spatial resolution needed to identify critical areas of LUC vulnerability and to provide insight into the local socio-economic and biophysical factors that affect LUC.[23]

To address these limitations, we present results for three biomass feedstocks (corn, MxG, and SG) using an approach that estimates LUC and resulting emissions based on high-resolution geospatial data and modeling (and is hence referred to as a "bottom-up" approach). This approach is unique in that the high-resolution enables a comprehensive and consistent approach to key drivers of LUC emissions. These drivers include the availability and suitability of land for biomass production and the aboveground and belowground carbon lost during conversion. We exclude protected lands from our assessment and incorporate shrubland, a land class typically omitted in other studies. Based on these high-resolution factors, we model county-level ethanol plant siting and LUC decision probabilities and generate economically plausible future biofuel production and LUC pathways at county level. We evaluate the environmental costs of these pathways in terms of land conversion, biomass loss, and CO_2 emissions and identify subnational LUC hotspots that can help policy-makers at all scales craft targeted policy and incentive programs to mitigate the LUC consequences of cellulosic ethanol.

2. MATERIALS AND METHODS

Figure 1 summarizes the methodology used for the present study. We first combined data from multiple sources to create a data set characterizing present-day land cover and availability at 30m spatial resolution over the conterminous U.S. (Section 2.1 and SI Section S-1). We used crop models driven by gridded soil data sets and a combination of observed- and reanalysis-based weather products to estimate land suitability in terms of the average yields of corn, MxG, and SG (Section 2.2 and SI Section S-2). Next, we combined the land-availability data set with above and below ground carbon data to estimate changes in carbon stock (Section 2.3, SI Sections S-3, and S-4). We apply a stochastic partial equilibrium production allocation framework to produce, for five scenarios (Sections 2.4 and SI Section S-5), spatial distributions and probabilistic county-, state-, and national-level assessments of potential LUC (Section 2.5 and SI Section S-7). Finally, we combine these different elements to estimate total biofuel-induced LUC and its associated GHG emissions (Section 3).

2.1. Availability of Land for Biofuel Feedstock Production. State- and national-level protection policies prevent conversion of significant amounts of natural land, especially forest and wetland, in key areas around the country. This protection can have a substantial effect on potential biomass feedstock production and the distribution of biofuel-induced LUC. Thus, a first step toward evaluating future LUC is to determine what land is available: that is, what land is not explicitly protected or engaged in high-value economic activity. We used the 30 m spatial resolution National Land Cover Data set (NLCD)[24] and Protected Areas Database (PAD-US)[25] to determine available land and to characterize the existing cover types on that land (see SI Section S-1 for details on these data products and their use).

2.2. Suitability of Available Land for Biofuel Feedstock Production. Feedstock yield is a key determinant of the spatial pattern of LUC and a key driver of both economic and environmental sustainability for bioenergy pathways over the long-term. To estimate the spatial distribution of grain and biomass yields for corn, MxG, and SG, we ran the gridded yield models pDSSAT[26,27] and BioCro[28] across the full conterminous U.S. at 8−50 km spatial resolution, driven by historical daily weather from 1980 to 2010 (see SI Section S-2 for more details). For the corn yield simulations (SI Figure S-1), we used the CERES-Maize model[29] from the Decision Support System for Agrotechnology Transfer (DSSAT). We used BioCro, a generic vegetation model, to estimate potential MxG and SG yields (SI Figure S-2). The model has been successfully tested for these crops in Illinois[27] and the yield assessments were extrapolated for the regions with no published data available considering the breeding efforts for those regions and environmental conditions. These simulations can also be used to anticipate changes to feedstock productivity and biofuel sustainability in the future driven by technology or environmental change.

2.3. Distribution of above and below Ground Carbon. To characterize above-ground carbon, we combined the 30 m resolution National Biomass and Carbon Data set (NBCD)[30] for the year 2000 with the NLCD × PAD-US data set developed for land availability analysis (see SI Section S-3). Protected lands account for about 30% of the total above-ground carbon stock and protected forests have on average 10.3% more above-ground carbon than available forests (SI Figure S-3a and S-3b). Aboveground carbon estimates were combined with soil carbon changes from Argonne National Laboratory's Carbon Calculator for LUC from Biofuels Production (CCLUB) model,[6] which is based on state-level simulations with the CENTURY model.[31,32] We assumed that 100% of the existing brush and undergrowth will be lost to the atmosphere, 42% of the live aboveground tree carbon will be permanently sequestered or offset by energy generation, and 100% of the live below ground tree carbon (stumps and roots) will stay in the soil (this is modeled as part of the century soil carbon changes). We further assumed that loss of forest means forgoing 12−19 MgC/ha in future sequestration (see SI Section S-4).

2.4. Multiscale Socio-Economic and Technological Scenarios. To capture the different drivers of biofuel-induced LUC, we combined local-scale (feedstock yield potential and land-availability), medium-scale (ethanol plant size and delivery radius scenarios), and large-scale (macro-economic scenarios) LUC drivers in a single model. The five macro-economic scenarios analyzed were: an increase in corn ethanol consumption from its 2006 level (4.9 BG) to 15 BG (10 BG of gasoline equivalent) in 2015 (**Corn-15**); an increase in consumption for ethanol produced from MxG from near-zero in 2011 to 7 BG (4.67 BG of gasoline equivalent) by 2022 (**MxG-7**) or 14 BG by 2022 (**MxG-14**), in addition to the 15 BG of corn ethanol demanded by 2015; and an increase in consumption for ethanol produced from switchgrass from near-zero in 2011 to 7 BG (4.67 BG of gasoline equivalent) by 2022 (**SG-7**) or 14 BG by 2022 (**SG-14**), in addition to the 15 BG of corn ethanol demanded by 2015.

In all five macro-economic scenarios, the rate of increase in corn ethanol consumption follows the observed trajectory from 2006 to the roughly 14 BG of corn ethanol produced in 2011, and then peaks at about 15 BG in 2015. Corn ethanol conversion efficiency remains constant at 110 gallons/tonne (2.8 gallons/bushel)[33] and corn yield after 2011 is assumed to increase linearly along the historical trend, implying an effective growth rate of 1.3−1.5% per year. Every tonne of corn used for ethanol production displaces $^1/_3$ tonne of corn used for animal feed through the sale of DDGS (Dried Distillers Grains with Solubles)[34] The demand for corn for animal feed in the U.S. has been inelastic to price historically, with the exception of recent years when DDGS provided a near perfect substitute[35] Demand for corn for feed is thus assumed to return to historical elasticity once corn ethanol and DDGS production flattens out in 2015.[36] Import and export demand for corn in the U.S. has been largely flat for decades and is assumed to recover quickly from the 2012 dip and remain inelastic and fixed at recent historical values of 0.3 and 50 Mt, respectively.[37] Demand for corn for food products is observed historically to be the most elastic component of total corn demand, and thus is modeled with a price elasticity of −0.3.[38] Annual percent change in corn price is modeled as a function of the residual of corn production and demand (i.e., the change in stock) each year, which is well-correlated with price changes in the historical record (R = 0.64; SI Figure S-4).

We assume that cellulosic ethanol production grows at a constant annual rate in order to meet the scenario targets, implying an average 38.2% annual growth to reach the 7 BG target level in MxG-7 and SG-7 and 47.1% annual growth for MxG-14 and SG-14. For comparison, production of U.S. corn ethanol increased by an average of 21.6% annually from 2000 to 2011, with a maximum year-overyear rate of growth over the period of 38.5% (in 2007). The growth rate assumption for cellulosic ethanol is questionable due to challenges associated with commercialization of cellulosic ethanol with respect to its supply chain logistics and conversion technology.[39] We compared each ethanol production scenario against a baseline scenario in which ethanol production is held constant. For the Corn-15 scenario (summarized in SI Figure S-5), the baseline is one in which ethanol production is frozen at 2006 levels (Figure S-5b: see SI). For the cellulosic ethanol scenarios, we use Corn-15 as the baseline.

For dedicated cellulosic feedstocks such as MxG and SG there are no historical data sets and few existing markets. Therefore, we assume for the latter scenarios that no other major economic use for dedicated grass feedstocks arises in future and thus that demand is determined strictly by the assumed ethanol production trajectory. The primary model assumptions instead concern biomass and ethanol supply dynamics. We assume conversion efficiency of 105 gallons/dry tonne for cellulosic feedstocks[7] and average nameplate production capacity in existing and installed cellulosic ethanol plants of 30 MG/yr in 2012 (783 dry tonnes feedstock/day), increasing to 150 MG/yr (3,913 dry tonnes/day) for plants built in 2022. For MxG-7 and SG-7 scenarios, 60 new cellulosic ethanol plants (Table S-2: SI) come into production between 2011 and 2022, with average capacity of 117 MG/yr (∼1.11 Mt/yr of cellulosic feedstock each). In the MxG-14 and SG-14 scenarios, 111 new cellulosic ethanol plants come into production between 2011 and 2022, with average capacity of 126 MG/yr (∼1.20 Mt/yr of cellulosic feedstock each).

We used the bale-truck transportation cost per mile to estimate maximum profitable transport distances for a given biorefinery size.[40] In all five scenarios, additional corn demand in 2012 relative to the fixed corn ethanol baseline was estimated as 91.8 Mt, while cellulosic ethanol feedstock demand in 2022 was 66.7 Mt in MxG-7 and SG-7 and 133.3 Mt in MxG-14 and SG-14.

2.5. Stochastic Partial Equilibrium LUC Allocation Model. We used the Partial Equilibrium Economic Land-use (PEEL) modeling framework[41] aggregated to county level (hence PEEL-Co) for the present study. This multiscale economic model uses a Monte Carlo approach to estimate ethanol plant siting probabilities based on county-level land availability, feedstock production suitability, and expected profit (Figure 2 and SI Section S-5). It then generates LUC pathways by allocating ethanol plants stochastically based on macro-economic scenarios and plant siting probabilities and allocates land conversion around sited plants based on profitability and conversion costs. Cellulosic biorefineries are likely to be located closer to biomass production sites due to the low bulk density of biomass and resulting higher transportation cost.[41,42] We assumed a biorefinery-feedstock radius of 30−50 miles (48−80 km) as it is economically feasible to transport biomass from distances in this range.[43,44] We based the county selection for location of cellulosic ethanol plants on simple measures of

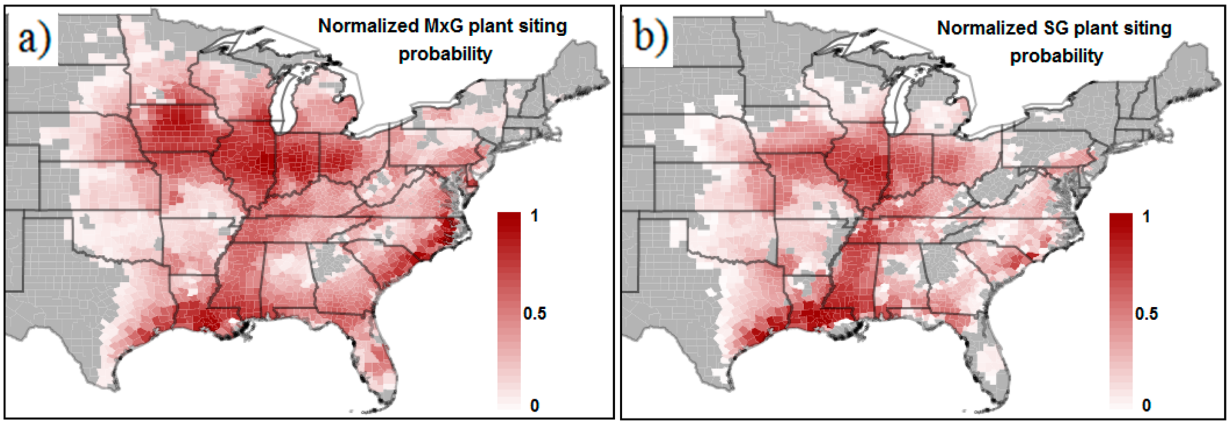

Figure 2. Normalized plant siting probabilities for (a) Miscanthus and (b) Switchgrass.

Table 1. Mean, Upper Bound and Lower Bound (95% Confidence Interval) For the Amount of Direct Land Conversion (Kha) from Each Cover Type to Biofuel Crops in Each of the Five Scenarios

	New agricultural land								Current cropland					
scenario[a]	forest and woody wetland		shrubland		open grassland		total new agriculture land		pasture/hay/fallow		other row crops		new cropland (ha per million gal)	
	mean	CI	mean	CI	mean	CI	mean	CI	mean	CI	mean	CI	mean	CI
Corn-15[b]	549.4	559.5 541.3	126.2	129.3 121.1	1020.5	1032.8 1012.2	1696.1	1721.6 1674.6	1224.3	1232.8 1216.1	644.8	652.5 634.6	56.5	57.4 55.8
MxG-7	119.2	179.3 76.1	47.4	75.5 21.9	462.0	586.2 335.8	628.6	841.0 433.8	1690.4	1833.7 1539.3	158.4	233.5 91.6	30.0	40.1 20.7
SG-7	9.7	18.6 4.0	19.2	36.9 9.1	796.4	1048.9 575.2	825.3	1104.4 588.3	3859.7	4069.2 3668.2	145.5	229.0 77.4	39.3	52.7 28.0
MxG- 14	236.6	311.3 169.5	94.1	125.8 58.5	916.7	1096.0 766.5	1247.4	1533.1 994.5	3409.7	3617.0 3210.6	322.9	441.0 215.8	29.6	36.4 23.6
SG-14	19.0	31.7 9.5	37.7	59.6 19.5	1590.5	1944.1 1228.4	1647.2	2035.4 1257.4	7757.4	8074.7 7430.2	281.3	413.7 182.1	39.1	48.3 29.8

[a]Results for scenarios 2−5 include only the *additional* land-use changes from cellulosic ethanol fuel crops. [b]The Corn-15 scenario measures LUC over a period when corn ethanol production increased by 10 BG, from 5 to 15 BG.

expected local feedstock capacity and knowledge/infrastructure availability. (Specifically, we assumed that cellulosic plants were more likely to be sited near existing plants, no matter what their feedstock, because of needed ethanol transportation logistics.) We assumed that ethanol plants can purchase biomass feedstock at equal cost from anywhere within the delivery radius. Finally we generate a Monte Carlo sample of 200 stochastic realizations for each scenario to generate county-level conversion probabilities and ranges of LUC and emissions at county, state and national level.

As the corn ethanol market is well-established, corn biorefinery siting decisions were based on the prevalence of existing corn production within a county and are assumed to have small impact on the spatial pattern of overall land conversions. Most U.S. corn ethanol plants are located in rural and mixed rural counties due to raw material availability and the proximity of byproduct users (livestock). The presence of ethanol biorefineries can also affect management decisions of local farmers such as substitution among crops, local agriculture, land ownership and cattle production.[45]

After selecting a location for a new cellulosic ethanol plant, we determine the necessary land conversions within the delivery radius. We then use a stochastic profit optimization framework to determine which lands converted for fuel crop cultivation. The model assumes that technology in each county is well represented by the distribution of simulated yields, and applies simple assumptions for the distributions of input and land conversion costs.

3. RESULTS

3.1. Land Converted Directly to Biofuel Feedstock Production.

Table 1 shows the mean and upper and lower bounds (95% confidence interval) for the amount of land converted for each cover type in each of the five scenarios. The land converted by cover class is categorized as either new agricultural land or current cropland. New agricultural land represents land that has entered the agricultural system as a result of biofuel feedstock production; it includes transitions from the forest, woody wetland, shrubland, and open grassland cover classes. Current cropland includes land used for pasture, grazing and fallow, and cultivation of other row crops that is converted to biofuel crop production. We include pasture, hay and fallow land under the cropland cover classification, as this land category can be used for crops without any additional improvements.

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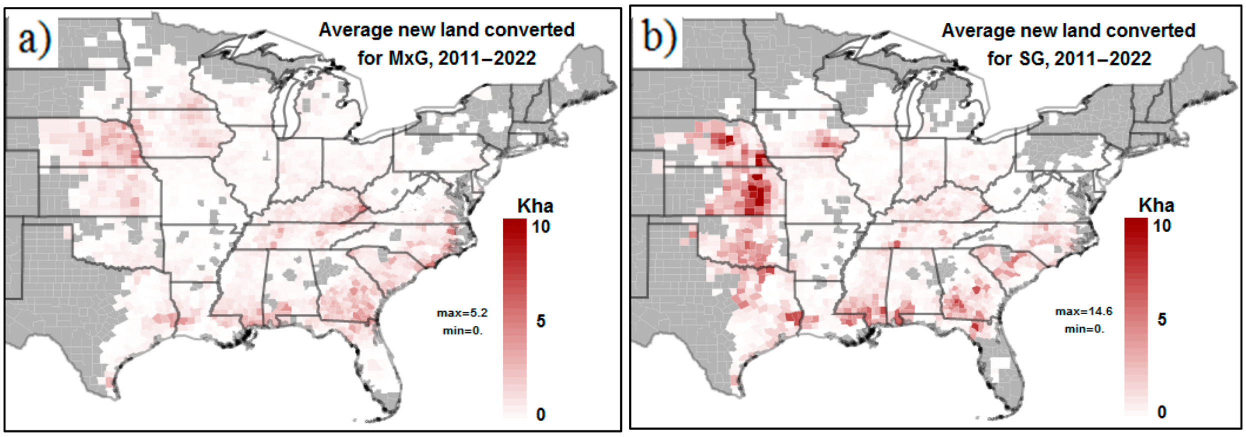

Figure 3. New land converted (from forest, shrub, or grass land) to feedstock for (a) the MxG-14 scenario and (b) the SG-14 scenario.

For the Corn-15, MxG-7, SG-7, MxG-14, and SG-14 scenarios (Table 1), our model estimates that the mean total new agricultural land converted to biofuel crop production is 1696, 629, 825, 1247, and 1647 kha, respectively. For the corn-15 scenario, 39% of the new agricultural land conversion was from forest, woody wetland, or shrubland. For the switchgrass scenarios (SG-7 and SG-14), only 4% of the new agricultural land comes from these woody cover classes, whereas for the Miscanthus scenarios (MxG-7 and MxG-14), approximately 27% of new land conversions from these classes. The share of grassland is higher than that of forest, woody wetlands, and shrubland cover classes for all scenarios—a result that is consistent with Wright and Wimberly[12] who found that grasslands declined by over 530 kha in the Western Corn Belt (WCB) over the period 2006 to 2011, partially driven by corn grown as a biofuel feedstock.

The mean total current cropland (pasture, grazing and fallow, and other row crops) converted to biofuel crop production for the Corn-15, MxG-7, SG-7, MxG-14, and SG-14 ethanol scenarios was 1869, 1849, 4005, 3733, and 8039 kha, respectively. Existing cropland and pasture account for the major portion of total land converted for biofuel feedstock production: 83% for SG-7 and SG-14 and 75% for MxG-7 and MxG-14. For Corn-15, current cropland accounts for 52% of the total land converted for biofuel feedstock production. On average, 91% of conversions in current cropland for the Miscanthus scenarios (MxG-7 and MxG-14) come from hay, pasture, and fallow, and only 9% from other row crops. Similarly, 97% of conversions in the switchgrass scenarios (SG-7 and SG-14) come from hay, pasture, and fallow, and 3% from other row crops. These results suggest that to support biofuels targets, large shifts from cropland used for hay, pasture and fallow to biofuel crop production will be required. The new cropland requirement was 57, 30, 39, 30, and 39 ha/MG for Corn-15, MxG-7, SG-7, MxG- 14, and SG-14, respectively.

Our model estimates that cellulosic plants are most likely to be located in the midwest and along the Gulf and south Atlantic coasts, mainly due to land and biomass availability and expected profit (Figure 2). Conversion of new land for biofuel feedstock in the miscanthus and switchgrass scenarios is concentrated in the plains states and along the South Atlantic and Gulf coasts (Figures 3a and 3b).

3.2. Direct LUC Emissions from Biofuel Feedstock Production. We next converted the direct LUC estimates from Section 3.1 to the associated CO_2 emissions (Table 2). The total direct LUC emissions for all scenarios were positive, representing net GHG release. Our model estimates mean total direct LUC emissions in the Corn-15 scenario of 4.43 gCO_2e/MJ. For new agricultural land, the mean total direct GHG emissions for Corn-15, MxG-7, SG-7, MxG-14, and SG-14 are 4.62, 1.69, 0.2, 1.66, and 0.18 gCO_2e/MJ, respectively. GHG emissions from current agricultural land were negative for all scenarios, with an approximate mean value of −0.17 gCO_2e/MJ, signifying carbon sequestration.

At the county level, estimated emissions for MxG-14 were concentrated in the west south central, east south central, and south Atlantic regions of the U.S., and for SG-14, carbon sequestration was largely concentrated in the Midwest U.S. (Figure 4a and b).

3.3. Indirect Land Conversion and Associated Emissions. In all scenarios, some part of the new land required for feedstock production comes from existing pastureland and some fraction of this pasture is likely to be replenished from forest or shrubland, resulting in an indirect LUC effect. Using GTAP results synthesized in the CCLUB model,[6] we estimated ranges for the fraction of lost pasture that is likely to be replenished from subsequent conversions of forest and shrubland to biofuel feedstock production. This fraction depends strongly on the total amount of pasture lost to feedstock, and was estimated as 0.25−0.50, 0.33−1.33, 1.0−2.1, 0.66−1.7, and 3.33−5.33 for Corn-15, MxG-7, SG-7, MxG-14, and SG-14, respectively (see Figure S-7 and Table S-3 in the SI for more details). The CCLUB model assumes that one-third of domestic indirect conversion to pastureland comes from shrubland; we make the same assumption here. We then used these fractions to estimate the indirect loss of forest and the resulting indirect LUC emissions that would occur as the result of the different biofuel scenarios considered in the present study (Table 3). Due to the relatively low yield of switchgrass and substantial conversion of domestic pastureland, switchgrass scenarios showed the largest indirect emissions effect from land conversion compared to all other scenarios. The range of foregone sequestration emissions was highest for the corn ethanol scenario. Among the cellulosic ethanol scenarios, miscanthus scenarios showed higher foregone sequestration because of the higher forestland conversion (Table 3).

4. DISCUSSION

We have presented a bottom-up approach to the assessment of the LUC and resulting GHG emissions that may result from pressure for increasing biofuel demand. Our approach combines high-resolution geospatial data and simulations of

Table 2. Mean and Upper and Lower Bounds (95% Confidence Interval) for Direct LUC Emissions per MJ of Energy Produced (Over 30 Years) In Each Scenario[a]

			new agricultural land							
	total LUC		forest and woody wetland		shrubland		open grassland		current cropland	
	emissions: gCO_2e/MJ									
scenario	mean	CI	mean	CI	mean	CI	mean	CI	mean	CI
Corn-15	4.43	4.54	4.14	4.23	0.49	0.50	−0.01	−0.01	−0.19	−0.18
		4.34		4.07		0.47		−0.01		−0.19
MxG-7	1.54	2.35	1.42	2.19	0.30	0.51	−0.03	−0.02	−0.15	−0.12
		0.89		0.88		0.15		−0.05		−0.18
SG-7	0.03	0.21	0.11	0.20	0.13	0.23	−0.04	−0.02	−0.17	−0.13
		−0.13		0.04		0.06		−0.06		−0.21
MxG-14	1.51	2.01	1.40	1.85	0.30	0.41	−0.04	−0.03	−0.15	−0.13
		0.99		0.98		0.19		−0.05		−0.17
SG-14	0.01	0.16	0.10	0.17	0.12	0.20	−0.04	−0.02	−0.17	−0.14
		−0.11		0.05		0.07		−0.05		−0.20

[a]Negative values indicate a sequestration credit due to an expected increase in soil carbon.

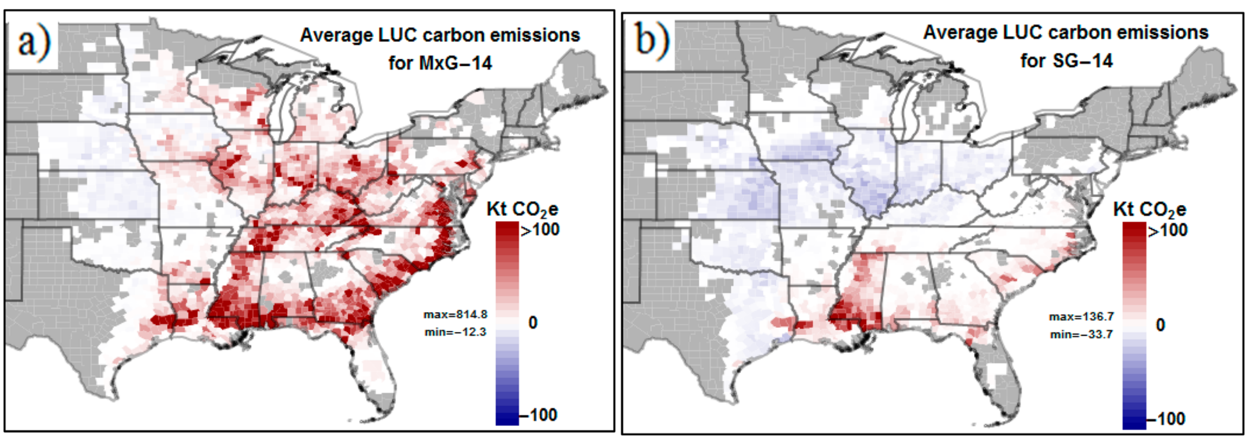

Figure 4. Average county-level direct LUC CO_2 emissions from 200 stochastic scenarios for (a) the MxG-14 scenario and (b) the SG-14 scenario.

yield potential for existing and promising fuel ethanol feedstocks. The simulation model consists of four essential components: land availability, land suitability, LUC decision-making, and induced emissions from land conversion. The modeling results showed that switchgrass requires more land compared to miscanthus in all scenarios due to relatively lower yield. It may be possible to blunt these effects through improved breeding. In Nebraska, two new switchgrass hybrids were found to have yields of 9.3 and 8.8 tons per acre, 50% greater than their parent cultivars.[46] Future high-yielding switchgrass cultivars may well greatly reduce the amount of land conversion needed to meet biofuel targets.

Regardless of technological change, biofuel production will almost certainly require conversion of natural land, most likely grasslands. This conversion can have negative impacts on the environment and on biodiversity, while also increasing risk of erosion, drought vulnerability, and threat to the natural habitat.[14] In addition, significant conversion from cropland used for row crops, pasture, hay, and fallow will result in additional LUC pressure from the livestock sector.[47]

Our results suggest that emissions factors vary significantly across land types and counties, with forest and shrubland having the highest values and grassland and pastureland the lowest. In all scenarios, conversion of open grasslands tend on average to cause small amounts of carbon sequestration, although for the corn and MxG scenarios, this small amount of sequestration was negligible compared to the loss of carbon from woody cover types.

The switchgrass scenarios considered showed low direct LUC carbon emissions. This apparently positive result arises only because production of switchgrass was not profitable enough to justify the large conversion costs associated with transforming dense forest and shrubland for its cultivation. Miscanthus scenarios showed higher direct LUC emissions because its relatively high yields (and thus profits) make the conversion of forest and shrubland economically feasible. This result is contrary to previous studies,[5] which did not consider conversion costs.

Corn ethanol showed the highest GHG emissions due to a more limited optimal growing area, greater soil carbon losses due to the requirements of intensive management,[4,5,32,48] and the implications of high potential profits on forest and shrubland conversion. However, estimates vary substantially

Table 3. LUC Emissions per MJ of Energy Produced from the Indirect Effect of Forestland and Shrubland Converted to Pastureland and Foregone Sequestration for Forestland Converted to Cropland for the Five Scenarios (Max/Min Estimates)

scenarios	indirect	direct	foregone sequestration	total
	range of emissions, gCO_2e/MJ			
Corn-15	0.06	4.70	1.72	6.48
	0.03	4.51	1.08	5.62
MxG-7	0.34	2.35	0.49	3.18
	0.08	0.89	0.31	1.28
SG-7	1.18	0.21	0.04	1.43
	0.57	−0.13	0.03	0.47
MxG- 14	0.44	2.01	0.49	2.94
	0.17	0.99	0.31	1.47
SG-14	2.83	0.16	0.04	3.03
	1.77	−0.11	0.02	1.68

among studies due to assumptions related to use of corn and DDGS for animal feed and their yield and price variation and consumption response.[5] The emissions uncertainty in past studies appears to be due to varying assumptions about above ground carbon stock, soil organic carbon stock, above ground forgone carbon sequestration data for different land types, time accounting method used to estimate emissions, and data sources used to calculate emissions factors.[5,49−51]

In addition to the direct effects resulting from biofuel production, there are significant indirect effects such as intensification of agriculture, change in consumption, and conversion of other land types.[52] In the present study, we considered the "price elasticity" for corn and crop switching from wheat and soybean to corn, miscanthus, and switchgrass. However, we did not consider possible indirect price effects such as an increase in soybean and wheat prices due to reduced supply, which could intensify land-use pressure for conversion of natural land into soybean and wheat production.

The disparity in direct LUC emissions between SG-7 and MxG-7 was compensated by indirect LUC pressure on forest and shrubland as a result of large hay and pasture land conversion for ethanol production. However, even with this indirect effect we estimate that emissions are lower in SG-7 than in MxG-7. For SG-14, we conclude that indirect LUC pressure due to the significantly higher loss of hay and pasture lands will result in higher total LUC emissions than in MxG-14.

Finally, we propose two policy options that might be exploited to reduce the LUC emissions from dedicated biofuel crops. For miscanthus, the major cause of LUC emissions is forestland conversion driven by strong economic incentives. To control emissions, policymakers should consider mechanisms to reduce incentives for forestland conversion or increase incentives for low-carbon conversions of marginal lands. LUC emissions from switchgrass stem primarily from the need to replenish lost hay and pastureland. It may be possible to use policy to make alternative marginal lands available that are not currently used for animals. For example, switchgrass is an approved fallow cover under the U.S. Conservation Reserve Program (CRP) in many parts of the country. Allowing controlled removal of switchgrass biomass from CRP lands for bioenergy, without strongly affecting ecosystem benefits, could be one such alternative.

■ ASSOCIATED CONTENT

Supporting Information

Review of land use change and emissions estimated by different studies (Table S-1); Section S-1: Estimating land availability from NLCD and PAD-US; Section S-2: Suitability maps for biofuel feedstock production from pDSSAT and BioCro (summarized in Figure S-1 and S-2); Section S-3: Estimating aboveground carbon from NBCD (Figure S-3a summarizes total US aboveground carbon in protected and unprotected cover-classes and Figure S-3b summarizes aboveground carbon in unprotected forests at county level); Section S-4: Foregone sequestration; Section S-5: Macro-economic policy assumptions (Figures S-4 and S-5 summarize assumptions for Corn-15 baseline and Table S-2 summarizes plant size assumptions for cellulosic scenarios); Section S-6: Ethanol plant siting probabilities and land conversion (Figure S-6 shows an example of the county-level LUC for a single stochastic realization of the MxG-14 scenario); Section S-7: Indirect effects (Figure S-7 and Table S-3 summarize the procedure for estimating fraction of indirect pastureland effect as a function of lost pastureland); Section S-8: Expanded results for additional scenarios (Figure S-8 shows the county-level emissions results for scenarios SG-7 and MxG-7). This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

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■ ABBREVIATIONS

GTAP	Global Trade Analysis Project
FAPRI	Food and Agricultural Policy Research Institute
CIM-EARTH	A community Integrated Model of Economic and Resource Trajectories for Humankind
DSSAT	Decision Support System for Agrotechnology Transfer

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