1 An Approach to Computing Marginal 2 Land-Use Change Carbon Intensities for 3 Bioenergy in Policy Applications

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18 **Keywords**

19 Bioenergy Crops; Land Use Change; Carbon Intensity; Integrated Assessment
20 Modeling

21

22 **Abstract**

23 Accurately characterizing the emissions implications of bioenergy is increasingly
24 important to the design of regional and global greenhouse gas mitigation policies.
25 Market-based policies, in particular, often use information about carbon intensity to
26 adjust relative deployment incentives for different energy sources. However, the
27 carbon intensity of bioenergy is difficult to quantify because carbon emissions can

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1 occur when land use changes to expand production of bioenergy crops rather than
2 simply when the fuel is consumed as for fossil fuels. Using a long-term, integrated
3 assessment model, this paper develops an approach for computing the carbon
4 intensity of bioenergy production that isolates the marginal impact of increasing
5 production of a specific bioenergy crop in a specific region, taking into account
6 economic competition among land uses. We explore several factors that affect
7 emissions intensity and explain these results in the context of previous studies that
8 use different approaches. Among the factors explored, our results suggest that the
9 carbon intensity of bioenergy production from land use change (LUC) differs by a
10 factor of two depending on the region in which the bioenergy crop is grown in the
11 United States. Assumptions about international land use policies (such as those
12 related to forest protection) and crop yields also significantly impact carbon
13 intensity. Finally, we develop and demonstrate a generalized method for
14 considering the varying time profile of LUC emissions from bioenergy production,
15 taking into account the time path of future carbon prices, the discount rate and the
16 time horizon. When evaluated in the context of power sector applications, we found
17 electricity from bioenergy crops to be less carbon-intensive than conventional coal-
18 fired electricity generation and often less carbon-intensive than natural-gas fired
19 generation.

20 **1. Introduction**

21 Bioenergy is a renewable energy resource whose deployment has the potential to
22 reduce carbon emissions relative to conventional fossil fuels (Luckow et al., 2010,
23 Chum et al., 2011). However, increased production of bioenergy can cause land use
24 change (LUC), which can increase CO₂ emissions to the atmosphere (Edmonds et al.,
25 2003, Gurgel et al., 2007, Fargione et al., 2008, Searchinger et al., 2008, Wise et al.,
26 2009, Melillo et al., 2009, Reilly et al., 2012). These emissions can be either direct
27 emissions or indirect emissions. Direct emissions are attributed to the change in
28 vegetative and soil carbon where the bioenergy crop is grown. Indirect emissions
29 occur when bioenergy production supplants local agricultural production, causing
30 increased agricultural production and associated land clearing elsewhere.
31 Interconnected global markets for agricultural products imply that much of the
32 associated LUC emissions from increased bioenergy production may be indirect,
33 occurring far from the bioenergy production itself (Chum et al., 2011).

34 Despite technical challenges in correctly accounting for total LUC emissions from
35 bioenergy production in an applied policy framework, governments have already
36 begun implementing policies that consider LUC emissions from bioenergy
37 production. Recent United States (U.S.) federal and state policies have considered
38 both direct and indirect bioenergy emissions when developing regulatory guidance
39 for renewable or low-carbon fuel standards (CARB, 2009, EPA, 2010). The
40 expanded U.S. Renewable Fuel Standard (RFS), enacted in 2007, considers direct

1 and indirect emissions for all bioenergy crops (EPA, 2010), while the California Low
2 Carbon Fuel Standard (LCFS) considers both direct and indirect emissions for
3 bioenergy produced from conventional food crops but does not consider indirect
4 emissions from lignocellulosic, or “second-generation”, bioenergy crops (CARB,
5 2009). In addition, future U.S. legislative energy policy proposals could mandate
6 consideration of LUC emissions from bioenergy production.¹

7
8 Although there is an established body of literature for computing LUC emissions
9 from bioenergy production, the understanding of the factors required to provide
10 desired deployment incentives and outcomes in an applied policy framework is
11 incomplete. Specifically, a greater understanding is needed about emissions from
12 dedicated, second-generation bioenergy crops across a range of different crop types
13 grown at scale in different regions. Many of the studies to date have focused on
14 biofuel production from conventional food crops (Hertel et al., 2010, Wang et al.,
15 2011, Edwards et al., 2010), rather than on production from second-generation
16 sources.

17 The relatively small but growing number of studies that have considered second-
18 generation sources have, by scope or by modeling approach, not considered all
19 aspects important for use in policy applications. For example, CARB (2009)
20 calculated emissions from second-generation sources (switchgrass) but assumed
21 production on non-commercial lands, and therefore did not include indirect
22 emissions. Melillo et al. (2009) focused on the global long-term average LUC
23 emissions impact rather than on marginal impacts, making attribution of LUC
24 emissions for policy development from increased bioenergy production of
25 particular crops in specific regions difficult. EPA (2010) did focus on marginal
26 impacts, but focused on the impact of a marginal increase in bioenergy demand
27 rather than production in specific regions. More recently, Taheripour et al. (2011)
28 and Dunn et al. (2013) used the Global Trade Analysis Project (GTAP) model to
29 calculate LUC and LUC emissions, respectively, from second-generation sources
30 (switchgrass) in the U.S. The GTAP and the EPA (2010) studies are among the most
31 comprehensive in scope, but they do not consider the implications of different
32 international land protection policies or of different methods of accounting for the
33 varying time profile of LUC emissions from bioenergy production.

34 In this paper, we specifically focus on quantifying direct and indirect LUC CO₂
35 emissions from large-scale production of lignocellulosic bioenergy. We do not,
36 however, attempt to compute total lifecycle emissions of bioenergy such as
37 emissions from transport or processing of biomass (note also that a comprehensive
38 life-cycle emissions comparison would consider these factors for all fuels). To

¹ See for example, the Clean Energy Standard Act of 2012 (S. 2146), considered in the 112th Congress.
Text can be found at <http://thomas.gov>.

1 address some of the limitations discussed above in computing LUC emissions, we
2 have developed an approach to isolate and compute the marginal emissions impact
3 of an increase in production of specific bioenergy crops starting in a specific year
4 and grown in specific regions of the contiguous U.S. This approach avoids averaging
5 emissions impacts from multiple bioenergy resources from multiple regions or
6 years, each with different associated emissions time profiles. The analysis is
7 performed using the Global Change Assessment Model (GCAM), a global integrated
8 assessment model of human and biogeophysical Earth systems, which links the
9 global energy, economic, and agriculture-land-use sectors (Calvin et al., 2011). As
10 GCAM is global in scope, this approach captures global CO₂ LUC emissions impacts
11 from increases in domestic bioenergy crop production. Finally, building on insights
12 provided by others (CARB, 2009, O'Hare et al., 2009, Reilly et al., 2012), we develop
13 and demonstrate a generalized approach for computing the carbon intensity of
14 bioenergy production and for comparing it to fossil fuels, taking into account the
15 specific time profile of emissions for each energy source.

16 **2. Methodology**

17 **2.1 The Global Change Assessment Model (GCAM)**

18 GCAM 3.0² is a long-term, integrated assessment model that links a global energy-
19 economy-agriculture-land-use model with a climate model of intermediate
20 complexity (Calvin et al., 2011, Kim et al., 2006, Clarke, et al., 2007, Edmonds and
21 Reilly, 1985). GCAM divides global land area into 151 agro-ecological zones (AEZs)
22 (see Wise et al., 2014 for a theoretical description and Wise and Calvin, 2011 for
23 detailed documentation) created by disaggregating each of GCAM's 14 global geo-
24 political regions into sub-regions using land use and land cover data from the GTAP
25 project (Monfreda et al., 2009). We cover the majority of land area in the contiguous
26 U.S. by focusing on six AEZs, AEZ 7-12 (Figure 1).

² Further detail is provided in the GCAM documentation (Calvin et al., 2011). Extensive documentation on the modeling of agriculture and land use can be found at <http://wiki.umd.edu/gcam/>. For simplicity, we will refer to GCAM 3.0 simply as GCAM in the remainder of this paper.

Figure 1. GCAM land use regions in the contiguous United States and Alaska.

Figure 2 shows the land use categories and nesting structure in GCAM. Arable land in each AEZ is divided into one of several categories, representing either land for commercial uses (cropland for food/fiber and bioenergy production, commercial pastureland, or commercial forestland) or land for non-commercial uses (non-commercial forestland, non-commercial pastureland, grassland, shrubland, or other arable land). Non-arable lands such as tundra, desert, and urban land are assumed to be fixed. This structure is contained in each of 151 AEZ sub-regions around the globe, with data specific to each (see Kyle et al., 2011).

Major land use data sources include Monfreda et al. (2009) for AEZ definitions and crop production (used in conjunction with cropland areas to calculate yields), HYDE data for cropland and total pastureland (Goldewijk and Ramankutty, 2004), and SAGE data for total forest and remaining non-commercial land areas (Ramankutty and Foley, 1999). As detailed in Kyle et al. (2011), GCAM makes distinctions between commercial and non-commercial forestland and pastureland based on production data. Commercial forestland is computed using regional annual commercial wood production from FAO (2010), and land areas for non-commercial forestland are then calculated as the difference between SAGE data for total forestland and commercial forestland. A similar process is used to compute non-commercial pastureland. Terrestrial carbon densities for all land use areas are from SAGE and Houghton (1999), with the exception of the vegetative carbon densities for food and bioenergy crops, which are assumed to be functions of crop yields. Terrestrial carbon stocks are tracked for each land use, with growth curves for modeling the dynamics of carbon accumulation in forests when forestland expands. Regional forestland is not modeled with discrete age classes of trees, so a change in

carbon stocks from reductions in forestland assumes that land with the regional average tree age and carbon density is displaced. (Wise and Calvin, 2011).

Within each of the 151 land use regions in GCAM, the allocation of land at any time is based on the relative profitability of using land for competing purposes. This logit approach, similar to that developed for modeling consumer choice among discrete options (McFadden, 1981), is based on the notion that there is a distribution of profits associated with each competing land use within a region, rather than a single value. The share of land allocated to any given use is determined by its distribution of profits relative to the distributions of profits for other land uses. Under this approach, all land use is allocated such that the marginal profits for competing options are equal, at which point no further increase in total profits can be realized by changing the land use shares in a region. However, market interactions between regions, which influence the prices of traded commodities, further influence land allocation within a region by altering the profits associated with a given land use. As described in Wise et al. (2014), the economic value of non-commercial lands in each region is inferred from the value of the neighboring commercial land as part of the model calibration, and expansion into these lands has to face non-linearly decreasing value at the margin.

Figure 2. GCAM land use nesting structure

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2 The GCAM nesting structure used in this paper (Figure 2) differs from the well-
3 known structure used by GTAP (Taheripour et al., 2011) by placing pastureland in a
4 separate node, whereas GTAP places cropland, forestland, and pastureland in the
5 same node. The justification for separating pastureland is that GCAM includes much
6 land that is classified as non-commercial pastureland, while GTAP includes only
7 commercial pastureland. Especially outside the U.S., a very large amount of land in
8 the databases used by GCAM is categorized as non-commercial pastureland. We
9 assume that much of this pastureland is less productive than forestland, given its
10 much lower carbon densities (see, e.g., Houghton 1999). Therefore, to be
11 conservative, we have placed pastureland in a separate node to allow flexibility to
12 assign a different value for the parameter that governs the ease of substitution
13 between cropland and forestland (as shown in Appendix B, analogous to an
14 elasticity term but treated differently in GCAM). However, in line with GTAP's
15 structure, our "Other Arable Land" category is analogous to GTAP's
16 "Cropland/Pasture" category in that it contains idled cropland and is the easiest
17 place for cropland expansion in regions in which it is available.

18 While the nesting structure is important, the allocation of land use in GCAM cannot
19 be explained by the nesting structure alone. For example, even though cropland is in
20 the same node as forestland, and pastureland is in a separate node, it does not
21 automatically follow that within each region cropland will preferentially expand
22 into forestland relative to pastureland. The expansion will depend on several factors
23 including the relative values of these land types, the parameterization of the
24 exponents between the nodes, and the calibration to base year land shares (see
25 Appendix A in the SOM for a mathematical demonstration). A simple example is that,
26 in a region with plentiful pastureland and little forestland, the expansion of cropland
27 will be concentrated into pastureland.

28 GCAM's logit land sharing structure is calibrated to reproduce a base year of 2005.
29 The base year information, including information about base year land use
30 allocation from the data described above, provides inferences about the profitability
31 of competing land uses, and GCAM incorporates these inferences (via parameters in
32 the logit formulation which are discussed in Appendix B of the SOM) when making
33 future land use allocation decisions. Future year land allocations deviate from the
34 base year only as key demand drivers, such as population growth or bioenergy
35 demand, and key supply drivers, such as crop yield improvements or land policies,
36 change the relative profits of competing land uses. The non-linear nature of the land
37 allocation implies diminishing marginal returns to expansion of any particular land
38 use. In the version of GCAM used in this study, all crop yields are assumed to be
39 fixed within each region in a given time period, with the assumption that
40 agricultural intensification will offset any yield reductions from within-region
41 extensification (i.e., expanding land devoted to crops). However, the approach to

1 computing LUC emissions developed in this study is generalizable to structures in
2 which crop yields are modeled as directly changing with intensification and
3 extensification.

4 **2.2 Bioenergy in the GCAM Reference Scenario**

5 The analysis in this paper is based on the GCAM reference scenario described in
6 Thomson et al. (2011). Although it does not directly affect the LUC analysis of
7 marginal bioenergy production, an understanding of how bioenergy is used in the
8 model provides useful context.³ In the reference scenario in 2020, the year in which
9 the bioenergy perturbation is introduced, approximately 105 EJ of primary energy is
10 consumed in the U.S. in GCAM, of which 4 EJ is bioenergy. Bioenergy is consumed in
11 several demand sectors, including electric power generation, industry, buildings,
12 and transportation. Among these sectors, the most bioenergy is consumed in the
13 industrial sector (2.0 EJ), followed by transport (1.2 EJ), buildings (0.6 EJ), and
14 electric power (0.2 EJ). The bioenergy consumed in the electric power sector and in
15 the industrial and buildings sectors comes from a combination of cellulosic
16 resources such as switchgrass, residues from agriculture and forestry, and other
17 waste products. Conversely, over 90% of the bioenergy production for liquid fuels
18 for transportation comes from food crops such as corn and soybeans. However,
19 cellulosic resources could become a larger share of transportation fuels in response
20 to future technological improvements or policy incentives.

21 Yield assumptions for switchgrass across U.S. regions and for other crops (all for the
22 year 2020) are shown in Table 1.⁴ Although the other crops could be grown in
23 several regions, we focus here on U.S. AEZ 10 just for comparison purposes. In this
24 paper, bioenergy crop yields reflect our assumptions that bioenergy crops will be
25 grown using agricultural practices consistent with other commercial crops in each
26 region and that bioenergy crop yields reflect production on land suitable for crops
27 rather than on “marginal lands” with lower productivities. Although we focus on
28 switchgrass as a representative bioenergy crop, the approach would also apply to
29 other perennial grasses.

30 All yields except those for AEZ 10 were derived from switchgrass yield data from
31 Wulschleger et al. (2011). In particular, the yield for switchgrass in U.S. AEZ 12 was

³ Since this paper is focused on bioenergy, we do not discuss details of the GCAM energy system. Although the energy system will affect the demand for bioenergy in any given scenario, the methodology used here does not depend on how the demand for bioenergy is created.

⁴ From Appendix B of DOE (2011b), the energy content of different lignocellulosic bioenergy resources is fairly uniform, ranging from 15-17 GJ/ton for residues to 18-19 GJ/ton for woody crops. For simplicity of converting several crops and residues to energy units in GCAM, the average energy density of dry biomass is assumed to be 17.5 GJ per metric ton.

taken directly from Wulschleger et al. (2011), while the yields for switchgrass in U.S. AEZs 7-9 and U.S. AEZ 11 were calculated by scaling the U.S. AEZ 12 value by the ratio of the wheat yield in a given region to the wheat yield in U.S. AEZ 12. The scaled regional Wulschleger et al. (2011) yields fall between the low and high yields reported in DOE (2011a), except in U.S. AEZ 10 where the scaled yield was higher. To maintain consistency with DOE (2011a), we lowered the U.S. AEZ 10 switchgrass yield to that shown in Table 1. Yields for miscanthus and a representative woody crop (shown here as “poplar/willow”) in U.S. AEZ 10 were also derived from representative values in DOE (2011a).

Table 1. Assumed Annual Bioenergy Crop Yields in 2020

U.S. Region	Bioenergy Crop	Yield [metric tons/acre]
AEZ 7	Switchgrass	7.1
AEZ 8	Switchgrass	6.2
AEZ 9	Switchgrass	7.2
AEZ 10	Switchgrass	9.0
AEZ 11	Switchgrass	9.9
AEZ 12	Switchgrass	9.2
AEZ 10	Miscanthus	13.5
AEZ 10	Poplar/Willow	4.5

We focus here on two regions as exemplary of regions where bioenergy crops are grown: AEZ 10 is a productive crop region while AEZ 7 is a marginal crop region. The other key physical assumption is the set of terrestrial carbon densities for different land uses, summarized in Table 2 for some of the major land uses and types in US AEZ 7 and AEZ 10 (see Kyle et al. (2011) for original sources and methodology). Based on the data sources used here, lands used for growing crops will generally have lower carbon densities than non-commercial uses of pasture and grasslands, and also considerably lower carbon intensities than both commercial and non-commercial forestlands. Switchgrass, as it is a perennial grass with lasting root structures, is assumed to have a terrestrial carbon density that is higher than the values for annual food crops and other commercial uses of land (other than commercial forestland) in AEZ 7. In US AEZ 10, the switchgrass carbon density is higher than commercial pasture but lower than other commercial uses.

1 Table 2. Average Terrestrial Carbon Densities for Major Land Types (kgC/m²)

	US AEZ 7			US AEZ 10		
	Vegetative ¹	Soil	Total	Vegetative	Soil	Total
Non-Commercial Forestland	15.1	13.6	28.7	12.7	12.5	25.3
Commercial Forestland	7.6	10.2	17.8	6.4	9.4	15.8
Shrubland	3.0	6.9	9.9	4.7	6.9	11.6
Grassland	0.7	8.6	9.2	1.9	10.7	12.6
Non-commercial Pastureland	0.6	8.6	9.2	0.7	10.7	11.4
Commercial Pastureland	0.3	6.4	6.7	0.4	8.0	8.4
Bioenergy Cropland (Switchgrass)	0.7	6.4	7.1	1.0	8.0	9.0
Food Cropland (Corn as representative)	0.5	6.0	6.5	0.4	9.0	9.4
Other Arable Land	0.3	6.0	6.3	0.3	9.0	9.3

¹Although some vegetative carbon stocks cycle annually (such as crops that are harvested), a change in land use from one vegetative carbon density to another must be counted in net emissions because it affects the average stock of carbon in the atmosphere.

2.3 Approach to Calculating Marginal LUC Emissions

In this paper, we calculate LUC emissions from bioenergy using a numerical derivative to estimate the marginal emissions that would result from land devoted to an additional unit of bioenergy production. Specifically, production is increased from a fixed starting point by an incremental amount for a specific type of bioenergy crop in a given region and year and kept at the increased production level for the remaining years in the model run. Demand for bioenergy is simultaneously increased by the same amount to ensure that the new bioenergy production is truly additional, that is, that the new production does not simply substitute for existing bioenergy production elsewhere.

This marginal approach is necessary for two reasons. First, it allows the LUC and associated emissions impact from a specific bioenergy source and from a specific region to be isolated. As such, this approach avoids averaging emissions impacts over different bioenergy resources from different regions that may individually have very different impacts (for example, a crop residue resource versus a dedicated energy crop resource). Second, this marginal approach avoids conflating the temporal emissions impact streams of repeated bioenergy cropland expansion that would occur in a scenario in which bioenergy production continues to increase in each future period. Therefore, even in scenarios in which there is an increasing amount of bioenergy production over time, this marginal approach is the appropriate method for computing the LUC impact of each unit of bioenergy.

When land is converted from non-commercial uses to commercial uses, on net, CO₂ is emitted to the atmosphere. These net emissions are the sum of terrestrial carbon lost when land is converted to commercial uses as well as the uptake of carbon from the atmosphere from the growth of those commercial crops, in this case bioenergy. Much of the emissions occur immediately as a reduction in vegetative carbon stocks (above ground carbon plus roots), while the remainder occurs over time as soil carbon stocks (below ground carbon minus roots) adjust to new equilibria (see Kyle et al., 2011 for more detail). These mechanisms lead to a characteristic time profile of net emissions that peaks at the time of the perturbation as vegetative carbon stocks are cleared and decays exponentially as soil carbon stocks adjust to new equilibrium levels over the next several years (Figure 3). This time-varying profile presents a challenge for comparing the carbon intensity of bioenergy production to that of fossil fuels, as discussed in the next section.

Figure 3. Illustrative time path of net emissions from a marginal increase in bioenergy production

2.4 Calculating carbon intensities from time-varying emissions sources

Several studies have acknowledged the need to consider the temporal aspect of bioenergy emissions when comparing their overall emissions to that of fossil fuels (CARB, 2009, Melillo et al., 2009, O'Hare et al., 2009, EPA, 2010, Reilly et al., 2012). For example, Melillo et al. (2009) propose that the cost of LUC emissions be paid by private firms as they occur, removing the need for explicit discounting. Reilly et al.

(2012) propose a formulation that would discount a stream of future carbon prices applied to bioenergy emissions, which would allow for comparison to fossil fuels.

A subset of the studies above have proposed explicit methods for comparing carbon intensities, typically defined as carbon emissions per unit of energy produced (EPA, 2010, CARB, 2009). For example, the California Air Resources Board (CARB, 2009) estimates an annual average emissions intensity by summing the emissions from a unit of bioenergy production over a fixed time period and dividing by the number of years in that period, typically 30 years. This simple approach has been widely used in research studies (e.g., Hertel et al., 2010, Wang et al., 2011) and in regulatory guidelines (e.g. EPA, 2010, CARB, 2009).

To incorporate the economic insights from the first set of studies into a policy-applicable methodology that directly translates an emissions stream into a carbon intensity, like the second set of studies, we propose a general approach for computing carbon intensities in terms of the emissions path, specified discount rate, time horizon, and carbon price escalation rate. This method is analogous to solving for an equivalent annualized carbon intensity value whose associated discounted present value is equal to the discounted present value of the future emissions stream. Consider the equation

$$P_0 \int_0^T E(t) \cdot e^{\nu t} \cdot e^{-rt} dt = CI \cdot P_0 \int_0^T e^{\nu t} \cdot e^{-rt} dt$$

where P_0 is the initial carbon price, $E(t)$ represents the emissions at time t associated with the continuous production of a unit of energy, ν is the rate of increase of the carbon price, r is the discount rate, T is the time horizon and CI is the carbon intensity (in units of emissions per unit energy). The left hand side of the equation is the discounted present value of the emissions stream, and the right hand side is the equivalent discounted present value, but stated instead in terms of a fixed carbon intensity, or CI . Solving for CI yields

$$CI = \frac{\int_0^T E(t) \cdot e^{\nu t} \cdot e^{-rt} dt}{\int_0^T e^{\nu t} \cdot e^{-rt} dt}$$

This formulation returns a fixed value for CI even though the emissions associated with bioenergy production are not constant (see Appendix C of the SOM for a closed-form solution when $r > \nu$).

In addition, when emissions are constant, as they are for fossil fuels, then $CI = E(t)$, regardless of the chosen values of r or ν . CI does not depend on either r or ν for

fossil fuels, because the time-varying component of the numerator simply reflects changes due to the rising carbon price and the discount rate, and that component is identical to the time-varying component of the denominator. More generally, the expression above normalizes the value of the emissions stream from a continuous unit increase in energy production by the value of a continuous release of a ton of emissions. This choice of normalization allows the carbon intensity of fossil fuels to be constant, while the carbon intensity of bioenergy varies with the chosen r and v .

The equation above can be solved for any assumptions about discount rate, time horizon or carbon price escalation rate. For example, it can be applied to cases in which there is either no discounting or no incorporation of carbon price escalation by setting r and v equal to zero, respectively. The CARB approach, which computes the average emissions over 30 years, is consistent with several choices for r and v as long as $r = v$, including $r = v = 0$. Finally, it is worth noting that our approach is both consistent with policy applications in which r and v represent judgments about the social discount rate and the social cost of carbon (USG, 2010, 2013), respectively, as well as with private decision-making, in which r and v represent choices about private discount rates and future realized carbon prices, respectively.

2.5 Bioenergy Production Scenarios

In this paper, we focus on switchgrass as a representative lignocellulosic bioenergy crop, since it has the potential to be grown widely in the United States. We use the marginal approach described above to compute the LUC emissions impact of growing switchgrass in each of six different regions of the contiguous US, namely AEZ 7 through AEZ 12 (Figure 1) in 2020. In addition, we conduct two sets of sensitivity scenarios. First, we compute LUC emissions for growing a representative higher-yield crop (miscanthus) as well as a lower yield representative woody crop (poplar or willow) in U.S. AEZ 10. This allows us to isolate the effect of yields on carbon intensity in a single U.S. region. Second, we examine the impact of protecting all non-commercial forestland in two scenarios above (switchgrass in AEZ 7 and AEZ 10) to illustrate the impact of hypothetical global land use policies on the carbon intensity of bioenergy production in U.S. regions with different starting land use allocations.

Since these scenarios are intended to explore the emissions impact of bioenergy crops grown at scale beyond niche applications, we grow the equivalent of 1 EJ/yr of bioenergy crops in each region as our baseline and grow an additional equivalent of 0.1 EJ/yr to compute the marginal impact starting in 2020. This method is applied to each region individually in order to isolate the impacts on LUC emissions from production in that region, as well as to distinguish the LUC that would occur within and outside of each region. In sensitivity scenarios, we find that neither the starting amount nor the size of the perturbation has a significant impact on the rate of carbon emissions per unit of bioenergy (See Appendix D of the SOM).

3. Results and Discussion

3.1 LUC Emissions from Switchgrass Grown in Different U.S. Regions

As seen in Table 3, our modeled total emissions results for switchgrass production vary by a factor of two between the production region with the lowest emissions (U.S. AEZ 7) and the production region with the highest emissions (U.S. AEZ 9). Total emissions consist of emissions that occur in the region of bioenergy production (“within region” emissions) and emissions that occur outside this region (“outside region” emissions), which result from increased commercial product production elsewhere that compensates for lost production in the region of enhanced bioenergy production.⁵ The share of “outside region” emissions varies between 22% in U.S. AEZ 12, a region with a relatively high share of forestland and relatively low share of cropland, to 55% in U.S. AEZ 9, a major agricultural region with little forestland.

Table 3. Cumulative Emissions from Switchgrass Production in Different U.S. AEZs

U.S. Region	Net Emissions [Cumulative ¹ metric tons CO ₂ /GJ]		
	Within Region	Outside Region	Total ²
AEZ 7	0.26	0.24	0.50
AEZ 8	0.52	0.40	0.92
AEZ 9	0.52	0.63	1.14
AEZ 10	0.57	0.50	1.08
AEZ 11	0.53	0.34	0.87
AEZ 12	0.79	0.23	1.01
All U.S.³	0.55	0.38	0.94

¹Cumulative over 2020-2095. A significant share of net emissions occurs in 2020, the year of the bioenergy perturbation and associated net release of vegetative carbon from converted lands. Although it varies by region, our results show that about one third of cumulative net emissions occur from changes in net soil carbon over the following years. Note that this disaggregation of net emissions into vegetative and soil carbon does not imply the same (relative) disaggregation of gross emissions or gross uptake.

²Sum of “within region” and “outside region” emissions may not exactly sum to total emissions due to rounding errors.

³In the “All U.S.” case, the model grows an additional 0.1 EJ/yr of switchgrass in any combination of regions, based on underlying economics. In general, about 25% was grown in each of AEZs 10 and 11, 15% each in AEZs 7, 8, and 12, and 5% in AEZ 9, which is a much smaller land area.

The observed emissions outcomes depend strongly on changes in patterns of LUC set in motion by the bioenergy perturbation in each region. In the context of a global

⁵ Expressed in terminology common in LUC emissions literature, “outside region” emissions can be entirely attributed to indirect emissions, while “within region” emissions consist of direct emissions plus some indirect emissions away from the site of bioenergy growth but within the same model region.

equilibrium model like GCAM, it is not possible to fully isolate the influence of different factors on the pattern of LUC, since whenever a change occurs, all prices and quantities across the energy and land use system readjust. However, it is possible to gain insights about key drivers by focusing on two regions with qualitatively different land use profiles: U.S. AEZ 7 and U.S. AEZ 10.

U.S. AEZ 10 is a major agricultural region, mainly covering the northeastern half of the U.S. (see Figure 1), with cropland for food production comprising 29% of the land area in 2020, and non-commercial forestland comprising 33%. In contrast, U.S. AEZ 7 covers much of the west and is nearly twice the size of U.S. AEZ 10. In U.S. AEZ 7, cropland for food production comprises about 8% of total land area, and forestland comprises about 5%, with over 80% of the land area devoted to non-commercial uses such as non-commercial pastureland, shrubland and grassland (Figure 4).

Figure 4. Baseline land allocation in 2020 shown as a percentage of each land use type in (a) U.S. AEZ 7 (total land area = $2.48 \times 10^6 \text{ km}^2$) and (b) U.S. AEZ 10 (total land area = $1.40 \times 10^6 \text{ km}^2$)

The first important driver of differences in LUC emissions is the crop yield. In U.S. AEZ 10, crop yields, including yields for bioenergy crops, are higher than in U.S. AEZ 7. Hence the land required to grow an incremental unit of switchgrass in U.S. AEZ 10 is smaller than that required to grow the same amount of switchgrass in U.S. AEZ 7. This, in turn, means that more land must be displaced in U.S. AEZ 7 to produce the same amount of bioenergy (Figure 5).

1 In addition to the crop yield, the starting land profiles of each AEZ heavily impact
2 LUC emissions from bioenergy production in two ways. First, non-bioenergy crops,
3 including food crops and those captured in the “other arable land” categories, will be
4 preferentially displaced relative to other land uses. This preference, reflected in the
5 nesting structure, arises from the fact that land used to grow bioenergy crops is
6 assumed to be most substitutable with other cropland (Figure 2). Thus, when
7 bioenergy is produced in regions with large starting shares of cropland, it displaces
8 large amounts of cropland in the region of bioenergy production, which needs to be
9 replaced in other regions of the world.

10 Second, bioenergy cropland also displaces other land use types within the region of
11 bioenergy production. The distribution of land shares at any given time is
12 determined by economic competition among land use types, based on their relative
13 profitability. Since the same competition that governs the initial allocation also
14 governs the adjustment, the shares of different land use types that are displaced in
15 response to the marginal bioenergy production approximately mirror the initial
16 distribution of shares in the region, all else equal.⁶

17 These two drivers, stemming from the starting land allocations, can be illustrated
18 using the same regions. In U.S. AEZ 10, the starting land allocation, ranked from
19 highest initial share to lowest initial share is: non-commercial forestland, cropland
20 for food production, non-commercial pastureland, other arable land, commercial
21 forestland, and grassland (Figure 4). The starting shares of commercial pastureland
22 and shrubland are negligible. After the incremental bioenergy production in U.S.
23 AEZ 10, the resulting displacement allocation, from largest displacement share to
24 smallest is: cropland for food production, non-commercial forestland, other arable
25 land, non-commercial pastureland, commercial forestland, and grassland. Thus,
26 cropland for food production and other arable land are disproportionately displaced
27 relative to their starting land allocation shares, with the ranking otherwise
28 reflecting the starting allocation shares (Figure 5).

29 The U.S. AEZ 10 example provides a starting point for tracing the global land use
30 impact of bioenergy production in a given region. However, it is important to
31 recognize that a reduction in commercial land uses (for food crops, grazing, or forest
32 products) in the region where the additional bioenergy crop is grown must be

⁶ Put differently, the ratio of the changes in land areas due to the marginal bioenergy production approximately equals the ratio of total land areas, because the underlying marginal profit functions for different land types are roughly linear in land area, with each having a different slope. These slopes determine the ratio of initial land use shares as well as the ratio of perturbation shares, and these ratios must be the same if the slopes are roughly constant for all land areas. A more formal demonstration of this principle is provided in Appendix A of the SOM.

1 compensated by expansion in other regions.⁷ When that expansion of commercial
2 product occurs in another region, the same displacement process, governed by the
3 same drivers, repeats in that region, further propagating a ripple effect across the
4 globe.

5 Once all of the global LUCs are determined, associated changes in CO₂ emissions can
6 be calculated by weighting LUCs by their terrestrial carbon densities, separated into
7 a vegetative carbon pool and a soil carbon pool. Changes in emissions do not directly
8 mirror changes in land areas, because carbon densities vary among land use types.
9 For example, the CO₂ emissions associated with a decrease in forestland are
10 substantially higher than those associated with a decrease in other types of land
11 uses. From the terrestrial carbon density values shown previously in Table 2,
12 displacing forestland, pastureland, grassland, and shrubland generally results in a
13 decrease of terrestrial carbon. Displacing annual cropland with switchgrass may
14 result in a slight increase or decrease in terrestrial carbon, depending on the region.

15 By combining all of the effects above, we can explain the LUC behavior and resulting
16 emissions for U.S. AEZ 7 and U.S. AEZ 10. U.S. AEZ 10 has a higher bioenergy crop
17 yield than U.S. AEZ 7, which results in less total land area converted to grow
18 bioenergy crops in U.S. AEZ 10. However, U.S. AEZ 10 has a larger initial share of
19 land devoted to cropland for food production, as well as a larger initial share of land
20 that is non-commercial forest. Thus, bioenergy production displaces more cropland
21 for food production in U.S. AEZ 10 than U.S. AEZ 7. This leads to more total land
22 (including non-commercial forestland) cleared in other regions (“outside region”) to
23 replace lost food production in U.S. AEZ 10, and thus greater “outside region” LUC
24 emissions. In addition, more non-commercial forest is displaced in U.S. AEZ 10 than
25 in U.S. AEZ 7, which leads to higher “within region” emissions in U.S. AEZ 10. The
26 combined effect is higher total LUC emissions in U.S. AEZ 10 than in U.S. AEZ 7
27 (Table 3 and Figure 6).

28

⁷ However, the net commercial LUC need not be exactly zero globally since the relevant commercial yields will differ by region, and, in some cases, the demand for the relevant products is somewhat elastic.

Figure 5. LUC (positive values imply land area expansion; negative values imply land area contraction) resulting from an additional 0.1 EJ of switchgrass production in (a) U.S. AEZ 7 and (b) U.S. AEZ 10

Figure 6. Cumulative CO₂ emissions or uptake from 2020 to 2095 (positive values indicate uptake; negative values imply emissions) resulting from an additional 0.1 EJ of switchgrass production in (a) U.S. AEZ 7 and (b) U.S. AEZ 10

3.2 Sensitivity of LUC emissions to bioenergy crop and land use policy

In addition to examining the sensitivity of LUC emissions to the U.S. region in which switchgrass is grown (above), we also tested the sensitivity to several other assumptions, including the type of bioenergy crop grown and assumptions about land use policy (Table 4). Among the crop types examined (assuming production in

1 U.S. AEZ 10 and no land use policy), our representative woody bioenergy crop
2 (poplar/willow) has the highest LUC emissions because it has the lowest annual
3 yield and requires more land than other crops to produce the same amount of
4 bioenergy. On the other hand, miscanthus has the lowest LUC emissions because it
5 has the highest annual yield. An important general implication of this result is that
6 LUC emissions from bioenergy production in a given region scale negatively with
7 the assumed annual yield of the bioenergy crop. It should also be noted that each of
8 these types of crops may have very different costs to plant, maintain, and harvest,
9 and very different characteristics in terms of land suitability. The differences in LUC
10 emissions may not be the only factor in the economic decision to plant these crops.

11 In the land use policy sensitivities (assuming switchgrass grown in U.S. AEZ 7 or 10),
12 the assumption of global non-commercial forestland protection has a large effect on
13 resulting LUC emissions, lowering LUC emissions by approximately 70% in U.S. AEZ
14 10 and by 55% in U.S. AEZ 7. The differences in impacts from forestland protection
15 between the two regions can be explained by two main factors. First, U.S. AEZ 7 is
16 less forested and therefore has less forestland to protect than U.S. AEZ 10. Second,
17 U.S. AEZ 7 has less cropland displaced and correspondingly less forestland indirectly
18 displaced outside the region in the unprotected case.

19

Table 4. Cumulative Net Emissions from Bioenergy Production under Different Assumptions

Scenario	U.S. Region of Additional Bioenergy Production	Bioenergy Crop	Land Use Policy	Net Emissions [Cumulative ¹ metric tons CO ₂ /GJ]
AEZ 7 Switchgrass No Pol. ²	AEZ 7	Switchgrass	None	0.50
AEZ 10 Switchgrass No Pol. ²	AEZ 10	Switchgrass	None	1.07
AEZ 10 Miscanthus No Pol.	AEZ 10	Miscanthus	None	0.68
AEZ 10 Poplar/Willow No Pol.	AEZ 10	Poplar/Willow	None	1.66
AEZ 7 Switchgrass Land Pol.	AEZ 7	Switchgrass	Protect forests	0.22
AEZ 10 Switchgrass Land Pol.	AEZ 10	Switchgrass	Protect forests	0.33

¹Cumulative over 2020-2095. Most emissions occur in 2020, the year of the bioenergy perturbation.

²These are the same scenarios as those labeled AEZ 7 and AEZ 10 in Table 3.

3.3 Comparison of LUC emissions to other studies

Surveys of the bioenergy LUC emissions literature illustrate the wide range of methodologies used in estimating bioenergy emissions and the correspondingly wide range of results (e.g., Chum et al., 2011, Edwards et al., 2010, and Prins et al., 2010). The majority of published studies examine LUC emissions from food crops (used for biofuels production) rather than lignocellulosic crops (used for either biofuels production or biopower), making comparison to this study difficult. However, some recent studies quantify LUC emissions from lignocellulosic bioenergy feedstocks, and it is instructive to compare our results to these.

Even though comparisons to all of these studies are not completely straightforward, it is still useful in providing context for this study (Figure 7). For comparing to studies in the literature, which are all based on liquid fuels, we have converted the GCAM results to a liquid fuel equivalent assuming a conversion rate of 50% for converting cellulosic stock to ethanol (van Vliet et al 2009) and a 30-year simple averaging method for computing annualized LUC emissions intensities. Note also that GCAM results include CO₂ emissions from LUC only, and they do not reflect a complete life cycle analysis of emissions at each stage of production and use (see, for example, Wang et al 2011).

Figure 7. Carbon intensities from GCAM compared to other studies.

CARB (2009) quantified direct LUC emissions from switchgrass on non-commercial grasslands, not considering the impacts of economic competition among land uses that would give rise to indirect emissions. With this straightforward approach, CARB (2009) calculated LUC emissions as the net loss in terrestrial carbon from converting grassland to switchgrass, resulting in a carbon intensity of 18 gCO₂/MJ of liquid fuel. This value falls between the two GCAM Protect Forest scenarios, which is consistent with the assumption in those scenarios that there would be no direct or indirect conversion of non-commercial forested lands.

As shown in Figure 7, Dunn et al. (2013) provide a range of carbon intensities from about 3 to 20 gCO_{2e}/MJ, with the low end being lower than any other studies and the high end falling between the two GCAM Protect Forest scenarios. This range is based on a range of negative and positive domestic LUC emissions of -3.9 to +13 g CO_{2e}/MJ combined with positive international emissions contribution of 6.7 gCO_{2e}/MJ. In contrast to CARB (2009), the central scenario of the GTAP-based Dunn et al (2013) study results in direct LUC emissions that are negative, meaning that the conversion of grasslands, croplands, and pasturelands to switchgrass is assumed to increase terrestrial carbon content, thus offsetting some of the indirect emissions.

1 Similarly, EPA (2010) quantified LUC emissions from switchgrass as part of its
2 analysis supporting the expanded Renewable Fuel Standard (RFS2). This study
3 combined a suite of models, data and techniques, including a detailed U.S.
4 agriculture and forestry model (FASOM model, Beach and McCarl, 2010), an
5 econometric model of international agriculture (FAPRI model, CARD, 2009), and
6 satellite data on recent historical land use transitions (EPA, 2010). It used a detailed
7 accounting methodology for U.S. emissions that is difficult to compare to our U.S.
8 results. However, we can compare our non-U.S., or “outside region” (which is
9 largely non-U.S.), LUC emissions to those from EPA (2010). In EPA (2010), most of
10 the switchgrass was grown in the southwest of the U.S., which makes it comparable
11 to our GCAM Switchgrass AEZ 7 scenario results. The EPA (2010) carbon intensity
12 from outside the U.S. is 15 gCO_{2e}/MJ, very similar to the GCAM US AEZ 7 portion of
13 emissions coming from outside the region (which is slightly less than half the total
14 shown in Figure 7).

15 Although the Melillo et al. (2009) study uses a global economic model with
16 bioenergy crops at large scales globally, the results are not perfectly comparable to
17 GCAM and to the other results shown here because they do not model a marginal
18 increase in bioenergy production. Instead, the production of bioenergy is expanding
19 each year in response to a climate policy, until the annual production rate levels off
20 around mid-century. As a result, the average LUC emission rates shown conflate
21 emission pulses from different time periods over the model runs, resulting in higher
22 average emissions intensities when bioenergy production is expanding. In Figure 7,
23 Case 1 assumes that cropland may expand to meet the direct and indirect land
24 requirements for growing bioenergy, while Case 2 assumes a constraint on cropland
25 expansion and relies on crop intensification and demand responses, resulting in
26 much lower emissions. Not shown here, Melillo et al. (2009) show that LUC carbon
27 emissions rates for both Cases 1 and 2 continue to diminish for this path of
28 bioenergy production if the integration period is extended to 100 years, but there
29 would still be continuing N₂O emissions from fertilizer.

30 The GCAM results fall within the range spanned by these other studies. The LUC
31 emissions from GCAM Switchgrass AEZ 10 results are relatively high due to the
32 amount of forest displaced in the region and the indirect LUC induced elsewhere
33 since this region also contains much high-yielding cropland.⁸ The two GCAM Protect
34 Forest cases reduce LUC emissions for switchgrass grown in AEZ 10 and AEZ 7 by
35 about 70% and 55%, respectively, putting LUC emissions closer to EPA (2010) and
36 CARB (2009) switchgrass results. The GCAM Protect Forest cases are relevant not

⁸ Note that GCAM does not use Armington elasticities (see Edwards et al 2010 for a definition and description), and instead assumes that increased demand is met by the global market rather than with preference for domestic production. All else equal, a preference for U.S. production would lower LUC because of generally higher yields.

only as a policy assumption but also as a comparison point. Many models, like GTAP (Taheripour et al. 2011) and FASOM (Beach and McCarl 2008), do not model non-commercial forestlands and thus in effect do not consider expansion of cropland into non-commercial forestland. The emissions from bioenergy grown in the grassland and pastureland-rich GCAM AEZ 7 in the Protect Forest case are just slightly higher than the GTAP studies. The low LUC emissions in the GCAM generic US demand case reflect supplies from a model-determined mix of about half switchgrass and half residue feedstocks that are assumed to have no LUC impact.

3.4 Comparison of bioenergy and fossil fuel carbon intensities

Figure 8 compares the carbon intensity of switchgrass grown in two different regions under different carbon price escalation rates, discount rates and time horizons to the carbon intensities of coal and natural gas. This comparison is made in the context of the electric power sector, so that carbon intensities reflect assumed conversion efficiencies of generation facilities⁹. However, our approach is general and, thus, just as applicable to liquid fuels used in transportation, provided that the appropriate conversion efficiencies are considered.

The switchgrass results are shown in Figure 8 as a function of the assumed time horizon, the region of bioenergy production, and the difference between two economic parameters, the discount rate (r) and carbon price escalation rate (v). The difference between r and v is effectively an “adjusted” discount rate that reflects the extent to which a rising carbon price counteracts the decreasing time value of money. We calculate carbon intensity for four values of the adjusted discount rate, including one that is negative, one that is zero, and two that are positive. It is theoretically possible for $r-v$ to be negative, i.e. for the carbon price escalation rate to exceed the discount rate. However, this case is less likely than the alternative in either the public or private decision-making context. An adjusted discount rate equal to zero is common in the literature and corresponds to the fixed-year averaging approach used in several studies, including CARB (2009) and EPA (2010). Our time horizon assumptions are chosen to reflect a common assumption of 30 years (e.g. CARB, 2009) and one longer alternative of 60 years. The two regions of

⁹ The assumed conversion efficiencies for coal and natural gas-fired electricity generation are 39% and 48%, respectively, based on assumptions for new coal integrated gasification combined cycle (IGCC) plants and new natural gas combined cycle plants from the 2013 Annual Energy Outlook (AEO) (EIA, 2013). For bioenergy, we assume a conversion efficiency of 37%, drawing on AEO 2010 (EIA, 2010), because the assumed bioenergy technology was changed in AEO 2011 from an efficient gasification technology to a less efficient direct combustion boiler (EIA, 2011). Average carbon intensities for coal and natural gas are assumed here to be 108 kgCO₂/GJ and 58 kgCO₂/GJ, which is broadly consistent with the range of intensities in EIA (2013). No attempt is made here to account for methane emissions from natural gas production.

1 bioenergy production correspond to those discussed in Section 3.1 and reflect two
2 U.S. regions with significantly different starting land use allocations.

3 Carbon intensities for switchgrass are lower for lower values of the adjusted
4 discount rate and longer time horizons. Generally, when future periods– the periods
5 when bioenergy LUC emissions are smallest (see Figure 3) – are more heavily
6 weighted, the carbon intensity is lower. This explains why the green and blue bars
7 are taller than the purple and red bars, respectively, for the range of adjusted
8 discount rates considered. It also explains why the gap between the green and
9 purple or blue and red bars decreases as the adjusted discount rate increases. For
10 example, when the adjusted discount rate is negative or zero, the carbon intensity of
11 switchgrass decreases sharply as the time horizon is increased in both regions. At
12 higher adjusted discount rates, it decreases less sharply as the time horizon is
13 increased since future period emissions are weighted less heavily.

14 Across the cases considered in Figure 8, the carbon intensity of generation from
15 bioenergy is always less than that of coal-fired generation, while it is often, but not
16 always less than that of natural-gas fired generation. For example, when $r - v = 0$, we
17 find that the carbon intensity of bioenergy is less than natural gas by a considerable
18 amount in U.S. AEZ 7 and by a smaller amount in U.S. AEZ 10. However, for biomass
19 grown in U.S. AEZ 10 at adjusted discount rates of 5% and higher (regardless of time
20 horizon), the carbon intensity of bioenergy is higher than natural gas.

21

22

Figure 8. Carbon intensities for coal, natural gas and biomass used in electric power applications, represented by GCAM results for switchgrass in U.S. AEZ 7 and U.S. AEZ 10 assuming no land use policy and different values for the discount rate (r), carbon price escalation rate (v) and time horizon.

4. Conclusions

Using an economic-energy-agriculture-land-use integrated assessment model, we have demonstrated a comprehensive approach for computing the LUC emissions from bioenergy considering the different factors that drive different estimates of carbon intensities. From this exercise, we find that total LUC emissions, as well as the shares occurring within and outside of the region of production, depend strongly on the starting allocation of land use in the region in which the bioenergy is produced. LUC emissions differ by approximately a factor of two across production regions, indicating that it is important for policy applications to consider the region of production as the direct and indirect emissions impacts will vary. Similarly, the carbon intensity scales negatively with annual yield, suggesting it is important to differentiate between bioenergy crops when using carbon intensities in policy applications. Also important are the assumptions about the differences between terrestrial carbon densities associated with land for bioenergy and those associated with the land use it replaces. Land use policy that protects forested lands significantly reduces the carbon intensity of bioenergy, confirming the important role that national and international land use policies can have on the emissions impacts of domestic bioenergy production.

1 Finally, we developed and demonstrated a generalized method for considering the
2 varying time profile of LUC emissions from bioenergy and for comparing the carbon
3 intensities of bioenergy to other sources, such as coal and natural gas used in
4 electric power generation. The discount rate, assumed carbon price path, time
5 horizon, along with the factors described above, all have significant impacts on the
6 resulting carbon intensity of bioenergy. In the examples shown here for switchgrass
7 in U.S. AEZ 7 and AEZ 10 with no land policy, we show that the carbon intensity of
8 LUC emissions from second-generation bioenergy used for electric power
9 generation is lower than the carbon intensity of coal-fired generation among the
10 cases considered, whereas it is often, but not always, lower than the carbon
11 intensity of natural gas-fired generation. These comparisons to fossil fuels would of
12 course be different for different bioenergy production and policy assumptions.
13 Careful consideration of the factors discussed here, among others, is needed to
14 correctly assign bioenergy carbon intensities in policy applications.

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