Sensitivity of Carbon Emission Estimates from Indirect Land-Use Change

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Abstract

We analyze the sensitivity of greenhouse gas (GHG) emissions from land-use change to modifications in assumptions concerning crop area, yield, and deforestation. For this purpose, we run a modified version of the Center for Agricultural and Rural Development (CARD) Agricultural Outlook Model, which was used previously to assess the impacts of energy price increases and biofuel policy changes on land conversion. To calculate the GHG implications of agricultural activity, we use *GreenAgSiM*, a model developed to evaluate emissions from land conversion and agricultural production. Both models are applied to scenarios that lead to higher US ethanol production. The results are contrasted with the findings of Searchinger et al., and we explain the role of model assumptions to elucidate the differences. We find that the payback period of corn ethanol's carbon debt is sensitive to assumptions concerning land conversion and yield growth and can range from 31 to 180 years.

Keywords: biofuel, crop yield, greenhouse gas emissions, indirect land-use change.

1. Introduction

Research published in *Science* by Searchinger et al. (2008) estimates that it would take 167 years of using corn ethanol rather than gasoline before the carbon debt from ethanol-induced conversion of natural lands to agriculture would be paid back. The purpose of this paper is to explore the sensitivity of this payback period to modeling assumptions concerning agricultural production, land-use change, and greenhouse gas (GHG) emissions. For this purpose, we use a modified version of the same Center of Agricultural and Rural Development (CARD) Agricultural Outlook Model used by Searchinger et al. and the *Greenhouse Gases from Agriculture Simulation Model* (*GreenAgSiM*), a model that assesses the GHG emissions from agriculture-induced land conversion and agricultural production. *GreenAgSiM* was developed at Iowa State University in response to the need to evaluate GHG emissions from agriculture and their sensitivity to policy changes.[1]

To assess the impact of each modified assumption, we proceed in a step-by-step approach. First, we take the scenario results ("Fall 2007") from the CARD Agricultural Outlook Model used in Searchinger et al. and run the *GreenAgSiM* under the same assumptions to verify that *GreenAgSiM* gives similar results. We then relax the assumption of deforestation in the United States made by Searchinger et al. because this seems to be unrealistic according to the Environmental Protection Agency's Greenhouse Gas Inventory Report (EPA, 2007). Between 1990 and 2005, forest area decreased by 4.1%, but it has remained stable over the last five years. Furthermore, data from the Economic Research Service of the US Department of Agriculture about major land uses in the US between 1945 and 2002 indicate that new cropland is taken from pasture and not forests (ERS/USDA). We then move to the results of a comparable scenario from the most recent version ("Fall 2008") of the CARD Agricultural Outlook Model and we retain the assumption of no US deforestation.

In the first run using the 2008 data, the land-use impact of an increase in crop yields is evaluated. The second and third runs with the fall 2008 data involve the addition of emissions (methane and nitrous oxide from global livestock and cropland management), and a change in the assumption of the CO_2 benefit of ethanol. Emissions from global agricultural production were not explicitly taken into account in Searchinger et al. but can be assessed by *GreenAgSiM*.

Note that the calculation procedure of the payback period is the same in this analysis and in Searchinger et al. First, the differences in crop area between a baseline and a scenario are taken to evaluate the difference in GHG emissions between the two forecasts. Searchinger et al. use data from the Woods Hole Research Center to estimate these emission calculations whereas here we use *GreenAgSiM*. Second, the difference in GHG emissions from land-use change is then incorporated into a life-cycle analysis (LCA) model to calculate the payback period. The LCA model used by Searchinger et al. was the *Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation* (*GREET*) model, which is maintained by the Argonne National Laboratory of the US Department of Energy. In addition to the GREET model, in this analysis we use the *Biofuel Energy Systems Simulator* (BESS) from the University of Nebraska to calculate the CO_2 benefit of ethanol. In practice, both models are commonly used for LCA of biofuels.

[1] See Dumortier and Hayes (2009) for documentation of GreenAgSiM.

Our findings are twofold: Given the assumptions made and the data used by Searchinger et al., *GreenAgSiM* computes a payback period of over 180 years. This shows that, with the same assumptions used by Searchinger et al. but using a different model, we get very similar results. However, changing these assumptions leads to very different results. For example, using the modified 2008 CARD model and the assumption of no U.S. deforestation, the payback period of corn ethanol is around 120 years. Changing assumptions such as crop yield projections or the direct CO_2 benefit of corn ethanol changes the payback period significantly. A yield increase over the next 10 years leading to 1% higher yields by 2018 would result in a payback period of 31 years. A similar change in the payback period is obtained depending on the assumptions used to calculate direct emissions from corn ethanol in the LCA. These results compound in the sense that if we assume a yield response and use the default assumptions embodied in BESS rather than GREET, then the payback period is about 15 years. In this case most ethanol plants would have paid back their carbon debt before the end of their expected lifespan. The lesson for policymakers is that results from economic models depend heavily on assumptions, and because we are trying to predict long-run human behavior, there can be legitimate differences in these assumptions.

The remainder of the paper is organized as follows. Section 2 gives an overview of the previous research on the increase in US corn ethanol production and land-use change. In section 3 we explain changes to the CARD model that were undertaken after the Searchinger et al. study, and in section 4, we analyze the sensitivity to different assumptions made in the modeling process. All tables mentioned can be found at the end of the paper.

2. Previous Work

In the fall of 2007, a CARD research team estimated the impact of an increase in ethanol production in the US on world agricultural markets (Tokgoz et al., 2007). For this purpose, they used the CARD Agricultural Outlook Model, which is used to project agricultural supply, utilization, and prices in 35 countries and world regions over the next 10 years. The model covers 13 crops and three major livestock categories (cattle, swine, and poultry) as well as the biofuel and dairy industries. They assumed an increase in crude oil prices of $10 per barrel over the projection period and compared the resulting increase in ethanol production ("HCO" or "High Crude Oil" scenario) to their baseline scenario ("Baseline 2007"). The results of the model indicated that the additional production of 55.9 billion liters of corn ethanol would bring in an extra 10.8 million hectares of cropland globally in 2016.

This increase in ethanol production and the associated land-use change was then used by Searchinger et al. to calculate the carbon emissions from land conversion of the additional cropland. The carbon loss due to this increase amounted to 3.8 billion tons of CO_2 equivalents. Based on these calculations, Searchinger et al. used the GREET model to calculate that the payback period of the carbon debt was 167 years in the case of corn ethanol.

In the fall of 2008, the CARD research group ran an updated version of the CARD Agricultural Outlook Model to establish a new baseline. The baseline ("Baseline 2008") takes the Energy Act of 2007 and the 2008 Farm Bill into account and assumes a crude oil price of approximately $75 per barrel. Besides the baseline, a high energy price scenario ("HEP") was simulated, which assumed an increase in crude oil prices by 40%, to $105 per barrel, and a 19% increase in natural gas prices (Hayes et al., 2009). This HEP scenario is comparable to the fall 2007 high crude oil price scenario in the sense that both induce increased ethanol production through higher energy prices. However, these two scenarios are not exactly equivalent because the 2007 high crude oil price scenario used by Searchinger et al. was a “no bottleneck” scenario and the one used in Hayes et al. was a “bottleneck” scenario. “No bottleneck” in the adoption and distribution of ethanol leads to higher expansion in ethanol demand than in the “bottleneck” scenario. In the HEP scenario, ethanol production increases by 29,859 million liters, which causes the conversion of 6.076 million hectares to cropland. The results of the two studies are normalized to a per-unit-of-ethanol basis.

In the analysis in section 4, we use the fall 2007 high crude oil scenario to test the performance of the *GreenAgSiM* model and evaluate the difference between the Searchinger et al. and the *GreenAgSiM* results. In the subsequent sensitivity analysis, however, we make use of the modified CARD model, i.e., we use the fall 2008 high energy price scenario.

3. Modified CARD Model and *GreenAgSiM*

The purpose of this section is twofold. First, we describe the updates made to the CARD Agricultural Outlook Model and the resulting changes in crop area. Second, we explain the functioning of the *GreenAgSiM* model and the assumptions made in the modeling process.

3.1 Changes to the CARD Model

Although both Hayes et al. and Tokgoz et al. used the same modeling structure and they both analyzed a higher crude oil price scenario, there are differences between these two studies that explain the differences in the response of US and international crop area to a higher crude oil price shock. We next discuss these differences in the model structure and summarize the scenario results for crop area. Note that 2018 represents the marketing year 2018/19 for crops. This holds true for other years mentioned in the paper. For each change in model structure we identify whether the change led to only a change in the volume of ethanol produced or whether the change affected the ratio of land expansion per unit of ethanol. A change in ethanol volume affects the total change in land expansion but not necessarily the ratio of land expansion per unit of ethanol.

3.1.1 Changes to the Structure of the Model

Changes were introduced in the CARD model between fall 2007 and fall 2008. The first change is the endogeneity of the US gasoline price. In the 2009 Hayes et al. study, a two-way link between the US ethanol and gasoline sectors was introduced. In the study, the gasoline price in the US is impacted by a change in the US ethanol production at a rate of $0.0079 per billion liters ($0.03 per billion gallons) based on Du and Hayes (2008). When a higher crude oil price is introduced (increase of $30 per barrel) in the scenario, both US ethanol production and consumption increase. The increase in ethanol production reduces the US gasoline price, which in turn reduces E-85 consumption since E-85 is a substitute to gasoline as a fuel for transportation. Thus, lower gasoline prices mean consumers switch back to gasoline from E-85. This leads to less US ethanol expansion per unit of change in the crude oil price. However, this changer has no impact on the ratio of land use per unit of ethanol.

Second, the fall 2008 CARD model introduced changes in the variable costs of production (e.g., fertilizer) with respect to changes in energy prices. The higher crude oil price in the US increases the cost of production for all crops. Thus, for a per-unit-of-crude-oil price increase, we see lower increases in the US crop area and production for all crops. The increase in production costs because of a crude oil price increase is also introduced in the international crop models for major producers. The producing countries are Argentina, Australia, Brazil, China, European Union, India, Canada, Russia, Ukraine, and Commonwealth of Independent States (CIS). The US crude oil price is used as a proxy for the world crude oil price. Therefore, an increase in the US crude oil price means higher crude oil prices in these countries and higher costs of production for farmers. This reduces crop area in these countries and we see less of an area expansion when crop prices increase. In Hayes et al., higher crude oil prices also increase non-feed costs in the US livestock and dairy sectors, reducing supply and feed demand as a result, thus relieving part of the demand pressure on corn. This leads to a lower increase in crop prices in the crude oil price shock scenario as compared to the Tokgoz et al. study. Additionally, in Tokgoz et al., livestock supply was maintained with changes in the crude oil price. Thus making the cost of agricultural production dependent on energy costs will result in less land expansion per unit of crude oil price increase.

Third, Hayes et al. used CARD models that projected out to the 2022/23 marketing year. Thus, long-run equilibrium in US ethanol production was imposed in 2022/23. Tokgoz et al. used CARD models with projections to 2016/17, and long-run equilibrium in the US ethanol production was imposed in 2016/17. The long-run equilibrium represents the equilibrium in the US ethanol industry when there is no incentive for ethanol plants to enter or exit the market, i.e., their profit margins are equal to zero, and the livestock sector adjusts back to “normal” returns. The characteristic of long-run market equilibrium differs in the two studies. In particular, in Tokgoz et al., the long-run equilibrium was imposed in both supply (zero profit) and demand (ethanol price at energy equivalent level). In the Hayes et al. study, a zero-profit condition was imposed only on the profits of ethanol producers, not on the profit of blenders. On the demand side, the price of ethanol was allowed to stay below its energy equivalent level at the end of the projection period. These differences limited the Hayes et al ethanol volumes, keeping them lower than if the Tokgoz et al. equilibrium conditions had been imposed.

Fourth, in Hayes et al., the international crop models were improved based on additional information and insight obtained from the previous work. Specifically, in the area equations for each crop, cross-price impacts from other crops were re-evaluated and additional relevant crop prices were added. For example, in the equation for Brazilian soybean area harvested, additional cross-price impacts were included. In Hayes et al., Brazilian soybean area was a function of the soybean price, wheat price, corn price, sugarcane price, lagged area, and fertilizer cost index. In Tokgoz et al., Brazilian soybean area was a function of the soybean price, wheat price, and a positive trend. This is one of the reasons why Brazilian soybean area expanded less in Hayes et al. relative to Tokgoz et al. in response to crop price increases. When more cross-price impacts are added, the soybean area expands less since prices of these other crops all increase. This change reduces crop supply responses, thus decreasing the ratio of land expansion per unit of ethanol.

Other differences between the two studies come from the fact that trend yields were assumed in both models and hence the crop yields in Hayes et al. are higher for the year in which the long-run equilibrium is imposed. This means that fewer acres of land are needed to produce a given volume of ethanol. Furthermore, the international cotton and rice models were run in the most recent version of the model. These changes the scenario results, since it allows more cross-price impacts for crop area allocation, which tends to lower the amount of land expansion per unit of ethanol. For the calculation of GHG emissions, these two commodities were not included in order to preserve comparable land-use change effects. In Hayes et al., corn oil was added as a by-product in ethanol production in the dry mill process. Specifically, for the revenue of the dry mills that produce ethanol, the profit from producing corn oil as a separate by-product was included. This reduces the yield for distillers grains as a by-product of ethanol production. The additional corn oil supply dampens the vegetable oil complex prices in the US and world markets, relative to Tokgoz et al., and may help explain the muted response of soybean area in Brazil. The change affects both the total volume of ethanol as well as the ratio of land use per unit of ethanol.

3.1.2 Comparison of Results

In Hayes et al., in the high energy price scenario, a crude oil price shock of $30 per barrel was run, whereas in Tokgoz et al. a crude oil price shock of $10 per barrel was run. In Hayes et al., this led to an increase in US corn-based ethanol production of 50.2% relative to the baseline (32.2 billion liters or 8.5 billion gallons) and an increase in total ethanol production of 25.9%. In Tokgoz et al., a smaller shock of $10 per barrel increased the US corn-based ethanol production by 100.5% (55 billion liters).

The Searchinger et al. study was based on the “crude oil price shock with no bottleneck” scenario. In this scenario, ethanol demand increased from 56.8 billion liters to 113.2 billion liters. In Hayes et al. the wholesale price of ethanol was $0.3725 per liter ($0.5072 per liter minus the tax credit of $0.1347 per liter). The wholesale price of gasoline was $0.5627 per liter. Thus, ethanol was selling very close to its energy value of $0.3751 per liter ($0.5627 × 2/3). In the fall 2008 scenario, the wholesale price of ethanol was $0.3276 per liter ($0.4623 per liter minus the tax credit of $0.1347 per liter). The wholesale price of gasoline was $0.5627 per liter. Thus, ethanol was selling much lower than its energy value of $0.3751 per liter ($0.5627 × 2/3) due to the bottleneck.

In Hayes et al., ethanol demand increased to 45.3 billion gallons from 36.9 billion gallons in the baseline in response to a crude oil price increase. Bottlenecks in the adoption and distribution of ethanol were assumed to still exist, so ethanol demand did not increase as much as it could have if these infrastructure problems were solved. Therefore, even though the crude oil price shock was higher relative to that in the Tokgoz et al. study, ethanol demand, particularly E-85 demand, did not increase as much as in a “no bottleneck” scenario.

In addition, there is a separate specification for ethanol demand by blenders in Hayes et al., and the profit margin for ethanol blenders was still positive. If there were no bottlenecks, this profit margin would have approached zero in equilibrium. In Tokgoz et al., there was no differentiation between ethanol demand by blenders and ethanol demand by final consumers, i.e., only ethanol demand by final consumers was included. In the comparison of scenario results for the two studies, the percentage changes in Table 1 are computed in deviation from the baseline for the “crude oil price shock” scenarios. The percentage changes are computed for the year 2022/23 for Hayes et al. and for 2016/17 for Tokgoz et al., since this is the year in which long-run equilibrium is imposed.

Hayes et al. found that in response to the increased demand for corn brought about by the ethanol expansion, the US corn price increases, leading to an increase in corn area and a decline in corn exports. In response to higher corn prices, both soybean and wheat area planted decrease. The lower supply results ssin an increase in their respective prices and a reduction in their exports. Higher US crop prices and lower US crop exports lead to higher crop prices in the world markets. As shown in Table 1, the results in Tokgoz et al. are the same in terms of direction to the Hayes et al. study, but the magnitudes differ because of the differences in the studies that we have outlined.

To account for differences in ethanol volumes between the two studies, we also calculate the percentage changes in scenario results for the two studies scaled by the change in US corn-based ethanol production in billion gallons for each case. For Hayes et al., percentage changes are divided by 32.2 billion liter change in ethanol production, i.e., for Tokgoz et al., the percentage changes are divided by the 55 billion liter change in ethanol production. Table 1 presents the results from the two studies expressed in percentage deviations from the baseline calculated in terms of per unit of ethanol. Note, however, that Table 1 represents the change in crop prices and area only in the year of long-run equilibrium and not on a year-by-year basis.

3.2 Description of the GreenAgSiM

Several issues precipitate the need to measure greenhouse gas emissions from agricultural activity. First, agriculture and forestry (including deforestation) are responsible for 13.5% and 17.4% of global anthropogenic GHG emissions respectively (IPCC, 2007). With the upcoming 15th Conference of Parties of the United Nations Framework Convention on Climate Change in Copenhagen in December 2009, which marks the beginning of a post-Kyoto framework on climate change, agriculture is likely to be part of the mitigation efforts. Second, a model to evaluate the impact of policy changes on greenhouse gases is needed to detect possible leakages in other countries.

The CARD research group was already able to simulate the path of world agricultural production; hence, a natural extension was to develop a greenhouse gas component to the model. The result of this effort is the *GreenAgSiM*. The *GreenAgSiM* estimates emissions according to categories of national greenhouse gas inventories established by the Intergovernmental Panel on Climate Change (IPCC). These categories include emission from enteric fermentation and manure management from livestock, agricultural soil management, rice cultivation, and land-use change. The present *GreenAgSiM* consists of three components, which can be run independently but use the same input data from the CARD Agricultural Outlook Model. The three modules of the GreenAgSiM are as follows.

- **International Agricultural Production:** The module includes enteric fermentation, manure management, and agricultural soil management. It covers all countries except the United States. Furthermore, it comprises only methane (CH_4) and nitrous oxide (N_2O) emissions.
- **US Agricultural Production:** Because of a higher level of data availability for the United States, we separate this module from the international counterpart. In particular, the fertilizer use in different states is taken into account in this module. Other than that, the same emission sources as in the International Agricultural Production module are used.
- **Land-Use Change:** Emissions induced by land-use change occur if forest and grassland are converted into cropland. Direct land-use change refers to the case in which new cropland devoted

to biofuel replaces forest and grassland. Existing cropland, which was originally used for food and feed production and is now diverted to biofuel production, causes indirect land-use change because part of the lost food and feed production will take place somewhere else. Large amounts of CO_2 are released in the case of deforestation in tropical regions. With the data derived from the CARD Agricultural Outlook Model, we estimate the emissions from direct and indirect land-use change. For the US, we assume that no deforestation takes place if cropland is expanded, i.e., we assume that new cropland comes from set-aside land, such as land in the Conservation Reserve Program and grassland. In addition, the model is able to capture carbon sequestration if cropland comes out of production and re-grows to natural vegetation.

Note that emissions from fuel burning (i.e., farm machinery) are not yet considered in *GreenAgSiM*. We are aware that in order to calculate emissions from agriculture accurately, farm machinery should be included, and we intend to make this change in a future version. At the moment, the *GreenAgSiM* follows very closely the emission categories established by the IPCC. Emissions from agricultural machinery are measured in IPCC category 1A4c (Energy – Fuel Combustion Activities – Other Sectors – Agriculture/Forestry/Fishing/Fish Farms).

The *GreenAgSiM* and the CARD Agricultural Outlook Model are global in scale. Major agricultural producers such as the US, the EU, Brazil, China, and India are explicitly represented in both models. In order to provide a closure of the models, minor countries are grouped together per continent. Note that certain countries such as the US, Russian Federation, and China are subdivided into their states. Because of the expanse of these countries, the subdivision is necessary to get accurate predictions about land-use change. Some countries are modeled on the national level, e.g., Algeria, whereas smaller countries are modeled at the continental level.

Our modeling approach is different from the one chosen by Searchinger et al. in several ways. First, Searchinger et al. used the difference in cropland area in the year the long-run equilibrium is imposed, i.e., 2016/17. *GreenAgSiM* is more dynamic in nature in the sense that we have a year-by-year analysis of emissions depending on whether cropland comes into or out of production. *GreenAgSiM* subdivides the world into 518 administrative units (e.g., 50 states in the US). For each of these units, the change in cropland is calculated from one year to the next. Immediate loss of biomass and soil carbon is assumed in case of cropland expansion. If cropland is taken out of production, we assume that the land sequesters carbon (biomass and soil) over 20 years. Second, in the GHG analysis by Searchinger et al., the loss of biomass and soil carbon was based on historical data from the 1990s. The spatial resolution of the data was very low in the sense that the world was subdivided into only 10 regions (the United States, North Africa and Middle East, Canada, Latin America, Pacific Developed, South and Southeast Asia, Africa, India/China/Pakistan, Europe, and Former Soviet Union) and uniform deforestation and grassland conversion rates were applied to these regions. As previously mentioned, the spatial resolution of the *GreenAgSiM* is much higher, at 518 administrative units. We base our loss of carbon not on historical data but on the "average" vegetation in an administrative unit based on vegetation maps and global ecological zones. Third, our emission rates are not uniform by country but by crop-country combination. That means that a one-hectare increase of crop A in a country has a different carbon implication than a one-hectare increase of crop B in that same country because we assume that cropland expansion takes place in units that already have a high proportion of cropland. A complete description of the model can be found in Dumortier and Hayes (2009). Note that tables 2 and 3 report the land-use emissions on a cumulative basis over the relevant time period. Figure 1 shows the cumulative emissions for the baseline and the HEP scenario (equivalent to column 5 in table 2).

4. Sensitivity Analysis

In this section, we report the effects on the payback period of changing one assumption at a time. In addition, we provide justifications for why we modify certain assumptions made previously. Table 2 provides a summary of the differences in results between the Searchinger et al. *Science* article and the results obtained from the most recent run of the CARD model. We express all the calculations on a per liter basis in order to avoid distortion of our results due to the difference in ethanol production (56 billion liters versus 30 billion liters). Furthermore, we analyze the same crops (barley, corn, peanuts, rapeseed, sorghum, soybeans, sugar, sunflower, and wheat) as those included in the *Science* article. In addition to the restriction in crops covered, we use 2018/19 as the end years instead of 2022/23, which is the long-run equilibrium in the Hayes et al. paper. This is necessary because the CARD model includes a trend yield, and using the 2022/23 equilibrium would ease the burden on cropland and hence alter our results.

The general calculations for the payback periods are based on the GREET model. First, we determine the amount of CO_2 per liter of ethanol produced. In the original *Science* article, this amounted to 67.976 kg/liter. The GREET assumption of 7.15 km/liter of pure ethanol leads to 9.493 kg/km. Given the benefit of 0.057 kg/km of corn ethanol leads to the discussed payback period of 167 years (9.493/0.057).

Our analysis is completed in six steps. First, we rerun the fall 2007 model (as used in Searchinger et al.) but use *GreenAgSiM* instead of the *Science* article coefficients. In a second step, we relax the assumption of U.S. deforestation. Third, we modify the slope of the trend yield to attain a 1% higher crop yield in 2018/19. Fourth, we use the fall 2008 model to determine the impact of ethanol production. Next, we add an additional component (agricultural production) to the calculations. Finally, we perform a switch from GREET to BESS. The results of the sensitivity analysis are summarized in Table 2. Table 3 summarizes the CO_2 emissions over the 10-year projection period for the fall 2008 baseline and HEP scenario (including HEP with higher yield).

For the first comparison, we use the fall 2007 scenario results and apply the *GreenAgSiM* (only the land-use module) to determine how it compares with the *Science* article. The results of this model run can be found in column 2 of Table 2. They are consistent with the Searchinger et al. results and even worsen the carbon balance of biofuels. Using *GreenAgSiM* increases the payback period slightly, from 167 to 183 years. The increase in emissions is due to the differences in modeling described in section 3.2 (*GreenAgSiM*). The payback period increases by less than 10%, to 183 years. This implies an average carbon loss of 386 tons of CO_2 equivalent per hectare compared to 352 tons of CO_2 equivalent per hectare in the *Science* article.

This leads us to an assumption made in the *Science* article about US deforestation that may not be realistic. Searchinger et al. assumed that 36% of new US cropland comes from forest. There is evidence that this assumption might not be valid. In the last three years, most of the additional cropland in the US has come from grassland that was in pasture as part of the Conservation Reserve Program. In addition, according to USDA and EPA GHG inventories, forest area in the US has remained constant between

1990 and 2005. If we assume that no forest land is converted to cropland, then CO_2 emissions are reduced and the payback period is reduced from 183 years to 141 years (column 3 in Table 2). For the remaining scenarios reported in Table 2, we use the updated model (see section 3.1 for details).

The scenario reported in column 4 of Table 2 is more along the lines of a thought experiment rather than a scenario run. We take five crops (barley, corn, sorghum, soybeans, and wheat) and increase the trend yield such that in 2018/19, the crop yield is 1% higher than in the high energy price scenario. We then calculate the area that is necessary to have the same production as in the high energy price scenario but with the increased yield. Note that the cumulative net change in land over the 10-year period is actually negative. There are two issues that explain this seemingly puzzling result. First, the difference in yield gain is very small at the beginning of the period when the initial shock occurs and land is converted. The yield gain starts to be noticeable after a couple of years when land can be taken out of production. Therefore most carbon emissions come from the beginning of the period. Second, carbon sequestration takes place at a much slower rate than carbon loss from land conversion.

The 1% higher yield scenario changes the payback period by a greater amount than any other scenario, reducing the payback period by a factor of approximately four. The higher yield would reduce the area needed for the same amount of crop production by a significant amount. Together with the changes in the model structure, the payback period is reduced to 31 years. For the yield increase, we assume that no additional fertilizer is applied. We assume that the yield response is triggered by higher prices in the high energy price scenario. This assumption is supported by Keeney and Hertel (2008), who reject the hypothesis of zero yield response to higher prices in the long run. As has been noted in the previous sections, *GreenAgSiM* is also able to evaluate emissions from livestock and crop management. This is something that has been neglected by the Searchinger et al. study. The difference in emissions between the two scenarios, however, is relatively small in terms of emissions from agricultural production. The major amount of the biofuel carbon debt comes from land-use change (column 6 in Table 2). The changes in the CARD modeling framework and the absence of deforestation in the US are the driving forces behind the reduction in greenhouse gas emissions attributed to land-use change. For comparative purposes, we included an alternative model to the GREET model (see Table 2). BESS calculates a corn ethanol emission benefit of 0.128 kg/km. This difference compared to the GREET model is due to different agronomic assumptions in the default settings of BESS. Incorporating this into the calculations (column 7 in Table 2) reduces GHG emissions induced by land-use change to 55 years.

Instead of using the 2018/2019 marketing year for our calculations rather than the 2022/23 marketing year, i.e., the year the long-run equilibrium is imposed, the CO_2 emissions from land-use change would be reduced by 42 million tons, to 1,383 million tons of CO_2 equivalents. This would reduce the payback period only slightly, to 114 years.

5. Conclusion

We demonstrate the sensitivity of model assumptions regarding GHG emissions from agriculture-induced land conversion and agricultural production. Our analysis is based on the CARD Agricultural Outlook Model and the *GreenAgSiM*. We look at model parameters concerning deforestation in the US, yield growth, agricultural production, and CO_2 benefit of ethanol. We show that deforestation, yield growth, and CO_2 benefit can have a major influence on the payback period of corn ethanol. The new model measuring GHG emissions from agriculture results in an increase of the payback period of corn ethanol. The payback period is only marginally influenced by the inclusion of agricultural emissions because the carbon loss from land conversion outweighs the difference in emissions from agricultural production.

Beyond illustrating the sensitivity of the estimated carbon impacts to differences in modeling assumptions, the results presented here have useful policy implications. In particular, and given the wide variation in the calculated payback periods, it is clear that the benefits in terms of carbon reduction that could be reaped from biofuels production are highly dependent on the strategy pursued to expand the supply of biofuels in response to external stimuli such as higher crude oil prices. As an example, long-run strategies aimed at increasing crop yields seem, in the light of our results, extremely effective in reducing the payback period. Enhanced research in this area may have a higher payoff in terms of carbon benefits (through reductions in land-use change effects) than would improvements in some downstream processes.

Apart from the assumption of deforestation in the US, it is not the intention of this paper to place any value judgment on which of the model assumptions are right or wrong.

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Table 1. Percentage Increase in Crude Oil Prices: Results for the US and Select Countries

Variable	Hayes et al. 2009	Tokgoz et al. 2007	Hayes et al. 2009	Tokgoz et al. 2007
	(% change from baseline)		(% change from baseline in per unit of ethanol)	
United States Corn				
Price	+19.6	+40.4	+2.3	+2.8
Area planted	+10.4	+22.1	+1.2	+1.5
Exports	-23.3	-62.0	-2.7	-4.3
United States Soybeans				
Price	+8.9	+19.7	+1.0	+1.4
Area Planted	-7.5	-14.2	-0.9	-1.0
Exports	+19.4	-28.7	-2.3	-2.0
United States Wheat				
Price	+9.4	17.6	+1.1	+1.2
Area Planted	-2.1	-9.3	-0.3	-0.6
Exports	-5.7	-30.9	-0.7	-2.1
Area Harvested in Selected Countries				
Brazilian corn	+3.6	+5.9	+0.4	+0.4
Brazilian soybean	+2.5	+6.4	+0.3	+0.4
Brazilian wheat	-1.4	-0.6	-0.2	-0.04
Brazilian rice	-0.1	NA	-0.02	NA
Argentine corn	+4.3	+13.3	+0.5	+0.9
Argentine	-0.2	-1.2	-0.02	-0.08
Argentine wheat	-0.7	-0.8	-0.08	-0.06
Chinese corn	+2.3	+2.7	+0.3	+0.2
Chinese soybean	+0.2	+0.4	+0.02	+0.03
Chinese wheat	+0.8	+1.3	+0.09	+0.09
Chinese rice	-1.2	NA	-0.14	NA
Indian corn	+2.6	+7.0	+0.3	+0.5
Indian wheat	+0.06	+1.3	+0.01	+0.2
Indian soybean	+1.1	+2.4	+0.13	+0.2
Indian rice	-0.4	NA	-0.05	NA
Indonesian corn	+3.9	+8.8	+0.5	+0.6
Indonesian rice	+0.2	NA	+0.02	NA
Philippine corn	+2.4	+9.6	+0.3	+0.7
Philippine rice	+1.5	NA	+0.2	NA
Mexican corn	+1.1	+2.1	+0.1	+0.2
Mexican soybean	+1.1		+0.1	
Mexican wheat	+1.6	+5.3	+0.2	+0.4
Mexican rice	+1.1	NA	+0.1	NA

Note: NA—not available since the rice model was not run in the Tokgoz et al. (2007) study.

Table 2. Sensitivity Analysis

	Searchinger Data			Fall 2008 CARD Data			
Model used	Searchinger et al.	GreenAgSiM	GreenAgSiM	GreenAgSiM	GreenAgSiM	GreenAgSiM	GreenAgSiM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
US Deforestation	Yes	Yes	No	No	No	No	No
Comparison	Baseline 07/ HCO	Baseline 07/ HCO	Baseline 07/ HCO	Baseline 08/ HEP Yield	Baseline 08/ HEP	Baseline 08/ HEP	Baseline 08/ HEP
Agricultural Production	No	No	No	No	No	Yes	Yes
Ethanol increase in million liters	55,950	55,950	55,950	29,859	29,859	29,859	29,859
Difference in Area Harvested (in thousand ha)	10,817	10,817	10,817	(1,281)	6,076	6,076	6,076
Difference in Emissions (in million tons of CO_2-equivalents	3,801	4,179	3,218	403	1,425	1,514	1,514
CO_2 produced per liter of ethanol (in kg)	67.94	74.69	57.52	13.50	47.76	50.70	50.70
Emissions in grams of CO_2 per MJ (over 30 years, Lower Heating Value)	107.38	118.00	90.86	21.33	75.45	80.09	80.09
Kilometers per liter of ethanol (GREET)	7.15	7.15	7.15	7.15	7.15	7.15	7.15
Emissions per km driven (in kg)	9.50	10.45	8.04	1.89	6.68	7.09	7.09
CO_2 benefit per km driven (in kg)	0.06	0.06	0.06	0.06	0.06	0.06	0.13
Payback period (in years)	166.69	183.27	141.13	31.50	117.18	124.41	55.40

Note: HEP is the high energy price scenario (2008) and HCO is the high crude oil scenario (2007). For the emissions per MJ, the value of 21.1 MJ/liter is used (Lower Heating Value). Furthermore, we assume an amortization period of 30 years (equivalent to Searchinger et al.).

Table 3. Carbon Dioxide Emissions

Country	Baseline	HEP	HEP Yield	Difference Baseline/HEP	Difference Baseline/HEP Yield
Algeria	32	36	33	4	1
Argentina	665	673	632	9	(32)
Australia	351	357	332	6	(19)
Brazil	5,441	5,928	5,756	488	316
Canada	242	242	227	(0)	(15)
China	972	1,123	1,048	151	76
Egypt	22	28	25	5	3
European Union	1,887	1,898	1,840	11	(47)
India	2,391	2,446	2,307	55	(84)
Indonesia	214	282	269	67	54
Iran	106	119	104	13	(2)
Japan	25	28	27	3	2
Malaysia	2	2	2	1	1
Mexico	292	354	320	61	28
Morocco	57	59	59	3	2
Nigeria	210	326	313	117	103
Other Africa	1,176	1,250	1,104	74	(71)
Other Asia	903	931	1,013	28	111
Other CIS	546	548	531	2	(15)
Other Eastern Europe	108	116	112	9	4
Other Latin America	1,712	1,820	1,629	108	(83)
Other Middle East	26	30	21	4	(6)
Pakistan	140	145	139	6	(1)
Philippines	123	152	145	29	22
Russian Federation	274	281	236	7	(38)
South Africa	33	44	41	11	8
Thailand	59	68	64	9	5
Turkey	3	2	2	(1)	(1)
Ukraine	262	249	222	(13)	(40)
USA	693	843	809	150	116
Viet Nam	31	40	38	9	6
Total Emissions in Million Tons of CO_2 equivalent	18,998	20,424	19,401	1,425	403

Note: HEP is the high energy price scenario.

Figure 1: Cumulative Emissions in CO_2 Equivalents