1. Current Legislative Context

Among current legislative approaches to the issue of biofuels and sustainability, see:

**United States:**
Section 202 of the 2007 Energy Independence and Security Act (EISA) requires 36 billion gallons of renewable fuel by 2022. Of that total, 15 billion gallons may be ‘conventional’, or corn-based ethanol. The renewable fuel standard under EISA includes life cycle GHG reduction performance requirements that include emissions from indirect land change. The US EPA’s notice of proposed rule-making (NPRM) and draft regulatory impact analysis, released in May 2009, are available at [http://www.epa.gov/OMSWWW/renewablefuels/](http://www.epa.gov/OMSWWW/renewablefuels/).

**United Kingdom:**
As part of the Gallagher Review, the independent Renewable Fuels Agency in the UK has recommended that the current Renewable Fuel Transport Obligation (RTFO) target for 2008/09 (2.5% by volume) should be retained, but the proposed rate of increase in biofuels be reduced to 0.5% (by volume) per annum rising to a maximum of 5% by volume by 2013/14. This compares with the RTFO’s current target trajectory of 5% by 2010. The review concluded that while uncertainty and data limitations prevent accurate estimation of the GHG emissions from biofuels-induced land use change, there is substantial risk that expanding biofuels production would lead to land conversion and greater GHG emissions. [http://www.dft.gov.uk/rfa/reportsandpublications/reviewoftheindirecteffectsofbiofuels/executivesummary.cfm](http://www.dft.gov.uk/rfa/reportsandpublications/reviewoftheindirecteffectsofbiofuels/executivesummary.cfm)

**State of California:**
In April 2009, the California Air Resources Board (CARB) approved rulemaking for state’s Low Carbon Fuel Standard (LCFS). The LCFS requires at least a 10% reduction in life cycle GHG emissions from the state’s transportation fuels by 2020. CARB based its estimates of emissions from indirect land use change on the modeling described herein and on additional modeling in GTAP by authors Golub and Hertel. Detailed information on the LCFS is available at [http://www.arb.ca.gov/fuels/lcfs/lcfs.htm](http://www.arb.ca.gov/fuels/lcfs/lcfs.htm).

2. Methodological Overview

To estimate the climate effects of market-mediated land use changes resulting from biofuels expansion, we combined economic modeling results with assumptions about the types of ecosystems affected, and the carbon fluxes from changes to those ecosystems.

The steps followed in our analysis are:

1. Select an increment to biofuels production levels.
2. “Shock” GTAP to force the desired increase in biofuel production, resulting in an estimate of the land area converted among cropland, forestry, and pasture use in various regions of the world.
3. Map the economic land area changes indicated by GTAP to existing ecosystem types.
4. Estimate the changes in carbon stocks and carbon sequestration owing to ecosystem conversions.
5. Compute a scalar value with which to compare the global warming intensities of the biofuel and its petroleum-based alternative.

To model indirect land use change emissions, we combine two models: (i) GTAP, which provides estimates of changes in area dedicated to forestry, pasture, and cropping by agro-ecological zone, and (ii) a carbon accounting model that estimates the emissions from land use conversion, based on Searchinger, Heimlich et al. (2008b) with modifications described below. We have combined the two models by importing regional emission factors generated by the carbon accounting model into GTAP. This facilitates complete analysis within one modeling framework and greatly simplifies the systematic sensitivity analysis described below. Our metric for LUC emissions is g CO₂ y MJ⁻¹, which measures a GHG discharge associated with maize ethanol production.

3. Modeling Approach
To estimate indirect land use change due to ethanol production in the US, we utilize a computable general equilibrium model (CGE). In this section, we provide: 1) a discussion of CGE models in general, 2) a brief description of the standard GTAP model, 3) a brief description of specific version of GTAP used in this work, followed by a discussion of several model-specific features relevant to this study.

3.1. General equilibrium modeling
General equilibrium, which dates back to Leon Walras (1834-1910), is one of the crowning intellectual achievements of economics. It recognizes that there are many markets and that they interact in complex ways so that loosely speaking, everything depends on everything else. Demand for any one good depends on the prices of all other goods and on income. Income, in turn, depends on wages, profits, and rents, which depend on technology, factor supplies and production, the last of which, in its turn, depends on sales (i.e., demand). Prices depend on wages and profits and vice versa.

To make such an insight useful, economists have to be able to simplify it sufficiently to derive predictions and conclusions. Theorists typically do this by slashing the dimensionality, say to just two goods, two factors and two countries, and often focusing on just a few parts of the system. An alternative approach is to keep the complex structure but to simplify the characterization of economic behavior and solve the whole system numerically rather than algebraically. This is the approach of Computable General Equilibrium (CGE) modeling. CGE models specify all their economic relationships in mathematical terms and put them together in a form that allows the model to predict the change in variables such as prices, output and economic welfare resulting from a change
in economic policies, given information about technology (the inputs required to produce a unit of output), policies and consumer preferences. They do this by seeking prices at which supply equals demand in every market – goods, factors, foreign exchange. One of the great strengths of CGE models is that they impose consistency of one’s view of the world, e.g., that all exports are imported by another country, that the sum of sectors’ employment does not exceed the labor force, or that all consumption is covered by production or imports. This consistency can often generate empirical insights that might otherwise be overlooked in complex policy analysis – such as the fact that ethanol mandates may result in reduced gasoline consumption when the industry is asked to pass increased costs on to consumers.

3.1 The GTAP Model

In this work we utilize a CGE model called GTAP (Hertel 1997). The mathematical relationships assumed in the GTAP model are generally rather simple, and although ‘many’ markets are recognized, they still have to be very aggregated – particularly for global economic analysis. The GTAP Data Base underlying the GTAP model has 57 sectors, so, for example, ‘transport and communications services’ appear as a single industry. In principle all the relationships in a model could be estimated from detailed data on the economy over many years. In practice, however, their number and parameterization generally outweigh the data available. In the GTAP model, only the most important relationships have been econometrically estimated. The remaining economic relationships are based on literature reviews, with a healthy dose of theory and intuition. An important limitation of CGE models is that very few of them are tested as a whole against historical experience—although GTAP is one such (Liu 2004; E. Valenzuela 2007).

CGE modeling is a very powerful tool, allowing economists to explore numerically a huge range of issues on which econometric estimation would be impossible; in particular to forecast the effects of future policy changes. The models have their limitations, however. First, CGE simulations are not unconditional predictions but rather ‘thought experiments’ about what the world would be like if the policy change had been operative in the assumed circumstances and year. The real world will doubtless have changed by the time we get there. Second, while CGE models are quantitative, they are not empirical in the sense of econometric modeling: they are basically theoretical, with limited possibilities for rigorous testing against experience. Third, one can readily do sensitivity analysis on the parameter values assumed for economic behavior, although less so on the data, because altering one element of the base data requires compensating changes elsewhere in order to keep the national accounts and social accounting matrix in balance. Of course, many of these criticisms apply to other types of economic modeling, and therefore, while imperfect, CGE models remain the preferred tool for analysis of economy-wide global economic issues.
3.2 GTAP-BIO-AEZ

The great strength of the standard GTAP model is the ease with which it can be modified. In this work we begin with a variant of the standard GTAP model nick-named GTAP-BIO \textit{(Birur 2008, forthcoming)}. GTAP-BIO is modification of GTAP-E model (Burniaux 2002) designed for climate mitigation policy. Birur \textit{et al.} modify the GTAP-E model to incorporate the potential for biofuels to substitute for petroleum products. They also alter the energy demand elasticities based on a historical validation exercise undertaken by Beckman (2008).

A very important feature of biofuel production is the role of by-products, which often compete with the feedstock in feed use. In the case of corn ethanol, the by product is called Dried Distillers Grains with Solubles (DDGS). We build on the work of Taheripour \textit{et al.} (2008) in incorporating DDGS our analysis.

Finally, we model land use following Hertel \textit{et al.} (2009) who introduce Agro-Ecological Zones (Lee 2008) into the GTAP model. This facilitates analysis of the competition for land within and across regions and the potential for changes in land use driven by biofuel policies. The importance of introduction of AEZs – explicit treatment of global land use competition and different land types – should not be understated. Corn, for example, competes with different crops in different AEZs. The expansion of corn in the US for ethanol use has had a large impact on soybeans in US. This, in turn, has had an impact on the incentive to grow soybeans in particular AEZ in other regions (e.g., Brazil), which can lead to shifts in land use (e.g., livestock and forestry).

We distinguish 18 AEZs, which differ along two dimensions: growing period (6 categories of 60 day growing period intervals), and climatic zones (3 categories: tropical, temperate and boreal). Following the work of the FAO and IIASA (IIASA 2000), the length of growing period depends on temperature, precipitation, soil characteristics and topography. The suitability of each AEZ for production of alternative crops and livestock is based on currently observed practices, so that the competition for land within a given AEZ across uses is constrained to include activities that have been observed to take place in that AEZ.

3.3 The Issue of Baseline Yields

With time and improved technologies, we expect the efficiency of ethanol conversion as well as corn yields to increase, both of which will reduce the land requirements for ethanol. While ethanol conversion efficiency has not changed significantly since our base period (2001), USDA reports that corn yields had risen by 9.3% by 2007. This has a direct impact on the amount of land required to fulfill a given level of ethanol mandate – reducing the land use requirement by a factor of 8.5% in US and globally. Some have argued that higher yields in non-US regions would diminish the need to additional crop area beyond 8.5% reduction. However, this is misleading. What matters is the \textit{ratio of US yields to RoW yields}. If yields worldwide rise at the same rate, then to find land use change in RoW required to offset the diversion of a given amount of US corn to biofuels
at higher current yields, it is sufficient to multiply land use change in ROW at base period (lower) yields by inverse of growth in yields (1/1.093).¹

Our reason for using the 2001 baseline in our analysis is that this is the latest year for which a published, publicly available global crop harvested area and yield database is available (Monfreda 2008). As we will see below, area and yields in the rest of the world are critical to our analysis of the global land use change from biofuels, so having a reliable database is essential. Of course, these yields could be “updated” via some set of projections, but this would further cloud the analysis and potentially compound the measurement errors. For this reason, we prefer the conservative approach of using the 2001 benchmark, and deflating obtained with GTAP global expansion of cropland, needed to produce additional corn ethanol, to reflect the intervening increase in feedstock yields. In the case cited above, we would deflate obtained with GTAP additional global cropland by 8.5%. This approach also has the virtue of allowing the reader to make further adjustments based on future projections of maize yields.

3.4 Intensive and Extensive Yield Responses

Our relatively simple approach to baseline yields does not mean that we do not pay close attention to yield changes in the wake of a biofuels program. Indeed these changes are central to our analysis, which is why we explicitly model changes in the intensive and extensive margins. As noted in the text, Keeney and Hertel (2008) review the literature on yield response to corn prices and find the simple average of recent studies results to give a yield elasticity of 0.25. This suggests that a permanent increase of 10% in the corn price, relative to variable input prices, would result in roughly a 2.5% rise in yields.² Utilizing this yield elasticity in our analysis, we obtain an average yield increase, due to intensification, of 2.8%, as reported in Table 2 of the text.

Turning to the extensive margin of yields there are two important contributors in our model. First, there is the change in corn yields as corn replaces other crops on existing crop land (e.g., shifting from a corn-soybean rotation to continuous corn). We can estimate this effect by referring to the differential in net returns to land in existing uses, on the assumption that land will be allocated to its highest value use. If corn production expands onto lower productivity land, then average corn yields will fall. The second extensive margin measures the change in average crop yields as cropland area is expanded into pasture, and possibly forest lands. In the absence of strong empirical evidence, we simply assume a value of 0.66 here – that is, it takes three additional acres of marginal cropland to offset the impact of diverting two hectares of current (average) cropland to biofuels production. The “extensive margin” row of the US panel in Table 2

¹ From the global market clearing condition for corn, the base period required RoW corn area is equal to global food demand, deflated by RoW yields minus the ratio of US yields to RoW yields, multiplied by the base year US corn acreage. Assuming fixed yields and fixed demand, and adjusting US corn acreage required for biofuels in light of the higher yields, all that matters is the ratio of US to RoW corn yields. If US yield had risen by 9.3% leading to 8.5% less land required for corn in US, and both US and ROW yields rise at the same rate, then RoW land use change is 100*(1-1/1.093) = 8.5% smaller.

² If the long run price of corn were to double, from $2/bu to $4/bu and the price of land substituting inputs merely increased by 50%, then the output-input price ratio would rise by 33% and the expected yield increase would be 0.25 * 33% = 8.25%.
of the text reports the impact of the two extensive margins on total land requirements in
the US. As can be seen, the extensive effect tends to offset the intensification effect,
resulting in a *net* yield increase for coarse grains of just about 0.4%. However, the
extensification effect varies widely by Agro-Ecological Zone and has an important
impact on estimated changes in land cover.

### 4. Additional Results on Global Land Use Change

Table S1 reports land cover changes for the world as a whole. As with the US, pasture
land falls in all regions of the world, but forest land rises or is unchanged in the less
productive regions where it competes less directly with crop production. Overall, forest
cover in RoW falls by just 0.25 Mha, while pasture land falls by nearly 2.4 Mha.

#### Table S1. Land Cover Changes (Mha)

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>US</th>
<th>ROW</th>
</tr>
</thead>
<tbody>
<tr>
<td>cropland</td>
<td>1.59</td>
<td>2.6</td>
</tr>
<tr>
<td>pasture</td>
<td>1.05</td>
<td>-2.35</td>
</tr>
<tr>
<td>forest</td>
<td>-0.54</td>
<td>-0.25</td>
</tr>
</tbody>
</table>

#### ROW disaggregated

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Canada</th>
<th>EU</th>
<th>Brazil</th>
<th>Japan</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>cropland</td>
<td>0.45</td>
<td>0.45</td>
<td>0.30</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>pasture</td>
<td>-0.15</td>
<td>-0.16</td>
<td>-0.24</td>
<td>0.00</td>
<td>-0.13</td>
</tr>
<tr>
<td>forest</td>
<td>-0.29</td>
<td>-0.29</td>
<td>-0.06</td>
<td>-0.01</td>
<td>0.09</td>
</tr>
</tbody>
</table>

#### ROW

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>LAEnExp</th>
<th>RoFLatAmérica</th>
<th>EEuropeFSU</th>
<th>RoEurope</th>
<th>MENA</th>
</tr>
</thead>
<tbody>
<tr>
<td>cropland</td>
<td>0.05</td>
<td>0.18</td>
<td>0.06</td>
<td>0.16</td>
<td>0.07</td>
</tr>
<tr>
<td>pasture</td>
<td>-0.02</td>
<td>-0.18</td>
<td>-0.14</td>
<td>-0.44</td>
<td>-0.05</td>
</tr>
<tr>
<td>forest</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.08</td>
<td>0.27</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

#### ROW

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>SSAEnExp</th>
<th>RoFSA</th>
<th>SASIAEEX</th>
<th>RoHIA</th>
<th>RoASIA</th>
<th>Oceania</th>
</tr>
</thead>
<tbody>
<tr>
<td>cropland</td>
<td>0.54</td>
<td>0.09</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.11</td>
</tr>
<tr>
<td>pasture</td>
<td>-0.53</td>
<td>-0.09</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.11</td>
</tr>
<tr>
<td>forest</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

*Source: Authors' Calculations*

**Market-Mediated Effects: Global Summary** Table S2 offers a global summary of the
market mediated effects of increasing corn ethanol production in the US from 6.63GL to
the target of 56.8 GL. Table S2 decomposes the change in global crop production into
yield and area components and further decomposes the yield component into the
intensive and extensive margins. The final column of Table S reports the change in direct
and indirect food consumption. This is simply global production, less energy uses of crop
products for liquid fuels.
The global economy will respond to a biofuels program that diverts crop land from food (and fiber) by increasing yields and by reducing consumption. Based on the results in the first panel of Table S2, we observe a global intensification of crop production, with the greatest intensification occurring for coarse grains and oilseeds. However, global yields decline at the extensive margin for all crops other than sugar, with the largest drops for coarse grains, oilseeds and other agriculture. Consequently, total yields rise less for these crops, with other agricultural yields actually declining slightly.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Yield</th>
<th>Area</th>
<th>Production</th>
<th>Nonfuel Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intensive</td>
<td>Extensive</td>
<td>Total</td>
<td></td>
</tr>
<tr>
<td>Coarse Grains</td>
<td>1.05</td>
<td>-0.68</td>
<td>0.36</td>
<td>5.45</td>
</tr>
<tr>
<td>Oilseeds</td>
<td>0.49</td>
<td>-0.31</td>
<td>0.18</td>
<td>-0.09</td>
</tr>
<tr>
<td>Sugarcane</td>
<td>0.26</td>
<td>0.03</td>
<td>0.29</td>
<td>-0.50</td>
</tr>
<tr>
<td>OthGrains</td>
<td>0.22</td>
<td>-0.01</td>
<td>0.21</td>
<td>-0.52</td>
</tr>
<tr>
<td>OthAgri</td>
<td>0.17</td>
<td>-0.26</td>
<td>-0.09</td>
<td>-0.20</td>
</tr>
</tbody>
</table>

*Source: Authors' Calculations*

Area expansion dominates the production increase for coarse grains, sugar crops, other grains and other agriculture, while higher oilseed yields dominate the area decline in the case of that crop category, so that total production rises. This rise in production facilitates increased (indirect) consumption of oilseeds through their use as a substitute for coarse grains in livestock feeding. Meanwhile, coarse grains consumption falls sharply as DDGS and other feedstuffs replace the use of this feedstock in livestock production. Consumption of sugar crops, other grains and other agriculture all fall, implying lower food consumption for households.

Given the potential importance of consumption impacts we explore these in greater detail in the next section of the SOM, taking account not only of direct consumption of bulk products, but also considering consumption of livestock and processed food products.

**A Closer Look at the Consumption Impacts:** Table S3 reports changes in food prices and consumption for all food categories in the US and globally. We find that US coarse grains prices rise by about 16% (7% rise is the global average) for the 50 GL y⁻¹ ethanol increase. This leads to reductions in consumption for coarse grains and many other agricultural and food products. Direct consumption of coarse grains is only modestly affected in the US (-0.9%), owing to price-inelastic demand. Despite a smaller price rise, consumption of livestock products (more price-sensitive) falls by more. In the world as a whole, consumption of all food falls. While lower food consumption may not translate directly into nutritional deficits amongst wealthy households, any decline in consumption can have a severe impact for households that are already malnourished.

As noted in the text, we sought to isolate the “nutritional cost” of corn ethanol by re-running the model holding consumption fixed with a series of country-by-commodity subsidies. In this case, we find that twice as much forest is converted to farming, and
emissions from LUC increase by 50%, to 1127 g CO₂ y MJ⁻¹ of capacity. Therefore, any efforts to mitigate adverse nutritional impacts will boost the GWI of the biofuel.

Table S3: Food price and consumption effects of a 57 GL y⁻¹ increase in US maize ethanol production.

<table>
<thead>
<tr>
<th>Food Consumption Category</th>
<th>“Current Policy” Experiment (reduction in food consumption)</th>
<th>Fixed Food Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>US</td>
<td>Global</td>
</tr>
<tr>
<td>Market Price, % change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumption Quantity, % change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Exports Price, % change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumption Quantity, % change, weighted by market values across regions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coarse Grains</td>
<td>16.33</td>
<td>-0.9</td>
</tr>
<tr>
<td>Other Grains</td>
<td>3.7</td>
<td>-0.3</td>
</tr>
<tr>
<td>Oilseeds</td>
<td>6.22</td>
<td>-0.44</td>
</tr>
<tr>
<td>Sugarcane</td>
<td>8.64</td>
<td>-0.56</td>
</tr>
<tr>
<td>Livestock</td>
<td>2.4</td>
<td>-1.24</td>
</tr>
<tr>
<td>Other Food Products</td>
<td>0.41</td>
<td>-0.3</td>
</tr>
<tr>
<td>Processed Livestock</td>
<td>0.85</td>
<td>-0.5</td>
</tr>
<tr>
<td>Other Agriculture</td>
<td>2.71</td>
<td>-1.15</td>
</tr>
</tbody>
</table>

5. Handling Time

A salient issue in this context is the actual global warming intensities (GWIs) of various crop-based biofuels, especially maize ethanol. The issue in large part turns on so-called land cover change (LCC) effects, which are emissions of greenhouse gases and changes in biophysical land surface properties that occur because cultivation of biofuel feedstock crops displace other uses of land without eliminating the demand for food products previously derived from that land. This backward shift in the supply of other land intensive goods leads, via a causal chain operating through world food, fuel, and forestry markets, to global changes in the pattern of land use and land cover to accommodate higher overall output of land-based goods. Both USEPA and the California Air Resources Board are currently planning to recognize and count LCC effects in assigning GWI values as part of their implementation.

When these upfront emissions are simply averaged over 30 years of ethanol production, land cover emissions outweigh all other emissions in the life cycle of maize ethanol. However, this simple treatment of emissions over time makes arbitrary assumptions about the length of a biofuels program and masks the actual damages to society of climate change associated with ethanol-induced land conversion. This is because, to a first approximation, social costs at some point in the future are proportional to cumulative warming, not net emissions. Thus, using the above values, even after 167 years, the cumulative damages of elevated temperature associated with maize ethanol would exceed the cumulative damages associated with continued fossil fuel consumption. We explore this issue in depth in a companion paper (O’Hare, Plevin et al. 2009).
6. Sensitivity Analysis

Modeling indirect land use change emissions is an inherently uncertain venture, involving combined economic and ecosystem models that each harbor many data and epistemic uncertainties. And quantifying the full uncertainty in the projected land change emissions is difficult, as described further below.

We estimate the uncertainty in LUC emissions using the Systematic Sensitivity Analysis (SSA) capability available in GTAP. The SSA uses the Gaussian Quadrature (GQ) approach to estimate means and standard deviations of model results, as described in (Arndt 1996). For large models, the GQ method is more tractable than a full Monte Carlo analysis\(^3\), but GQ is subject to several limitations, described in section 8. Our analysis examined the sensitivity of model results to the economic parameters described in Table S4, and to an approximate representation of the probability distributions around emissions factors, as shown in Table S5.

6.1. Parameters included in the SSA

As noted previously, our model results are sensitive to the economic parameters governing the extensive and intensive margins of land use, the acreage response to land rents and the trade elasticities. From prior study (Searchinger, Heimlich et al. 2008b), we have identified parameter value assumptions that make the most difference in estimates of iLUC, and the results here illustrate selected variations in these parameters and their consequences.

The SSA is performed with respect to the following variables and parameters:

1) yield elasticity;
2) elasticity of land transformation across uses;
3) elasticity of effective crop land with respect to harvested crop land;
4) crops and other food products trade elasticities;
5) elasticity of substitution among imports from different sectors

6.1.1. Yield elasticity

Historically, agricultural crop yields have tended to increase over time owing to scientific progress, new varieties, agronomic practice improvements, etc. The higher the average yields, the less land is required to accommodate a given amount of ethanol production. Yields also increase in response to commodity price changes.

Crops in the model are produced using various factors of production: land, capital, labor and intermediate inputs (e.g. fertilizers). The substitution among these factors is governed by a substitution parameter. When land rents are higher, cost minimizing producers will substitute away from land. The larger the elasticity of substitution between land and non-

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\(^3\) Our model solves in approximately 12 minutes. A Monte Carlo analysis using just 1,000 simulations, would take more than 8 days.
land inputs, the easier it is to boost yields. The substitution parameter in our model is calibrated to achieve desired yield responsiveness following the work of (Hertel 2007).

We use 0.25 as our central value of this parameter. This value reflects a simple average of the most recent studies of corn yield response to corn price in the US (Keeney and Hertel 2008). As those authors note, earlier studies had shown higher yield response, so there is some evidence that this value has declined with time. (This value is currently modeled with a single global parameter, yet we recognize that the effect will vary across crops, as well as across regions.) In our sensitivity analysis we consider range 0.0–0.5 for this critical parameter.

6.1.2. Elasticity of land transformation across cropland, pasture and forestry

Empirical evidence on land rental differentials suggests that land does not move freely between alternative uses—cropland, pasture, forestry—within an AEZ. Therefore, in the model, such movement is constrained by a Constant Elasticity of Transformation (CET) frontier. Thus, within an AEZ in the CGE model, the returns to land in different uses are allowed to differ. With this structure, we can calibrate the partial equilibrium land supply response to available econometric estimates.

The absolute value of the CET parameter (0.2 in our central set of the parameters) represents the upper bound (the case of an infinitesimal share for that use) on the elasticity of supply to a given use of land in response to a change in its rental rate. The more dominant a given use in total land revenue, the smaller its own-price elasticity of acreage supply. The lower bound on this supply elasticity is zero (the whereby all land is already devoted to that activity). Therefore, the actual supply elasticity is dependent on the relative importance (measured by land rents share) of a given land use in the overall market for land and is therefore endogenous.

By way of example, consider the supply of land to crops when CET parameter is set to 0.2 and the share of cropland in total AEZ land rents is 0.4. If pasture and forestry land rents do not change (which is impossible in GE model unless we fix them exogenously), then 1% increase in cropland rents results in the following response in crop land area: 0.2*(1- 0.4) = 0.2*0.6 = 0.12% increase.

In the model, a nested CET structure of land supply is implemented whereby the rent-maximizing land owner first decides on the allocation of land among three land cover types, i.e. forest, cropland and grazing land, based on relative returns to land. The land owner then decides on the allocation of land between various crops, again based on relative returns in crop sectors. To set the CET parameter among three land cover types and among crops, we follow the recommendations in (Ahmed 2008, forthcoming). In our sensitivity analysis we consider 0.1 and 0.3 as bounds on this CET parameter.

The CET parameter governing the ease of land mobility across crops is set at 0.5. As with the land cover elasticity, this represents the upper bound on crop acreage response to an increase in the rental rate on a specific crop type. The lower bound is zero (when all crop land in an AEZ is devoted to a single crop). This CET parameter is taken from (Ahmed
2008, forthcoming) who base their estimate on the parameter file for the FAPRI model which, in turn underpins the analysis in Searchinger et al. (Searchinger, Heimlich et al. 2008b). In our sensitivity analysis, we vary this between 0.1 and 0.9.

6.1.3. Elasticity of effective crop land with respect to harvested crop land

Pasture and forest lands converted to agriculture are presumed to be less productive than the average of land already in production. The argument is that if it were more productive it would probably be in use already. Again, the assumed yield from this marginal land greatly affects the land use change induced by biofuel production. Our central value for this parameter (ETA), again a global average, is 0.66. This means that marginal land brought into crop production is only two-thirds as productive as average cropland. Values of ETA ranging from 0.32 to 1.0 are considered in the sensitivity analysis. To our knowledge there are no studies presently available that estimate this key parameter. It should be a high priority for future research in this area.

In the global land use databases, there is often a large gap between crop land cover and crop land harvested area. Of course this is partly due to crop failures. However, when multiple cropping is present, this works in the opposite direction, as harvested hectares exceed cropland cover. In the US, cropland cover also includes crop land used for pasture, idle land and CRP land. Here, we assume that this difference remains unchanged (e.g., total CRP land remains fixed).

Table S4. Distributions for economic parameters used in the Systematic Sensitivity Analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sector</th>
<th>Central value</th>
<th>Std. Dev.</th>
<th>Absolute change,/+</th>
<th>Percent change,/+</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elasticity of effective crop land w.r.t.</td>
<td>n.a.</td>
<td>0.66</td>
<td>n.a.</td>
<td>0.34</td>
<td>n.a.</td>
<td>uniform</td>
</tr>
<tr>
<td>harvested crop land expansion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elasticity of crop yield w.r.t. to crop price</td>
<td>n.a.</td>
<td>0.25</td>
<td>n.a.</td>
<td>0.25</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
<tr>
<td>Elasticity of land transformation across</td>
<td>n.a.</td>
<td>-0.2</td>
<td>n.a.</td>
<td>n.a.</td>
<td>80</td>
<td>triangular</td>
</tr>
<tr>
<td>cropland, pasture and forestry</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elasticity of land transformation across</td>
<td>n.a.</td>
<td>-0.5</td>
<td>n.a.</td>
<td>n.a.</td>
<td>80</td>
<td>triangular</td>
</tr>
<tr>
<td>crops within cropland</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elasticity of substitution among imports</td>
<td>CrGrains</td>
<td>2.60</td>
<td>1.10</td>
<td>2.69</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
<tr>
<td>from different sources</td>
<td>OthGrains</td>
<td>9.06</td>
<td>4.17</td>
<td>10.22</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
<tr>
<td></td>
<td>Oilseeds</td>
<td>4.90</td>
<td>0.80</td>
<td>1.96</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
<tr>
<td></td>
<td>Sugarcane</td>
<td>5.40</td>
<td>2.00</td>
<td>4.90</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
<tr>
<td></td>
<td>OthAgri</td>
<td>4.14</td>
<td>1.52</td>
<td>3.73</td>
<td>n.a.</td>
<td>triangular</td>
</tr>
</tbody>
</table>
6.1.4. Trade elasticities

Patterns of trade have a significant impact on the composition of land-using activities, inducing significant shifts between crops, livestock and forestry uses. Keeney and Hertel (Keeney and Hertel 2008) have shown that bilateral trade specification of a multi-country model is an important source of parametric uncertainty in predicting global land use change from the biofuels programs. When we simulate increased corn ethanol production in the US, more US land is devoted to corn which changes production and land use patterns in US and globally through trade channels. Changes in global land use patterns are important for our emissions per MJ calculations because the emission factors differ across regions.

How readily a shock in the US is transmitted to other countries’ land markets is determined through trade elasticities. We consider how sensitive our results with respect to the elasticity of substitution among imports from different sources. In our “central” and sensitivity runs (one standard deviation below and one standard deviation above central value) we use econometric estimates reported in Table S4 and reported in (Hertel 2007).

6.1.5. Uncertainty in Carbon Fluxes

Estimates of the carbon lost upon land conversion include uncertainties in several underlying quantities: the carbon in the above-ground biomass, the carbon in the below-ground biomass (generally estimated as a percentage of the above-ground biomass), the carbon in the soil, and the fraction of these carbon stocks lost upon conversion. Estimates of the carbon lost from conversion of each ecosystem type reflect variation in field observations in different places and times of a phenomenon with intrinsic actual variation across locations. However, there is also uncertainty in how well these data represent the deforestation our analysis attempts to model. For example, the use of average carbon content of particular forest ecosystems (e.g. temperate evergreen forest) may be too coarse since the processes underlying deforestation are unlikely to randomly select forest stands for removal; rather, selection criteria may include factors such as tree density and salability which may favor conversion of certain forest stands over others (Houghton 2005). We have no data upon which to base estimates of this uncertainty within ecosystem types, and our analysis does not incorporate this factor. In addition, there are insufficient data on the carbon content of some ecosystems. Of particular note, the Searchinger et al (2008b) model assumes that the grasslands of the China-Pakistan-India region have the average carbon content estimated for the grasslands of Europe. We cannot quantify this epistemic uncertainty.

We estimate the uncertainty in the carbon accounting subsystem using a stochastic implementation of the computational model described in the Searchinger et al supporting materials (Searchinger, Heimlich et al. 2008a), adding probability distributions around all key point estimate assumptions, and using Crystal Ball™ to evaluate the model in a Monte Carlo simulation. The result of this simulation is a set of probability distributions for the emissions

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4 A Monte Carlo simulation repeatedly recalculates the model by selecting randomly chosen values according to each input parameter’s defined probability distribution and saving the designated output results. The model is run a large number of times; the frequency distribution of results defines an output probability distribution. All simulation runs in this study were performed
factors (Mg CO$_2$ ha$^{-1}$) for each region, shown in Table S5. Although the generated distributions were asymmetric, the SSA requires that parameters be assigned symmetric uniform or triangular distributions. To meet this requirement, we used the average of the bounds of the interquartile range as the central value, and half the difference between the 25$^{th}$ and 75$^{th}$ percentile values as the deviation around that central value, to assign symmetrical uniform distributions to each emissions factor. The resulting distributions are show in Table S5.

using 6,000 iterations and Latin Hypercube Sampling (this sampling scheme provides better definition of the tails of the result distribution).
Table S5. Central value and deviations used in the SSA for emission factors (Mg CO₂e ha⁻¹)

<table>
<thead>
<tr>
<th></th>
<th>Forestry (lost)</th>
<th>Forestry (gained)</th>
<th>Cropland</th>
<th>Pasture</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean deviation</td>
<td>mean deviation</td>
<td>mean deviation</td>
<td>mean deviation</td>
</tr>
<tr>
<td>1 USA</td>
<td>770 136</td>
<td>243 49</td>
<td>16 7</td>
<td>111 34</td>
</tr>
<tr>
<td>2 CAN</td>
<td>707 138</td>
<td>476 82</td>
<td>16 7</td>
<td>206 83</td>
</tr>
<tr>
<td>3 EU27</td>
<td>314 36</td>
<td>407 66</td>
<td>16 7</td>
<td>162 60</td>
</tr>
<tr>
<td>4 BRAZIL</td>
<td>403 68</td>
<td>181 39</td>
<td>16 7</td>
<td>75 20</td>
</tr>
<tr>
<td>5 JAPAN</td>
<td>573 80</td>
<td>236 25</td>
<td>16 7</td>
<td>93 15</td>
</tr>
<tr>
<td>6 CHIHKG</td>
<td>573 80</td>
<td>236 25</td>
<td>16 7</td>
<td>206 81</td>
</tr>
<tr>
<td>7 INDIA</td>
<td>573 80</td>
<td>236 25</td>
<td>16 7</td>
<td>206 81</td>
</tr>
<tr>
<td>8 LAEEX</td>
<td>403 68</td>
<td>181 39</td>
<td>16 7</td>
<td>75 20</td>
</tr>
<tr>
<td>9 RoLAC</td>
<td>403 68</td>
<td>181 39</td>
<td>16 7</td>
<td>75 20</td>
</tr>
<tr>
<td>10 EEFSUEX</td>
<td>324 37</td>
<td>433 72</td>
<td>16 7</td>
<td>165 64</td>
</tr>
<tr>
<td>11 RoE</td>
<td>314 36</td>
<td>407 66</td>
<td>16 7</td>
<td>162 60</td>
</tr>
<tr>
<td>12 MEASTNAEX</td>
<td>157 37</td>
<td>73 22</td>
<td>16 7</td>
<td>87 20</td>
</tr>
<tr>
<td>13 SSAEX</td>
<td>317 50</td>
<td>140 26</td>
<td>16 7</td>
<td>44 13</td>
</tr>
<tr>
<td>14 RoAFR</td>
<td>317 50</td>
<td>140 26</td>
<td>16 7</td>
<td>44 13</td>
</tr>
<tr>
<td>15 SASIAEEX</td>
<td>917 161</td>
<td>350 37</td>
<td>16 7</td>
<td>93 15</td>
</tr>
<tr>
<td>16 RoHIA</td>
<td>573 80</td>
<td>236 25</td>
<td>16 7</td>
<td>93 15</td>
</tr>
<tr>
<td>17 RoASIA</td>
<td>917 161</td>
<td>350 37</td>
<td>16 7</td>
<td>93 15</td>
</tr>
<tr>
<td>18 Oceania</td>
<td>395 99</td>
<td>216 53</td>
<td>16 7</td>
<td>101 24</td>
</tr>
</tbody>
</table>

*a* A higher carbon value reflecting the amount lost when trees are burnt and tilled for crops. These values are used in AEZs where forest is lost.

*b* A lower value reflecting the re-sequestered standing biomass and regained soil carbon above and beyond the soil carbon in pastures. These values are used in AEZs where forest is gained. Note that since almost all predicted transitions to forestry are from pasture, this makes sense. If we were seeing transitions from crops to forestry, a different factor would be appropriate. We’ve assumed that if commercial forest plantations are planted on existing pasture, the aboveground pasture carbon is first cleared. However, commercial plantations, may regain carbon faster than typical forest ecosystems.

*c* The small amount of aboveground biomass in annual crops

*d* The amount of carbon lost when pasture is converted to crops.

### 6.1.6. SSA Results for Land Cover

As described above, we implemented the Gaussian Quadrature approach to systematic sensitivity analysis, sampling from the distributions outlined in tables S5 and S6 above. This generated a mean and standard deviation for each endogenous variable in the model. For ease of presentation, we focus on the coefficient of variation (CV), which is the ratio of the latter to the former. A low CV, corresponds to an outcome in which we can place greater confidence. We adopt CV=0.5 – the value at which the mean is twice the standard deviation as a focal point in our discussions.

There are 3 land covers x 18 AEZs x 18 Regions = 972 possible land cover changes in our global model. To reduce these dimensions, we aggregate over AEZs using physical hectare shares for a given AEZ in each region. These weighted CVs are reported in figures S2-S4 for each of the land cover types.
Figure S2 reports the CV outcomes for cropland cover change, by region. From this it can be seen that the cover changes in the US and its major trading partners are fairly robust (CV<0.5). However, the changes in China and South Asia as less certain. And, in the case of the South Asian energy exporters, there is some cropland loss.

**Figure S2. Weighted average CVs of cropland expansion and contraction**

Figure S3 reports the area-weighted CVs for the 18 regions in our model. Apart from the EU, where some AEZs show increased pasture area, all of these are below 0.5 and therefore reasonably robust, by our criterion.

**Figure S3. Weighted average CVs of pasture expansion and contraction**
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Forestry land cover is the most uncertain component of our analysis. As discussed previously, forest lands increase in the less productive AEZs, in response to higher timber prices, while shrinking in AEZs where forestry is competitive with maize, oilseed and other grains. While the CV for forestry losses in USA, Canada and EU are less than 0.5, this is not the case with forestry losses in other regions. And forestry area gains are also quite uncertain.

**Figure S4 Weighted average CVs of forestry expansion and contraction**

![Bar chart showing weighted average CVs of forestry expansion and contraction for different regions.](chart)

### 6.1.7. SSA for Results for Greenhouse Gas Emissions

In the end, we are most interested in the uncertainty associated with global GHG emissions. Here, we find that the CV associated with global emissions is 0.46, suggesting that, under the assumption of normality, a 95% confidence interval for emissions would range from 64 to 1534 g CO₂ MJ⁻¹. Most notably, this does not include zero – a value which some industry groups have suggested adopting due to the presence of too much uncertainty associated with LUC estimates.

It is also instructive to consider some “bounding runs” of the model. Here, we simply choose a combination of parameters to illustrate the sensitivity of the model to key assumptions. Table S6 reports our findings. The first row reports our base case results of 799 g CO₂ MJ⁻¹. The second row reports the case where we set the yield elasticity at its highest value (0.5) and ETA at its highest value (1.0) as well, thereby maximizing the potential for yields to offset the increased biofuels requirements. This gives a result of 444 g CO₂ MJ⁻¹. When we eliminate the potential for yield response to price, and set ETA at its lower bound of 0.32, we estimate a global emissions rate of 2702 g CO₂ MJ⁻¹.

The final two rows of Table S6 report the outcomes in special cases where we ignore other elements of the market-mediated responses. In the first case, we eliminate the potential for livestock sectors to substitute co-products for other feedstuffs. This boosts the land requirements associated with biofuels and gives an emissions outcome of 1,285 g
CO₂ MJ⁻¹. Finally, we report the case, discussed above and in the text, where we hold food consumption constant globally via a set of commodity/region specific subsidies. With food consumption failing to drop, global emissions rise by 41% above the base.

Table S6. Bounding runs on the model: Global GHG emissions in g CO₂ MJ⁻¹

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Emissions (g CO₂ MJ⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>799</td>
</tr>
<tr>
<td>Low LUC</td>
<td>444</td>
</tr>
<tr>
<td>High LUC</td>
<td>2702</td>
</tr>
<tr>
<td>No Co-products</td>
<td>1285</td>
</tr>
<tr>
<td>Constant Food Consumption</td>
<td>1127</td>
</tr>
</tbody>
</table>

6.1.8. Limitations
Both the economic and ecosystem carbon model contain several epistemic uncertainties that cannot be easily represented using the SSA or Monte Carlo methods. Some of these can be explored using discrete scenarios, however. For example, in the economic model, features susceptible to scenario analysis include the choice of functional forms used to implement the model (McKitrick 1998), the choice of model closure (Roberts 1994; Mitra-Kahn 2008), the choice of base year (Roberts 1994), the data chosen to represent the base year, and the level of sectoral and regional aggregation used (Hertel 1999). Although these can, in theory, be examined in scenario analyses, the data requirement to construct these alternatives is prohibitive. In the ecosystem model, epistemic uncertainties include the assumption that the location of the historic agricultural frontier can predict the pattern of biofuels-induced LUC, or that economic pressure alone is a valid predictor of LUC (Geist and Lambin 2002; Schaeffer, Vianna et al. 2005). These are much more difficult to analyze as our understanding of these processes is weak.

7. Discussion: caveats and cautions
The present paper describes findings in a form close to the “language” established by Searchinger (a GW index term that adds LUC to direct discharges independently of time). It does not exhaust the analysis needed for this policy area, and we have already observed three areas in which more work is needed.

As noted above, we think that a simple allocation of LUC discharge to biofuel produced over decades is not a proper representation of the GW effects of biofuel policy. Discounting discharges as though they were economic phenomena is theoretically unsound, and even this crude recognition of time value ignores both the cumulative but non-linear global warming effect of long-lived gases and the risk of irreversible calamities, a risk that increases with GHG concentrations. In parallel work, we examine more sophisticated and scientifically responsible ways to account for time in analyzing LUC, noting here that these factors properly included, because the LUC discharge distinctively occurs at the beginning of the analytic period, will only increase the GW index of crop biofuels relative to petroleum.
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We have also begun to elaborate ways to recognize the intrinsic uncertainties in estimates like these so as to include the distributions appropriate for model parameters, and model uncertainties not easily described as statistical distributions of random variables. In future work we will present these results, findings that will greatly enrich the approach of showing selected key parameter values’ effects used here.

Finally, we observe an additional indirect effect of a US biofuel mandate that may be relevant to policymakers, namely that forcing a fuel more expensive than gasoline into the motor fuel mix without a parallel subsidy will reduce consumption of the mix and therefore induce a reduction in total emissions from transportation in the US, while (by reducing US demand for gasoline) increasing emissions in the rest of the world. This effect needs to be estimated but is much more difficult to interpret as a biofuel GW index, as it depends on the policy by which the biofuel’s use is forced, on market prices for petroleum and biofuels, and on whether any price increase should be treated as intrinsic to the biofuel policy or as a separate policy equivalent to a tax on motor fuel.

In addition to these refinements requiring conceptual advances, we note the following opportunities to refine the present estimates in more technical ways:

*Other market-mediated effects on emissions:* Changes in livestock intensity and quantity, and in rice farming, induce changes in methane releases that are not captured here; corn farming, especially as higher yields are sought, induces releases of N₂O that may be greatly underestimated in current studies.

*Land cover transitions:* GTAP does not estimate conversions of particular ecosystems to cropland. Rather it estimates conversions among different economic uses of land. Thus, part of constructing emissions factors for land conversions is determining which ecosystems are converted when pasture or forest becomes cropland. As a starting point, we have used a database from Woods Hole that provides data on historic rates of conversion from specific ecosystems to crops as well as estimates of aboveground carbon loss, below ground carbon loss, and foregone sequestration. Most of these ecosystems can be classified as forests or grasslands. Thus, we use the forestry values, weighted by their historical conversion rates by region for conversion from forestry to cropland and we use the grassland values, similarly weighted by region, for conversions from pasture to cropland.

The current version of GTAP does not estimate conversions from unmanaged land to cropland. Thus the model could be overestimating conversions from forestry and pasture (since conversion of unmanaged land would take pressure off of already managed land) and underestimating conversion overall (since the conversion of unmanaged land would only occur if it was cheaper than converting managed land, meaning the total cost of land conversion would be lower than currently modeled). Unmanaged lands that are likely to be important include abandoned croplands and currently inaccessible forests. In the US there has been considerable discussion about the use of CRP land for biofuels. However, USDA has stated that it plans to defend CRP acreage at the level of 32 million acres, and US-EPA analyses have accordingly kept CRP acreage unchanged, relative to baseline. In
order to explore variation owing to conversion of different ecosystem types—either
different ratios of forest and pasture conversion or conversion of ecosystems outside the
market such as CRP—we also considered emissions scenarios in which all conversion is
assumed to come from grassland pasture.
Supporting Materials References


