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the productivity of newly converted cropland (from forestry and pasture) contributing most of the variance in estimated ILUC emissions intensity. Although the experiments performed here allow us to characterize parametric uncertainty, changes to the model structure have the potential to shift the mean by tens of grams of CO_2e per megajoule and further broaden distributions for ILUC emission intensities.

Carbon accounting and economic model uncertainty of emissions from biofuels-induced land use change

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Abstract
Few of the numerous published studies of the emissions from biofuels-induced "indirect" land use change (ILUC) attempt to propagate and quantify uncertainty, and those that have done so have restricted their analysis to a portion of the modeling systems used. In this study, we pair a global, computable general equilibrium model with a model of greenhouse gas emissions from land-use change to quantify the parametric uncertainty in the paired modeling system's estimates of greenhouse gas emissions from ILUC induced by expanded production of three biofuels. We find that for the three fuel systems examined—US corn ethanol, Brazilian sugarcane ethanol, and US soybean biodiesel—95% of the results occurred within ±20 g CO_2e MJ^{-1} of the mean (coefficient of variation of 20-45%), with economic model parameters related to crop yield and the productivity of newly converted cropland (from forestry and pasture) contributing most of the variance in estimated ILUC emissions intensity. Although the experiments performed here allow us to characterize *parametric* uncertainty, changes to the model structure have the potential to shift the mean by tens of grams of CO_2e per megajoule and further broaden distributions for ILUC emission intensities.

1 Introduction

Increasing production of crop-based biofuels induces land use conversion, resulting in emissions of greenhouse gases (GHGs) commonly called *indirect land use change* (ILUC) emissions [e.g., 1, 2]. We present, for three important biofuels, the first estimates of uncertainty ranges that encompass parameter uncertainty in both economic and carbon accounting models—the two components of modeling systems commonly used to estimate ILUC emissions—and show coefficients of variation between approximately 20% and 45%.

Estimates of the magnitude of ILUC emissions vary owing to both model parameter choices and model structure [3, 4], and different studies have produced a wide range of results [5, 6]. The uncertainty surrounding ILUC emissions challenges regulators who must make and defend specific choices within this range of alternatives. Notably, the US [7], Europe [8, 9], and the state of California [10] have used different models and assumptions to estimate ILUC, resulting in different estimates for the same set of fuel production systems. As of this writing, transport fuel greenhouse gas (GHG) regulations in both British Columbia and the EU exclude ILUC emissions [9, 11].

Models of ILUC emissions typically combine an economic modeling component that propagates market-mediated changes in commodity production and land use induced by increased demand for biofuel globally, and a carbon accounting component that calculates the GHG emissions associated with (some) of these induced changes. Both model components are subject to substantial uncertainty, and differences in the location of projected land use changes can result in greater variance in ILUC emissions estimates. Uncertainties in the economic component are amplified in the carbon accounting component [3]: varying input parameters to the economic model can alter the magnitude and location of projected land conversion, and since carbon stocks are spatially heterogeneous, variation in location can produce large changes in CO_2 emissions.

To understand this cascading effect requires an analysis of the combined system, yet no existing estimate of ILUC has examined its own uncertainty comprehensively, although a few have recently gone beyond performing one-at-a-time sensitivity analyses on a small number of parameters. The US EPA's partial Monte Carlo uncertainty simulation (MCS) in the regulatory impact analysis for the Renewable Fuel Standard (RFS2) addressed only the carbon accounting portion of their modeling system [7]. Plevin [12] similarly quantified only the uncertainty in carbon accounting parameters used in ILUC emissions estimates based on the Searchinger et al. [1] model, limited by an inability to include the underlying economic model directly in the uncertainty analysis.

Hertel et al. [2] examined uncertainty in ILUC emissions estimates using the RunGTAP built-in systematic sensitivity analysis (SSA) tool, including distributions for a small set of economic parameters and for the GHG emission factors, noting however that the SSA they used can represent only independent or perfectly correlated, symmetric distributions. The standard SSA cannot represent skewed input distributions, which Hertel et al. approximated by using the mid-point of a 95% confidence interval as the mean for the distribution used in the SSA. Another limitation of the SSA method is that it does not support robust conclusions about the shape of output distributions.

In their study of European biofuel policies, Laborde and Valin [13] evaluated uncertainty in ILUC emissions estimates related to six parameters in IFPRI's MIRAGE general equilibrium model using a systematic sensitivity analysis for boundary values, but held parameters for the carbon accounting component fixed. Plevin et al. [3] used a reduced-form model to estimate a plausible range for ILUC emissions from corn ethanol given uncertainty in ecosystem carbon accounting and uncertainty related to the choice of economic model using a range of results from different economic models, but did not estimate the uncertainty inherent to a single model. The widely varying estimates of new cropland required in the economic models led to the conclusion that the economic model uncertainty was the dominant contributor to uncertainty in the resulting estimate of ILUC emissions.

The present article uses a joint economic and carbon accounting model under MCS to (i) characterize parametric uncertainty in the estimate of ILUC emissions produced by this modeling system; (ii) understand the contribution to the variance of estimated ILUC emissions from the economic and carbon accounting model components; and (iii) identify which model parameters were responsible for the majority of the contribution to variance from each model component. ILUC emission estimates depend on various modeling choices, such as whether a reduction of food consumption resulting from biofuel expansion is treated as a climate benefit [2, 14], and whether non-CO_2 emissions associated with changes in agricultural output are included in the definition of ILUC emissions. These choices are discussed further in section 1.1 and in the supporting information (SI).

We emphasize that owing to numerous model, data, and computational limitations, computable general equilibrium (CGE) models are at best coarse representations of the real world [15]. Important limitations exist in carbon accounting as well: the available data on biomass carbon are uncertain [16, 17], as are estimates of soil carbon and fluxes resulting from land-cover change [18]; the spatial resolution of these data cannot represent the high spatial variability on the ground [19]; and the remote sensing used to estimate some of the carbon stocks has high error rates [20]. Monte Carlo simulation of this modeling system does not produce a prediction; it is best viewed as a method of conducting a systematic, global sensitivity analysis of parametric uncertainty that informs us about model behavior and relationships with respect to specific distributions assigned to a select set of model parameters, in the context of a given model structure [21].

Recognizing those cautions, and the common economic principles on which CGE models are built even as they vary in internal structure and data-to-parameter inferences, the frequency distributions for ILUC emissions presented herein can be viewed as (1) useful indicators of the variation to be expected from any of the existing economic/carbon accounting models around their respective point-estimate outputs, as well as (2) 'best available' distributions given our choices of modeling framework and structure, parameters to treat as stochastic, and distributions to use—so long as these caveats are clearly understood.

1.1 Other market-mediated effects

We note that ILUC is not the only, nor necessarily the largest, source of market-mediated GHG emissions resulting from an increase in biofuel production. According to several; studies, the GHG emissions resulting from a macro-economic rebound effect on petroleum use may be larger than emissions from ILUC.

Biofuel production also affects food prices: price increases reduce consumption, shrinking total land area required to replace displaced crop production. Hertel et al. [2] estimated that market-mediated reduced nutrition would make a substantial contribution to a lower ILUC emission intensity estimate -- holding food consumption fixed increased estimated emissions from biofuel expansion in their model by 41%. Other market-mediated effects considered by US EPA [7] in their analysis for the US Renewable Fuel Standard included changes in (i) on-farm energy use, (ii) fertilizer use and N_2O emissions therefrom, (iii) livestock and rice production and associated CH_4 emissions.

2 Methods

2.1 Overview

Our model, *ILUC Monte Carlo Simulation* (ILUC-MCS), comprises a version of the Global Trade Analysis Project (GTAP) model [22], called *GTAP-BIO-ADV* [28], and the *Agro-Ecological Zone Emission Factor model* (AEZ-EF) [23].

In this study, GTAP-BIO-ADV is used to project the cascade of crop-shifting and land use changes resulting from increased biofuel production. AEZ-EF takes the GTAP land use change results as an input to estimate the corresponding GHG emissions. Combined with an assumption of 30 years of biofuel production at the level used to shock GTAP-BIO-ADV, the model produces an estimate of annualized ILUC emissions intensity (sometimes referred to as an "ILUC factor") in units of grams of CO_2-equivalent per megajoule of fuel (g CO_2e MJ^{-1}). We examine parametric uncertainty in the joint model using Monte Carlo simulation.

We use the assumption of 30 years of fuel production to facilitate comparison with other studies (Table 3), though we recognize that this choice is arbitrary and amortizing up-front emissions linearly understates the climate forcing of ILUC since CO_2 lingers in the atmosphere [24]. We emphasize the importance of this number (30 years) to the unit (per MJ of fuel) emissions intensity [3] and the fact that our analysis neither treats it as a variable parameter nor endorses it as a best or certain estimate of a biofuel system's actual operational life. It is a tacit convention of the field that deserves further examination [25].

The analysis was performed in two stages. In the first stage, we assigned distributions—based primarily on expert judgment—to a wide range of GTAP-BIO-ADV and AEZ-EF model parameters, and used this analysis to identify the most important contributors to variance in the estimate of ILUC emissions. Sixteen parameters each contributed at least 1% of the variance (Table S9 in the SI); others were deemed inconsequential to the uncertainty in ILUC emissions estimates and treated as certain. For each of three fuel pathways—corn ethanol, sugarcane ethanol, and soybean biodiesel—we ran the combined modeling system 6,000 times to simulate effects of a given increase in productionand collected several model outputs (described in section 2.4) for analysis (simulation 1). We found that at least 5,000 trials were required to achieve a stable representation of the most important parameters' effects. In the second stage, we held the parameters of either the carbon accounting model (simulation 2) or the economic model (simulation 3) constant at their default values to characterize the contribution to uncertainty in estimated ILUC emissions by the individual models. The Monte Carlo framework developed for this analysis, parameter definitions and distributions are described further in the SI.

2.2 GTAP-BIO-ADV

The GTAP-BIO-ADV database represents a global economy with 19 regions, 18 agro-ecological zones (AEZs), and 43 industrial sectors, including individual sectors for biofuels produced from soybean oil, rapeseed oil, palm oil, corn, sugarcane, and sorghum. For brevity, we consider only three of these—soybean biodiesel and ethanol from corn and sugarcane. The GTAP-BIO-ADV model represents the complex economic relationships among sectors throughout the economy through equations that, when satisfied, indicate a state of economic equilibrium. The changes in model variables between an initial equilibrium and a new one after the modeled shock constitute the economic model results.

GTAP-BIO-ADV model inputs include version 7 of the GTAP database (representing the global economy, including land uses, in 2004) [26], with biofuels and their by-products disaggregated from standard GTAP sectors [27, 28]; behavioral parameters that are used as coefficients in the model equations; and data on non-CO_2 greenhouse gas (GHG) emissions from each sector and region [29]. Non-CO_2 emissions are based on national greenhouse gas inventories and tied in each sector to specific emissions drivers: factor inputs (endowments), intermediate inputs, or output. Changes in non-CO_2 emissions are assumed to be proportional to changes to the respective input or output drivers as a result of the modeled shock. The model is described further in the SI.

We note that GTAP-BIO-ADV is a comparative static model, not a dynamic one: although changes in the quantity of biofuels produced occur over a period of years during which macro-economic (population, GDP, capital, etc.) variables and other phenomena (e.g., improvements in crop yields driven by technology) are changing, the model treats the change in production as instantaneous. Introducing dynamics increases model complexity, which generally increases parametric uncertainty and adds a new type of uncertainty related to projecting the dynamic baseline. Neglecting these dynamics, however, introduces the model uncertainty associated with using a static representation of a dynamic system.

Although global economic model results are subject to uncertainty in several areas (e.g., behavioral parameters, base data, functional forms, choice of base year, and level of database aggregation, among others), we examined only behavioral parameter uncertainty in this study. These limitations are discussed further in the SI.

2.3 AEZ-EF

The agro-ecological zone emission factor model (AEZ-EF) estimates the CO_2-equivalent emissions from land use changes projected by GTAP-BIO-ADV in response to the modeled shock [23]. Changes in land use may result from any policy intervention or phenomenon that affects land use, including expanded production of biofuels as modeled here.

The GTAP model outputs required by AEZ-EF are (i) the area changes in land used for cropping, forestry, and livestock production in each AEZ, (ii) the change in CH_4 and N_2O emissions from fertilizer application and from rice and livestock production, and (iii) estimates of crop yield, which are used to estimate changes in average standing crop biomass from the land conversion. AEZ-EF relies on a database of carbon stocks (Mg C ha^{-1}) for biomass carbon and soil carbon in various land uses, aggregated to and indexed by GTAP region and AEZ [30], and GTAP land use categories. AEZ-EF combines these carbon stock data with assumptions about carbon loss from soils and biomass, mode of conversion (i.e., by fire), quantity and species of carbonaceous and other GHG emissions resulting from conversion, carbon remaining in harvested wood products and char, and foregone sequestration, to estimate the net CO_2-equivalent emissions resulting from a shock to biofuel production as projected by GTAP-BIO-ADV.

2.4 Model outputs examined

Our simulations generated frequency distributions for several model outputs, including CO_2-equivalent emissions from (i) soil and biomass carbon resulting from ILUC and (ii) CH_4 and N_2O from agricultural activities, (iii) total emissions (the sum of *i* and *ii*), and (iv) net displacement factor (NDF). NDF is the total number of hectares globally of forestry and pasture converted to cropland, divided by gross hectares of land required to produce the feedstock needed to meet the biofuel shock at baseline crop yield in the region in which the shock is applied [3].

2.5 Experiments performed

We examined several combinations of "experiments" (i.e., closures—configuration of exogenous and endogenous variables—and shocks) and simulations (i.e., alternative treatments of parameter distributions), as described in Table 1 and Table 2. All simulations used Latin Hypercube Sampling (LHS), a form of stratified sampling that ensures more even coverage of the entire probability distribution and, in particular, better description of the tails.

2.5.1 Varying parameters for both models

This simulation consisted of separate experiments shocking production of each of the three fuel pathways (corn ethanol, sugarcane ethanol, and soybean biodiesel), both with and without holding food consumption in developing countries fixed. In this simulation, each fuel pathway / food treatment combination was run 6,000 times (Table 1). These experiments are described in Table 2.

We assigned distributions (described in the SI) to nearly all parameters in both GTAP-BIO-ADV and AEZ-EF. The purpose of this simulation was to identify the model parameters contributing most of the uncertainty in the estimated ILUC emissions intensity. To accomplish this, we computed the squared rank correlation between the values for each stochastic input parameter and a chosen model output (e.g., ILUC emissions intensity), normalized to sum to 100%. (We restored the sign of the correlation for plotting purposes.) We refer to each of these computed correlations as the *uncertainty importance* of the corresponding parameter to the chosen output parameter.

Table 1. Description of simulations.

Sim ID	Trials	Description
1	6000	Vary parameters of both models
2	3000	Freeze AEZ-EF parameters; vary GTAP-BIO-ADV parameters
3	3000	Freeze GTAP-BIO-ADV parameters; vary AEZ-EF parameters

To answer the question "If we do not 'take carbon credit for' reductions in food consumption, what would be the effect on our estimate of ILUC emissions intensity?", we estimated the GHG emissions intensity attributable to reduced food consumption in the developing world. We compared estimates of ILUC emissions intensity with and without holding food consumption constant in non-Annex-I (i.e., developing) countries. (For this exercise, "food" refers to all goods used by humans as food: unprocessed and processed crops, milk and dairy, meat and processed meat, vegetable oils, other processed food, and beverages.) Laborde and Valin [13] perform a similar experiment.

We also estimated emissions of nitrous oxide (N_2O) and methane (CH_4) resulting from changes in the use of organic and inorganic fertilizer and changes in rice and livestock production. These non-CO_2 emissions results are presented in the SI. Estimating all changes in GHG emissions from all sectors of the economy is beyond the scope of this analysis, but could be undertaken in the future.

Table 2. Description of experiments performed varying parameters in both GTAP-BIO-ADV and AEZ-EF. FF=food consumption fixed in developing (non-Annex I) countries; FNF=food consumption not fixed.

Experiment Name	Description
CornFNF	Increase production of US corn ethanol by 11.59 billion gallons per year, i.e., from 2004 level to 15 billion gallons per year.
CaneFNF	Increase Brazilian sugarcane ethanol production by 3 billion gal/y.
SoyFNF	Increase production of US soybean ethanol by 0.812 billion gal/y.
CornFF CaneFF SoyFF	The same as their "FNF" counterparts except that food consumption was held fixed in non-Annex I countries.

2.5.2 Submodel contribution to variance

Simulations 2 and 3 allowed us to quantify the relative contribution of the GTAP-BIO-ADV and AEZ-EF models to variance in the selected outputs. In simulation 2, we held the parameters of the AEZ-EF model at their default values while applying the same distributions to GTAP-BIO-ADV parameters used in simulation 1. Simulation 3 held GTAP-BIO-ADV parameters fixed at their default values while allowing AEZ-EF parameters to vary as in simulation 1. For this simulation, we set the values of several GTAP-BIO-ADV parameters that are represented with uniform distributions to the midpoint of their distribution. In the case of parameter YDEL (crop price-yield elasticity), the default value was at the high end of the range in the literature, so we used the midpoint of the distribution as a "central" value when computing model-specific contribution to uncertainty.

2.6 Parameter distributions

Intergovernmental Panel on Climate Change (IPCC) guidelines for the treatment of uncertainty in national GHG inventories recognize that the pragmatic approach to characterizing parameter uncertainty is to use the best available parameter distributions, whether these are based on measurements, prior literature, other model outputs, or expert judgment [31]. Some observers deride the use of anything but empirically derived distributions, but in many cases including ours, this merely precludes modeling uncertainty at all. We believe this critique is relevant only if the modeled results are treated as a prediction. Rather, the purpose of this exercise is to examine model sensitivity to parameters characterized by wide uncertainty ranges. The choice of distributions to use in a MCS is not generally any more subjective than the choice of bounds to use in one-at-a-time sensitivity analyses, yet the MCS approach has the advantage of enabling global rather than local sensitivity analysis [32].

The parameters in GTAP-BIO-ADV and AEZ-EF include simple scalar values, vectors, and multi-dimensional matrices. For the uncertainty analysis, one can treat an entire vector or matrix as a single "parameter" with multiple values, as a set of rows or columns, or as a set of individual data elements, varying each separately. In most cases, we drew a value from a single random variable for each matrix or vector and multiplied all elements by this value to produce the matrix or vector used in a particular trial. Laborde and Valin [13] used this approach in their uncertainty analysis for select economic parameters based on the expectation that they would be correlated across regions and sectors.

2.6.1 Key parameters

As discussed further in section 3.2, three parameters appeared among the four with the highest uncertainty importance for ILUC emissions intensity estimation for all three fuel systems: from the economic model (i) the elasticity of crop yield with respect to price, (ii) the relative productivity of land converted to cropland compared to the average productivity of current crop production, and, from the emission factor model, (iii) the ratio of emissions from converting cropland-pasture to cropland to those of converting pasture. Beyond these, the set of the next most important parameters varied by feedstock type, as described below. Here, we describe these three key parameters, plus parameters used to capture trading patterns in the model, which shape the location of land use change.

2.6.1.1 Elasticity of crop yield with respect to price (YDEL)

By far, the greatest contributor to variance in the estimate of ILUC emissions intensity was YDEL, the elasticity of crop yield with respect to price. Experts disagree about the most appropriate value for this parameter [33]. In GTAP-BIO-ADV, YDEL is a single scalar value (0.25), . Several of the studies used to support a value of 0.25 for YDEL are dated and collectively based on observations from the 1950s through 1980s, for one crop (corn) in one agro-ecological zone of one region (the US corn belt) [34], yet this value has been applied in GTAP to all crops, in all AEZs and all regions [33, 35].

Berry [35] criticized not only the narrow evidence base of the 0.25 value but also the econometrics of, or interpretation of results in, the papers on which it is based, estimated 0.03 for US corn using a long time-series, and proposed 0.10 as a best central value for a world YDEL. Huang and Khanna [36] estimated differentiated values of 0.15 for corn, 0.06 for soybeans, and 0.43 for wheat—all in the US. Laborde and Valin [13] assigned different yield elasticities by region to account for potential intensification and double-cropping, with values of approximately 0.15 for the EU, 0.2 for the US, and 0.3 in developing countries. Recognizing that there is no single "correct" value for the response of all crops in all regions to price changes, and noting the disagreement among experts about the most appropriate value, we assigned to YDEL a uniform distribution from 0.03 to 0.25.

2.6.1.2 Relative productivity of newly converted cropland (ETA)

The ETA parameter describes the average productivity of newly converted cropland relative to the average productivity of cropland currently employed in production, by region and agro-ecological zone. The parameter is calculated using the Terrestrial Ecosystem Model (TEM) of plant growth [37]. Those authors employed TEM to calculate Net Primary Production (NPP) at 0.5^{o} x 0.5^{o} spatial resolution for all grid cells across the world. NPPs are then converted to AEZ and region specific ratios of average yield on new cropland to average yield on existing cropland (in the range from 0.43 to 1). We multiplied the values of ETA by a single scalar factor represented by a uniform distribution from 0.8 and 1.2, truncating the resulting values at 1.0. We note that there are concerns that the TEM-based estimate of NPP may not completely represent yield potential of new lands, which could also be shaped by costs of conversion or local management practices [33].

2.6.1.3 Armington trade elasticities

Armington elasticities portray the imperfect substitutability between domestically produced and imported products (parameter ESBD), and determine the ease of substitution among products imported from different countries (parameter ESBM). These parameters influence where ILUC is estimated to occur (regions with relatively high or low agricultural productivity), and thus influence ILUC emissions estimates. We used Armington elasticity estimates among imported products (ESBM) from [38]. In our simulations, we treated ESBM stochastically and followed others in computing ESBD as ESBM/2 [39, 40].

2.6.1.4 Emissions from the conversion of cropland-pasture

"Cropland-pasture" is land in a long-term crop rotation and considered marginal for cropping [41]. In GTAP-BIO-ADV, crops compete for this land more readily than they do for either pasture or forest land, and, as for crops, there is a yield response to price. Data on the extent of cropland-pasture are difficult to come by, and the model currently includes this land category only for the US and Brazil.

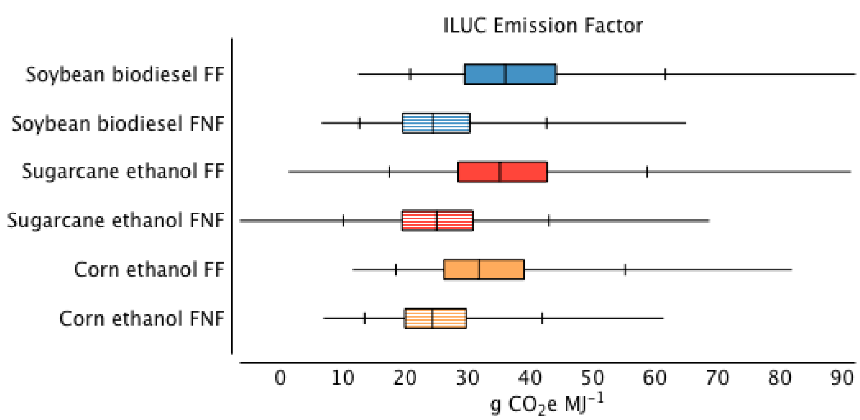
The AEZ-EF parameter that most contributes to uncertainty in ILUC emissions intensity is the *CroplandPastureEmissionRatio*, a fraction that when multiplied by the emission factor for pasture land produces the emissions for cropland-pasture conversion, by region and AEZ. In the absence of data on emissions from the conversion of cropland-pasture, the use of *CroplandPastureEmissionRatio* implements an assumption that conversion of this area will produce emissions somewhere between 0 and the emissions estimated for converting pasture to cropland. The parameter is represented using a triangular parameter distribution with a minimum of 0, mode of 0.5 and maximum of 1. The coarse approach is necessitated by the vague cropland-pasture definition plus lack of intra-regional specificity on land conversion. In the supporting information, we compare this simple approach to the more complex approach taken in the CCLUB model from Argonne National Lab [42].

3 Results

3.1 ILUC emissions

Simulation 1 (6000 trials, all parameters varied) did not generate large differences among fuel pathway results in either experiment (Figure 1). The 95% confidence intervals of the distributions bracketed ILUC emission intensities by about ±20 g CO_2e, for experiments that allowed food consumption to adjust in the developing world. As expected, holding food consumption constant in developing countries increased all estimated ILUC emissions intensities; it also increased the total variance (Figure 1; see supporting information for additional statistics.) None of the experiments results in zero or negative emission intensity.

Figure 1. Distribution of ILUC emissions factor amortized over 30 years, for different fuel pathways and experiments. Box depicts interquartile range; vertical line across box shows the median. Whiskers depict minimum and maximum values; cross marks on whiskers indicate the 2.5 and 97.5 percentile values (i.e., central 95% of distribution.) FF=food fixed in developing world; FNF=food not fixed.



3.2 Contribution to variance of individual parameters

We examined the contribution to variance in the ILUC emission intensity for simulations with corn ethanol, cane ethanol, and soybean biodiesel without fixing food consumption. We note that contribution to variance depends greatly on the assigned distributions: in our case, the elasticity of crop yield with respect to price (YDEL) was assigned a broad uniform distribution (reflecting substantial expert disagreement), resulting in a dominant contribution to uncertainty across all three fuel systems. Using a distribution with a distinct mode would reduce the importance of YDEL to ILUC variation. Fixing food consumption results in somewhat more land conversion, increasing the relative importance of related parameters such as total tree carbon and pasture soil carbon.

We present below the parameter contributions to variance in the estimated ILUC emissions intensities; other outputs are discussed in the supporting information.

3.2.1 Corn ethanol

Eleven parameters each contributed at least 1% of the variance, accounting together for ~80% of the total variance (Figure 2a). The next 57 parameters contributed the remaining 20%.

Three tiers of importance emerged:

1. Crop yield elasticity with respect to price (YDEL) was by far the most important parameter in all simulations, contributing nearly 50% of the variance.
2. Parameters capturing marginal yield, emissions from cropland-pasture conversion, and substitutability among imports from different sources (ETA, Cropland-pasture emission ratio, and ESBM, respectively) each contributed 5.5 to 8%.
3. The remaining 7 parameters contributed between about 1% and 3.4% of the variance each.

Significant parameters (top two tiers) affected uncertainty in expected directions, but effects on variance somewhat offset (YDEL and ETA correlated negatively, and cropland-pasture emission ratio and ESBM positively, with ILUC emission intensity). Higher yield response to prices and improved marginal land productivity both allow more output per unit of land, lowering the need for land conversion (and thus ILUC emissions) to meet additional biofuel demand from the modeled shock. Assuming higher emissions from cropland pasture, all else equal, increases ILUC emissions. Interestingly, improved substitution for imports among various country sources also increases ILUC emissions. This is because US corn yields are highest in the world. As we increase Armington parameters, more of the shock originating in the US is transmitted to other regions with lower yields resulting in larger global cropland expansion and LUC emissions. Overall, economic model parameters dominated in the top 5 parameters (contributing over 65% of total variance), and the top contributors of '3rd tier' importance came from the emission factor model (see Figure S10.)

3.2.2 Sugarcane ethanol

The top 16 parameters accounted for about 75% of the total variance in ILUC emission intensity (Figure 2b). As with corn ethanol, YDEL dominated, though with a lower contribution to the variance (20%) than for corn. Once again, economic model parameters dominated: of the top 16 parameters, GTAP-BIO-ADV parameters contributed about 50% of total variance, while the AEZ-EF parameters contributed about 25%. Cropland-pasture related parameters from both models appeared among the top 5 contributors to variance: the AEZ-EF parameter cropland-pasture emissions ratio, and the economic model parameter PAEL, which measures elasticity of yield response to price for cropland-pasture (analogous to YDEL).

3.2.3 Soybean biodiesel

The top 5 parameters contributed close to 80% of the variance in ILUC emission intensity (Figure 2c). YDEL was again the leading contributor. The next four most important contributors were the same as for corn ethanol, though in a slightly different order.

3.2.4 Main contributors to variance for corn ethanol, sugarcane ethanol and soy biodiesel experiments

The parameters with uncertainty importance greater than 1% for any fuel system considered are described in Table S9. These parameters generally accounted for about 80% of the variance in ILUC emission intensity.

More top-contributing parameters in terms of uncertainty came from the economic model than the AEZ-EF model. This finding complements work by Plevin et al. [3], which indicated, looking across multiple modeling systems, more variance from economic modeling results than emission factors. Here, we find the greater contribution to uncertainty coming from the economic model in a given modeling system (with given distributional assumptions on parameters).

The relative similarity of uncertainty results for the US-based fuel systems, compared to Brazilian sugarcane ethanol, is worthy of note. US corn and soybean – often linked in a rotation system – shared the same top 5 contributors to uncertainty, and economic model parameters dominated within this group. Trade and economic substitution parameters were more important for uncertainty results for the US systems than for Brazilian sugarcane ethanol; cropland-pasture yield response to price (from the economic model) emerged in the top tier only for sugarcane ethanol; and overall economic model dominance in uncertainty was less marked for sugarcane ethanol than for the US production systems.

In addition, some of the parameters with uncertainty importance greater than 1% do not directly relate to land use. These include parameters relating to the substitutability of types of energy (those used in production activities, and household consumption of liquid fuels), demonstrating how changes anywhere in a complex, coupled modeling system with feedbacks can have an impact on outcomes of interest. Sensitivity analyses that focus only on parameters expected to have a direct impact on the result of interest can hide the importance of other parameters.

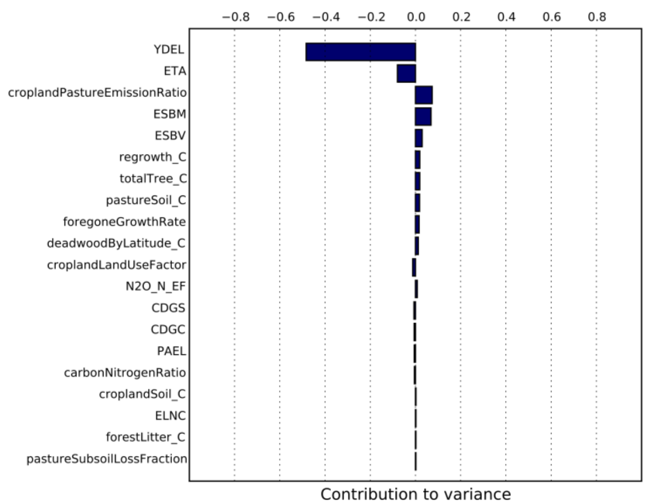
3.3 Contribution to variance by GTAP-BIO-ADV and AEZ-EF models

To compare the contribution to variance of the two individual models, GTAP-BIO-ADV and AEZ-EF, we ran two additional simulations (3000 trials each) for each of the three fuels, holding all parameters in one of the models fixed while allowing the other model's parameters to vary. (The simulations used the 'food not fixed' experiment, allowing developing world food consumption to adjust in response to price changes.) In the case of corn ethanol (Figure S11a), fixing all the AEZ-EF parameters reduced the width of the central 95% interval for the ILUC emission factor by only 10% and had little effect on the mean values. In contrast, fixing GTAP's parameters reduced the width by 58%, and produced a slightly lower mean value (23 vs. 25 g

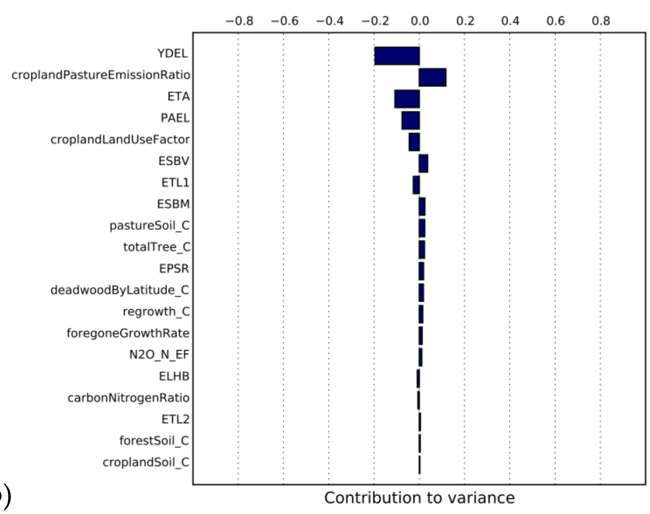
CO_2e MJ^{-1}). For sugarcane ethanol (Figure S11b), fixing AEZ-EF parameters reduced the width of the central 95% interval by 12%; fixing GTAP parameters reduced it by 47%. Similarly, for soybean biodiesel (Figure S11c), fixing AEZ-EF parameters reduced the width by 7%; fixing GTAP parameters reduced it by 52%.

For all fuel systems, the GTAP-BIO-ADV model dominated the contribution to uncertainty, as indicated by the large decline in variance when its parameters were fixed. If we assume these are general results for ILUC emissions models of this type, it suggests that uncertainty analyses of only the carbon accounting model fail to capture the majority of the uncertainty. In contrast, analyses that consider uncertainty only in the economic model capture most of the parametric uncertainty in the combined modeling system. We note, however, that each model's relative contribution to variance may depend on where we fix parameters in the other model.

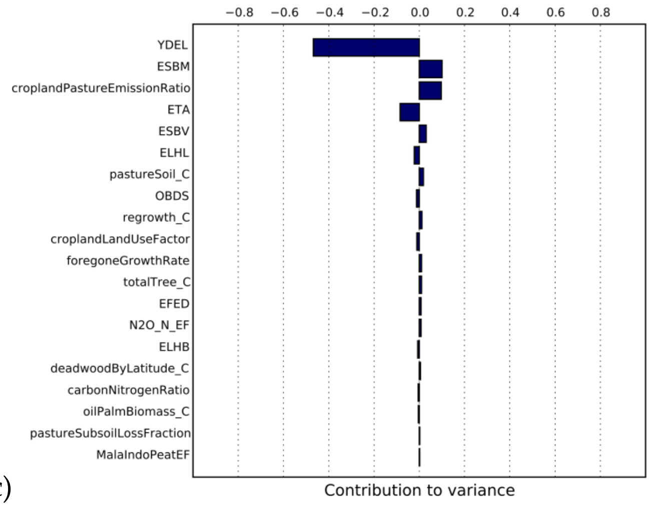
Figure 2. Uncertainty importance for ILUC emissions (food not fixed) for (a) corn ethanol, (b) sugarcane ethanol, and (c) soybean biodiesel. Additional plots and description of all parameters are available in the SI.



(a)



(b)



(c)

3.4 Comparison with other studies

Table 3 compares results for corn ethanol uncertainty analysis from this paper and with those from other studies, indicating which type of model parameters (economic or GHG accounting) were incorporated in the uncertainty analysis.

Table 3. Uncertainty ranges estimated for indirect land-use change emission intensity from expanded corn ethanol production. See SI for detailed explanation.

	Parameters varied		ILUC emission factor (g CO_2e MJ^{-1})		
Model	Economic	GHG Acct'g	2.5% value	Mean	97.5% value
ILUC-MCS (A)	✓	✓	13	25	42
ILUC-MCS (B)	✓	✓	18	33	55
Hertel et al. (2010)[a]	✓	✓	2	27	52
Plevin (2010)[b]	✓	✓	21	62	142
ILUC-MCS (C)	✓		15	25	41
Laborde & Valin (2011)[c]	✓		4[d]	7	8.8[e]
ILUC-MCS (D)		✓	18	23	29
US EPA (2010)[f]		✓	22	30	40

[a] The 95% CI was computed from mean (27) and coefficient of variation (0.46) assuming a normal distribution.[b] Based on the results using uniform distributions.

[c] Modified to use a 30-year rather than 20-year amortization period.

[d] 5% value

[e] 95% value

[f] LUC emissions only outside the US only, for year 2022.

4 Discussion

Our finding that the economic model contributes the majority of the uncertainty is not unexpected, since carbon accounting is based on physical sciences and observable behavior in a comparatively stationary system. In contrast, economic models are based on statistical abstractions of observations of the less stationary global economic system [43] that are generally calibrated to match a particular set of data [44, 45], leading to disagreement amongst experts about the most appropriate value for some model parameters (e.g., YDEL). Given these properties, we expect that the dominance of economic model uncertainties in the modeling of ILUC emissions generalizes beyond the modeling framework examined in this study.

The disagreement over the elasticity of crop yield with respect to price—and the resulting high contribution of this parameter's uncertainty to variance in ILUC emission intensities—provides a particularly germane example of the challenges faced by economic modelers. Given the broad distribution we assigned to this parameter, and the critical role of YDEL in determining land requirements, it is unsurprising that YDEL appeared as the top contributor to variance in ILUC emissions in all experiments.

The greatest contributor from the AEZ-EF model to variance in ILUC emission intensity was the cropland-pasture emission ratio. Other pasture-related parameters were also important, i.e., pasture soil carbon content from the ecosystem model, and especially for sugarcane ethanol, cropland-pasture yield-price response, ease of substitution between pasture-crop and pasture-cover, and ease of land conversion among the forest, pasture, and cropland (including cropland-pasture), all from the economic model. This highlights the need to better understand the relationship between crops, cropland-pasture, and pasture in land use decisions.

The few prior quantitative analyses of uncertainty in ILUC emission intensity considered only a fraction of the parametric uncertainty, and thereby understated the actual uncertainty in this quantity. The present analysis also understates actual uncertainty by considering only parametric uncertainty in one (joint) model. We note in particular that changes to the model structure to allow for the access and conversion of unmanaged forests and other natural ecosystems to cropland and to limit agricultural expansion to areas with adequate water supply may shift the entire distribution, perhaps substantially [see, e.g., 46].

As expected, the mean value of ILUC emission intensity from a Monte Carlo simulation produced a different value than the result of running the models with all parameters fixed at their central values [47], particularly for more skewed output distributions. The Monte Carlo means for corn ethanol, sugarcane ethanol, and soybean biodiesel were remarkably similar at 25.3, 25.4, and 25.4 g CO_2e MJ^{-1}, respectively, whereas the results of single runs using central parameter values were 22.9, 24.7, and 25.8 g CO_2e MJ^{-1}, respectively. We note that the central value used for YDEL in these single runs (0.14; the mid-point of the distribution) has a large influence on the resulting ILUC emissions estimate.

We discuss important limitations of these models in the supporting information.

4.1 Policy implications

Given the uncertainties in key parameters and in the resulting estimates of ILUC emission intensity it is possible to produce point estimates that are quite low or quite high, suggesting that no single point estimate should be taken as representative of actual ILUC emissions intensities, even for a single well-defined scenario. Deterministic point estimates with several significant digits offer a misleading sense of confidence [48] and do not allow consumers of this information to judge the adequacy of the analysis [49].

The range of results from different models, and the presence of many forms of uncertainty and model simplification suggest that models of ILUC emission intensity should be treated as illustrative rather than as precisely estimating this component of the emission intensity of biofuels. However, while the modeled results cannot perfectly portray the distribution of real ILUC emissions, they may suffice to inform an administrative action like publishing an operational global warming intensity, and for reasons stated in section 2, they strongly indicate the amount of parametric uncertainty with which point estimates from other models of the same general form (economic plus carbon accounting) should be regarded. To incorporate model uncertainty, a policy-maker could generate distributions for ILUC emissions intensity by using multiple models and combining these into a single distribution by assigning subjective weights to each model's result.

This still leaves the question of which value to extract from the overall distribution for regulatory purposes. The refractory uncertainty in biofuel GHG intensity, and especially the asymmetry in the indicated distributions, should cause regulators to attend to the cost of error in operative intensity values and examine the application of "safety factor" practice. For regulations requiring a choice of a point estimate, the mean (or median, depending on the shape of the function relating estimation errors to the cost of being wrong) value from the Monte Carlo simulation is a better choice for regulatory purposes than the point estimate produced using "best" values for all model parameters. Alternatively, policy-makers with a subjective risk assessment may favor values in particular parts of the distribution, as indicated by their risk profile [50].

To compare our results with those of other modeling frameworks, we suggest evaluating those models under MCS as well. We expect that, owing to uncertainty, the results from competing models may be less statistically distinguishable than appears to be the case when only point values are considered.

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Supporting Information for
Analysis of uncertainty in emissions from biofuels-induced land use change

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S1 Model components

Modeling system comprises GTAP-BIO-ADV and the Agro-ecological zone Emission Factor (AEZ-EF) model.

S1.1 GTAP-BIO-ADV

The computable general equilibrium (CGE) framework used in this study[1] is an extension of GTAP-BIO-ADV documented in Tyner et al. (2010).[2]. First, the data base employed in this study is further disaggregated to explicitly introduce various vegetable oils (soy, palm, rape and other vegetable oils), and to include vegetable oil-specific biodiesels; sorghum is separated from coarse grains and ethanol from sorghum is a separate biofuel (Taheripour and Tyner, 2014). Second, non-CO_2 emissions are incorporated into the model (Golub, 2013).

Each model's region land endowment is disaggregated into agro-ecological zones (AEZs; figure S1) in the effort to reduce land heterogeneity. In each region of the model, there may be as many as 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). Even after introduction of AEZs, there is still considerable heterogeneity within these units, and this, in turn, is likely to limit the mobility of land across uses within an AEZ.

To further limit land mobility within each AEZ, in the model land mobility across uses is further restricted by a Constant Elasticity of Transformation (CET) frontier. The elasticity of land transformation parameter is meant to reflect how easy or difficult to transform land from one use to another (e.g. from pasture to cropland) due to: biophysical land heterogeneity within AEZ; region-specific infrastructure, socioeconomic factors, ownership of land; costs of conversion, managerial inertia, unmeasured benefits from crop rotation, etc. The parameter, together with land rents share of a given land use in total AEZ land rents, determines the land supply elasticity to the given land use.

S1.1.1 Land-cover changes

The GTAP TABLO code (gtap.tab) was modified to write out land cover changes (in hectares) for forestry, pastureland, and cropland, as well as breaking out separately changes in cropland-pasture, sugar crops, and oil palm. These data are required by the AEZ-EF model, which computes the total greenhouse gas (GHG) emissions associated with these land-cover changes. The AEZ-EF model is described further in section 1.2, and elsewhere (Plevin et al., 2014).

S1.1.2 Armington elasticities

The default values for the Armington elasticities follow the "rule of 2" which states that the substitution elasticities among domestic and imported goods (ESBD) are half of their corresponding substitution elasticities among imported goods (ESBM) (Keeney and Hertel, 2005). To maintain this relationship in the Monte Carlo simulation, we assign a random variable to ESBM and compute ESBD = 0.5 * ESBM.

S1.1.3 Land net displacement factor

The land net displacement factor (NDF) is the ratio of the total increase in cropland area globally resulting from a biofuel shock to the land area required to produce the increased amount of biofuel, at nominal yields,

[1] The model, data, and and parameters are available at https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=4347

[2] See http://www.transportation.anl.gov/pdfs/MC/625.PDF

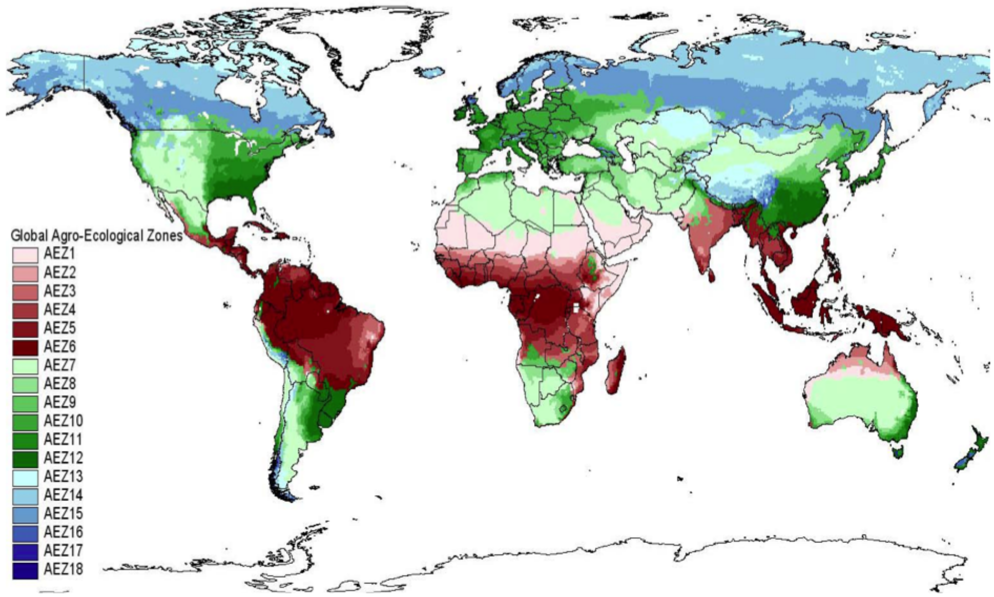


Figure S1: Distribution of agro-ecological zones (AEZs 1-18) and regions used in GTAP (Monfreda et al., 2009)

before accounting for co-products. This metric was first defined in the reduced-form model of ILUC (RFMI) by (Plevin, 2010) and subsequently computed by Laborde and Valin (2012) using the MIRAGE model to estimate LUC for EU biofuel policies.

We modified the GTAP model code (gtap.tab) to compute areal fuel yield (gal/ha). The AEZ-EF model retrieves this result and computes the nominal land requirement (ha) as areal fuel yield divided by shock gallons. The total change in cropland area (ha) is divided by nominal land requirement to produce NDF for each trial. A distribution for NDF is then produced from the MCS results.

S1.2 Agro-ecological zone emission factor (AEZ-EF) model

The agro-ecological zone emission factor (AEZ-EF) model estimates the total CO_2-equivalent emissions from land use changes, e.g., from an analysis of biofuels impacts or policy analyses such as estimating the effect of changes in agricultural productivity on emissions from land use. The model combines matrices of carbon fluxes (Mg CO_2 ha^{-1} y^{-1}) with matrices of changes in land use (ha) according to land-use category as projected by GTAP or similar AEZ-oriented models.

The AEZ-EF model contains separate carbon stock estimates (Mg C ha^{-1}) for biomass and soil carbon, indexed by GTAP region and AEZ (Gibbs et al., 2014). The model combines these carbon stock data with assumptions about carbon loss from soils and biomass, mode of conversion (i.e., whether fire is used), quantity and species of carbonaceous and other GHG emissions resulting from conversion, carbon remaining in harvested wood products and char, and foregone sequestration. The model relies heavily on IPCC greenhouse gas inventory methods and default values (IPCC, 2006), augmented with more detailed and recent data where available. We refer the reader to the model documentation for complete details (Plevin et al., 2014).

S2 Model Parameters

S2.1 GTAP-BIO-ADV behavioral parameters

The GTAP-BIO-ADV behavioral parameters file contains 44 named parameters, 38 of which are appropriate for manipulation in an MCS.[3] The parameters relevant to this study are listed in table S1. Most parameters are vectors or matrices; together they represent 18,319 values that can be manipulated independently. Owing to a paucity of supporting data, however, several of these named parameters consist of one or a few values that are repeated across all regions, AEZs, or sectors. In effect, the model implements these parameters as a single (or few) parameter(s) applied to a range of circumstances. We take advantage of this to simplify the definition of parameter distributions.

The general approach taken here is to allow vectors or matrices of parameters to be manipulated using a single random variable, e.g., by selecting a value from a range and adding this to, or multiplying this by, each element of the matrix. In a few cases, parameters are manipulated by row, column, or specific cell. These approaches can be used in combination: it is possible to define a random factor that is applied to all values except for those singled out for different treatment. The syntax for specifying parameter distributions is described in section S3.3.

We did not include distributions for consumer demand behavioral parameters. These are calibrated to mimic certain income and price elasticities (Hertel et al., 2008), so estimating distributions for them would ideally be done in the calibration stage by varying inputs to that process (target income and price elasticities).

S2.1.1 Additional issues

The rapid increase in corn-based ethanol led to an equally large increase in dried distillers grains with solubles (DDGS), however estimates of the substitution between this feed and coarse grains (corn) were nonexistent before Taheripour et al. (2010). We utilize their estimate as the upper bound and the estimate from Beckman et al. (2011) as the lower bound. The two estimates result from different calibration procedures.

The GTAP-BIO-ADV model allocates land among the three land use categories crops, pasture land, and forest (with cropland-pasture considered part of cropland). The ease of transformation of land from one use to another is modeled by the elasticity of transformation (ETL1). Among crops (including cropland-pasture), the ease of land transformation is determined by a second elasticity of transformation (ETL2). For these parameters, we use of default values and ranges suggested in modeling done for the CARB Low Carbon Fuel Standard (LCFS) (Taheripour and Tyner, 2014). CARB modeling includes regionalized default values for ETL1 and ETL2 found in Taheripour and Tyner (2013), updating an earlier model with a single value for each of these parameters, both applied in every Region-AEZ. Though the parameter is same across regions and AEZs, the actual region and AEZ land supply elasticities in the model are not uniform because they are endogenous to the model and determined not only by the chosen transformation elasticity but also by land rent share of the given land use in total land rents (Golub and Hertel, 2012). Default values were determined by examining recent historical evidence on land use change, categorizing regions based on their patterns of deforestation and expansion of agricultural area or crop switching (based on maize and oilseeds vis--vis other crops), and assigning elasticity values ranked according to land use change category. The approach differs from the prior approach, which derived a global ETL1 from an econometric determination of land supply elasticity in the US controlling for factors such as exogenous time trend, and used expert judgment about crop switching, again grounded in US data, for a global ETL2. Lack of sufficient data prevents broad replication of US-based econometrics in other model regions and for all relevant land use categories. The trend analysis applied to derive these new parameters should be subject to additional analysis to assess how

[3] Other parameters contain metadata, are not referred to in the model code, are structural parameters (e.g., identifying sluggish commodities), or are not relevant to our study (e.g., emission factors).

uncontrolled-for elements inherent in the empirical data trends used affect assigned elasticity values (and model results). While we maintained the regionalized values as in the model for consistency with existing regulatory modeling, we emphasize a need to undertake an exercise along these lines (outside our scope here), and note that applying uncertainty analysis along the lines undertaken here (MCS) can investigate the importance of the choice of the parameter to ILUC emission intensity (within bounds set by the parameter ranges and distributions). Only ETL1 emerged as an important parameter in the primary analysis, and only for sugarcane ethanol, food not fixed, with less than 10% contribution to ILUC emission intensity variance). Lacking additional analysis, we state a modeling preference for using as defaults the prior global values, or implementing strategies employed in other CGE-based ILUC emission studies that have regionalized land transformation elasticities in empirical data, more isolated from trends exogenous to the model.

For example, Golub et al. (2012) constructed a heterogeneity index based on biophysical characteristics and derived regionalized ETL1 values for GTAP based on this index, reasoning that heterogeneity of biophysical characteristics critical to productivity would capture much of the factors that hinder land transformation in a given Region-AEZ. Laborde and Valin (2012) derived model parameters roughly analogous to ETL2 in GTAP-BIO-ADV that is, capturing ease of crop switching – for the MIRAGE model (using a modified GTAP database), calibrated to approximate crop-based land supply elasticities determined for key region/crop combinations in the international agricultural commodity and trade model FAPRI.

GTAP-BIO-ADV model parameter specifications lacking empirical justification (likely because few or no estimates of values were available in the literature) might be important in our MCS and have to be reviewed. In particular, the elasticity of substitution in vegetable oils sub-consumption is specified in our analysis (and the CARB model) as less elastic for developed countries due to an assumption (expert judgment) that consumers base their decisions on nutrition, while in developing countries it is based on price (and likely to be more elastic). Because this parameter has emerged as particularly important in the assessment of biodiesel ILUC emissions from policy especially for the EU (Laborde and Valin, 2012), it is worthy of additional investigation.

Table S1: GTAP model parameters. The first column shows the unique header name used to reference the parameter; the second column shows the parameters dimensions; the third column shows the number of distinct values for each parameter.

Name	Dimensions	Values	Description
CDDG	ALL_INDS*REG	817	Elasticity of substitution in CDDGC and CDDGS feed subproduction
CDGC	ALL_INDS*REG	817	Elasticity of substitution in Oth_CrGr and DDGS feed subproduction
CDGS	ALL_INDS*REG	817	Elasticity of substitution in Sorghum and DDGSS feed subproduction
CRFD	ALL_INDS*REG	817	Elasticity of substitution in crop-based feed subproduction
EAEZ	ALL_INDS	43	Elasticity of substitution in AEZ nest
EFED	ALL_INDS*REG	817	Elasticity of substitution in feed subproduction
ELBO	ALL_INDS*REG	817	Elasticity of subst. in bio-oil subproduction
ELEG	REG	19	Elasticity of substitution in energy consumption
ELEN	ALL_INDS*REG	817	Substitution elasticity in energy sub-production
ELHB	REG	19	Elasticity of substitution in biofuel subconsumption
ELHL	REG	19	Elasticity of substitution in veg. oils subconsumption
ELKE	ALL_INDS*REG	817	Elasticity of substitution in capital-energy subproduction
ELNC	ALL_INDS*REG	817	Substitution elasticity in non-coal energy subproduction
ELNE	ALL_INDS*REG	817	Substitution elasticity in non-electr.energy subproduction
ELVL	ALL_INDS*REG	817	Elasticity of substitution between oils in production
EPSR	ALL_INDS*REG	817	Elasticity of substitution in pasturecrop and pasturecover
ESBD	TRAD_COMM	48	Armington CES for domestic/imported allocation
ESBM	TRAD_COMM	48	Armington CES for regional allocation of imports
ESBT	ALL_INDS	43	Elasticity of intermediate input substitution

Table S1 GTAP model parameters (cont.)

Name	Dimensions	Values	Description
ESBV	ALL_INDS*REG	817	Elasticity of substitution in value-added-en. subproduction
ETA	AEZ18*REG	342	Elasticity of effective hectares with respect to harvested area
ETBD	6	6	Elasticity of transformation among outputs
ETL1	REG	19	Elasticity of transformation among land cover categories
ETL2	REG	19	Elasticity of transformation for crop land in supply tree
ETL3	1	1	Elasticity of transformation for land between beef and milk
ETRE	ENDW_COMM	22	CET between sectors for sluggish primary factors
INCP	CDE_COMM*REG	646	CDE expansion parameter
LVFD	ALL_INDS*REG	817	Elasticity of substitution in livestock-based feed subproduction
OBCD	ALL_INDS*REG	817	Elasticity of substitution between soy-based and corn-based feed
OBDB	ALL_INDS*REG	817	Elasticity of subst. in OBDBS, OBDBO, OBDBO in feed subproduction
OBDO	ALL_INDS*REG	817	Elasticity of subst. in Oth_Oilseed and OBDBO feed subproduction
OBDP	ALL_INDS*REG	817	Elasticity of substitution in palmf and OBDBP feed subproduction
OBDR	ALL_INDS*REG	817	Elasticity of substitution in Rapeseed and OBDBR feed subproduction
OBDS	ALL_INDS*REG	817	Elasticity of substitution in soybeans and OBDBS feed subproduction
PAEL	REG	19	Scalar yield elasticity target for cropland pasture
SUBP	CDE_COMM*REG	646	CDE substitution parameter
YDEL	1	1	Scalar yield elasticity target
YDRS	REG	19	Scale of yield elasticity target relative to base value for given region

Table S2 lists the 19 regions used in GTAP-BIO-ADV.

Table S2: Region definitions used in the GTAP-BIO-ADV model

Region ID	Description
USA	United States
EU27	European Union 27
Brazil	Brazil
Canada	Canada
Japan	Japan
ChiHkg	China and Hong Kong
India	India
C_C_Amer	Central and Caribbean Americas
S_O_Amer	South and Other Americas
E_Asia	East Asia
Mala_Indo	Malaysia and Indonesia
R_SE_Asia	Rest of South East Asia
R_S_Asia	Rest of South Asia
Russia	Russia
Oth_CEE_CIS	East Europe and Rest of Former Soviet Union
Oth_Europe	Rest of European Countries
ME_N_Afr	Middle Eastern and North Africa
S_S_Afr	Sub Saharan Africa
Oceania	Oceania

S2.2 AEZ-EF model parameters

Table S3: AEZ-EF model parameters. The first column shows the unique header name used to reference the parameter; the second column shows the parameters dimensions; the third column shows the number of distinct values for each parameter. In the "dimensions" column, AEZ refers to the 18 agro-ecological zones shown in figure S1; REG refers to the 19 regions used in GTAP-BIO-ADV, described in table S2; LATITUDE refers to the 3 major climate zones: boreal, temperate, and tropical; SPECIES refers to 5 combustion emissions: CO_2, CO, CH_4, N_2O, and non-methane hydrocarbons.

Name	Dimensions	Values	Description
GWP_CO2	scalar	1	CO_2 global warming potential
GWP_CH4	scalar	1	CH_4 global warming potential
GWP_N2O	scalar	1	N_2O global warming potential
MalaIndoPeatEF	scalar	1	Emissions from peatland conversion (Mg C ha^{-1})
MalaIndoPeatFraction	scalar	1	The faction of conversion to oil palm occurring on peatland
N2O_N_EF	scalar	1	Fraction of N in applied fertilizer that is released as N_2O
carbonNitrogenRatio	scalar	1	Represents the mass ratio of carbon to nitrogen loss
cropCarbonAnnualizationFactor	scalar	1	Ratio of annual average to maximum crop carbon
croplandLandUseFactor	AEZ	18	IPCC land use factor for cropland
croplandPastureEmissionRatio	scalar	1	The ratio of emissions from converting cropland-pasture to cropland to those from converting pasture to cropland
croplandSoil_C	AEZ*REG	342	Cropland soil carbon density (Mg C ha^{-1}) to 30 cm depth
croplandSubsoil_C	AEZ*REG	342	Cropland soil carbon density (Mg C ha^{-1}) from 30 to 100 cm depth
deadwoodByLatitude_C	LATITUDE	3	Deadwood carbon density (Mg C ha^{-1}) by latitude
deadwoodByRegion_C	REG	19	Deadwood carbon density (Mg C ha^{-1}) by region
deforestedFraction	REG	19	Fraction of forest cover change that is deforestation rather than afforestation
excludedLitterFraction	scalar	1	Litter fraction not included in regrowth
fireClearingFraction	REG	19	Fraction of land-cover cleared using fire
foregoneGrowthRate	AEZ*REG	342	Foregone sequestration rate (Mg C ha^{-1} y^{-1})
forestBurningEF	LATITUDE*SPECIES	15	Emissions of 5 species for forest burning (kg per Mg dry matter)
forestCombustionFactor	LATITUDE	3	Fraction of fuel biomass combusted when clearing forests with fire
forestDefaultRootShootRatio	scalar	1	Default ratio of live root biomass to above-ground live biomass for forests
forestLandUseFactor	AEZ	18	IPCC land use factor for forest land
forestLitter_C	AEZ	18	Forest litter carbon density (Mg C ha^{-1})
forestRegrowthRate	AEZ*LATITUDE	54	Forest regrowth rate (Mg C ha^{-1} y^{-1})
forestRootShootRatio	AEZ*REG	342	Ratio of live root biomass to above-ground live biomass for forests
forestSoilLossFraction	LATITUDE	3	Fraction of forest soil (to 30 cm) lost during conversion to cropland

Table S3 AEZ-EF model parameters (cont.)

Name	Dimensions	Values	Description
forestSoil_C	AEZ*REG	342	Forest soil carbon density (Mg C ha^{-1}) to 30 cm depth
forestSubsoilLossFraction	LATITUDE	3	Fraction of forest soil (30 to 100 cm) lost during conversion to cropland
forestSubsoil_C	AEZ*REG	342	Forest soil carbon density (Mg C ha^{-1}) from 30 to 100 cm depth
grassCarbonFraction	scalar	1	Fraction of herbaceous biomass composed of carbon
hwpFraction	REG	19	Fraction of above-ground biomass removed in harvested wood products
oilPalmBiomass_C	scalar	1	Carbon density (Mg C ha^{-1}) of oil palm trees
pastureAgb	AEZ	18	Carbon density (Mg C ha^{-1}) of above-ground pasture biomass
pastureBgb	AEZ	18	Carbon density (Mg C ha^{-1}) of below-ground pasture biomass
pastureBurningEF	LATITUDE*SPECIES	15	Emissions of 5 species for pasture burning (kg per Mg dry matter)
pastureCombustionFactor	LATITUDE	3	Fraction of fuel biomass combusted when clearing pastures with fire
pastureLitter_C	scalar	1	Pasture litter carbon density (Mg C ha^{-1})
pastureSoil_C	AEZ*REG	342	Pasture soil carbon density (Mg C ha^{-1}) to 30 cm depth
pastureSoilLossFraction	LATITUDE	3	Fraction of forest soil (to 30 cm) lost during conversion to cropland
pastureSubsoilLossFraction	LATITUDE	3	Fraction of forest soil (30 to 100 cm) lost during conversion to cropland
pastureSubsoil_C	AEZ*REG	342	Pasture soil carbon density (Mg C ha^{-1}) from 30 to 100 cm depth
regrowth_C	AEZ*REG	342	Estimated C stored in afforestation over 30 years (Mg C ha^{-1})
totalTree_C	AEZ*REG	342	Carbon density (Mg C ha^{-1}) of total tree (above- plus below-ground)
tropicalForestRootShootRatio	scalar	1	Ratio of live root biomass to above-ground live biomass for tropical forests
understory_C	LATITUDE	3	Understory soil carbon density (Mg C ha^{-1}) to 30 cm depth
woodyCarbonFraction	scalar	1	Fraction of woody biomass composed of carbon

S3 Monte Carlo framework

One challenge to performing Monte Carlo simulation with models such as GTAP is the length of time the models require to complete a single simulation. The GTAP model used in this analysis typically required 5-15 minutes per solution on a desktop computer. Thus, a Monte Carlo analysis using 1000 trials could require over a week of continuous computation. To address this, our analysis was performed on a high-performance parallel computing cluster at the National Energy Research Scientific Computing (www.nersc.gov) facility, managed by the US Department of Energys Lawrence Berkeley National Lab. The ILUC-MCS model is based on a new software framework called *Distributed MCS*, or DMCS, developed in the Python language. DMCS will be made freely available as under an open-source license. Please contact the authors for more information.

S3.1 What is represented by parameter distributions

The Monte Carlo approach produces a joint output frequency distribution by executing the model numerous times with alternative parameter values drawn from defined input distributions. Although this correctly represents the joint probability, the semantics of this distribution depends critically on what exactly is represented by the input parameter distributions.

In many cases, there are inadequate data to draw parameter distributions, or in many cases, to distinguish values by region or industry. We treat values that are constant across regions or industries in the GTAP database as single parameters rather than individual parameters.

There is disagreement among experts as to the best value for many parameters. Elliott et al. (2011) compared values from GTAP and MITs EPPA model and fail to distinguish any pattern to the disagreement, with GTAP values sometimes the highest and sometimes the lowest. So one setting for sensitivity analysis is to examine the sensitivity to different expert opinion, which can vary quite widely for any single parameter. In our analysis, we have examples of DDGS substitution elasticities of Taheripour versus those of Beckman, and disagreement over the most appropriate value for YDEL.

Another setting examines the sensitivity to the uncertainty around a value that is treated as reasonably well-characterized, i.e., there is strong data or expert agreement supporting the approximate value, but there is still measurement or approximation uncertainty. Yet another setting—the one we focus on here—is to understand the sensitivity of the model and the range of plausible output values that result from all of the above, regardless of the source.

Its important to note that our output distributions indicate the uncertainty in the final result based on the described uncertainty in parameters—treating the model structure and underlying base data as certain. Thus our results should not be treated as characterizing probabilities of any real-world outcome; rather, they represent the distribution of results for this model, as implemented, given our choice of distributions.

Tables S5 and S6 list the parameter distributions used in the Monte Carlo simulation. Table S4 shows the values from the IPCC's Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) which were used to define distributions for the AEZ-EF model parameter "croplandUseFactor".

S3.2 Correlations

Frey et al. (2006, p 3.25) note that dependencies among inputs matter only if the parameters are important contributors to variance and the dependency (correlation or covariance) is strong. Otherwise, modeling this dependence is unimportant to the resulting uncertainty.

The modeling framework used in this study supports the implementation of rank correlations among random variables based on the method of Iman and Davenport (1982). We used this to impose rank correlations in only one situation: we assigned a rank correlation coefficient of 0.9 to the elasticities of substitution between (i) other coarse grains (predominantly corn) and distillers dried grains with solubles (DDGS) and (ii) sorghum and DDGS given the similarity of these products.

S3.3 Distribution definition file format

Many of the parameters to these models are matrices of values with a common purpose, e.g., the carbon density of soil in each region represented in the model, or the elasticities of substitution among a set of industrial sectors, by region. These parameter groups can be manipulated stochastically in various ways: using a single random variable (RV) assigned to the entire group, or by RVs for each row, column, cell in a matrix. One goal of the analysis is to identify important parameter groups affected by one or more RV, as well as individual RVs.

- Values drawn from the distributions can be used either to substitute directly for the default value for that parameter, or as a factor multiplied by the default value to produce a value to which is then substituted for the default value.
- Distributions can be applied to scalar values, entire matrices, or individual rows, columns, or cells of a matrix.
- The distributions currently supported include: Uniform, Normal, Lognormal, Triangle, Binary, and Discrete. The system is design to allow additional distributions to be added fairly easily.
- Scalar parameters are equivalent to $1*1$ matrices, so whenever matrix parameters are mentioned, this includes scalar and vector $(1*N)$ parameters.
- It is possible to declare (rank) correlations between pairs of model parameters, as long as they have the identical dimensions, and the distribution must be assigned to the same dimensions for both parameters (see more on this below). In the matrix case, the cells at the same location within the matrix are treated as correlated.
- Also possible to declare that random variables associated with a matrix are correlated, but use with caution: this can generate hundreds of random variables. Most practical to use with small distribution dimensions.

S3.3.1 Defining distributions

Here we describe the assignment of distributions to model parameters using the Distributed-MCS framework. Note that this framework will be released as an open-source project; please contact the authors for more information.

- Blank lines are ignored
- Text after # are treated as comments and ignored
- Two types of entries are processed: distribution declarations and correlation declarations
- A single distribution declaration can produce multiple random variables (RV).

The general format for a distribution declaration is:

```
parameter target distro arg1=value arg2=value ...
```

`Parameter` Specifies the model parameter to which this distribution applies.

`Target` One of: None, Single, Rows, Cols, Cells, [*row*] or [*row, col*]

`None` The parameter is treated as constant using the value given in the parameter file.

`Single` A single random variable (RV) is created, the value of which is applied to all non-zero elements of the matrix (unless the modifier `_updateZero=1` is specified, in which case all matrix elements are updated). Note that "applying" a value can mean either assigning the value directly, or using it as a multiplier, in which case the parameter value used in the trial is the product of the RV value and the default parameter value.

`Rows` Similar to "single" except that an RV is created for each row of the matrix.

`Cols` Similar to "single" except that an RV is created for each column of the matrix.

`Cells` Similar to "single" except that an RV is created for each individual cell of the matrix.

[***row***] The *row* value specifies a row index by name or numeric value. A separate RV is generated for this row. If declared after a matrix that includes this row, the subsequent definition overrides the prior one.

[***row, col***] The *row* and *col* values specify the row and column indices by name (e.g., regions, industries) or numeric value. or are an asterisk (*) to indicate an entire row or column. For example, to specify column 3 only, you would write [*,3], meaning "all rows of column 3".

`Distro` One of: UniformFactor, LogFactor, TriangleFactor, Normal, Lognormal, Uniform, Triangle, Binary.

`UniformFactor` Args: min=*arg1*, max=*arg2* or factor=*arg1*
Adds random noise factor of [*arg1, arg2*] by multiplying all values indicated by the noise factor selected from this range. If only one value is given, it must be a fraction between 0 and 1, which defines a range of ±*arg1*, i.e., the range is [1-*arg1*, 1+*arg1*]

`LogFactor` Args: factor=*arg1*
Similar to `UniformFactor` but multipliers are chosen from lognormal with a 95% confidence interval of [1/*arg1*, *arg1*]. For example, a value of 3 means that multiplier values are selected from a lognormal distribution with 95% CI = [1/3, 3].

`TriangleFactor` Args: width=*arg1* or min=*arg1*, mode=*arg2*, max=*arg3*
Similar to `UniformFactor` but multipliers are chosen from a triangular distribution with the given *min*, *mode*, and *max*, or centered on zero with *min* and *max* set to ±*width*.

`Normal` Args: mean=*arg1*, std=*arg2*
Set values to a random choice from normal distribution with mean of *arg1* and standard deviation of *arg2*.

`Lognormal` Args: mean=*arg1*, std=*arg2* *or* low95=*arg1*, high95=*arg2*
Set values to a random choice from a lognormal distribution, either with (i) mean value (of the lognormal, not the underlying normal distribution) of *arg1* and standard deviation (of the lognormal) of *arg2*, or (ii) 95% confidence interval of [*arg1, arg2*]

`Uniform` Args: min=arg1, max=arg2
Set values to a random choice from interval [arg1, arg2]

`Triangle` Args: min=*arg1*, mode=*arg2*, max=*arg3*
Set values from triangular distribution with minimum value *arg1*, mode *arg2*, and maximum value of *arg3*.

`Binary` Args: none.
Choose randomly from the set {0, 1}

```
parameter[row,col] value1:prob1 val2=prob2 ...
```

S3.3.2 Modifiers

Some distributions accept modifiers, which are like arguments but the names must being with an underscore).

- Random values are directly assigned by default. Alternative specifications are `_apply=mult` and `_apply=add`, which cause the random value to be multiplied by, or added to (respectively) the default value for the parameter.
- In conjunction with `_apply=mult`, distributions can specify `_lowBound=`*arg1* and/or `_highBound=`*arg2*, in which case after multiplying the default value by the value drawn from the random variable, the new value is set to *arg1* if `_lowBound` is specified and the value is less than *arg1*, and the value is set to *arg2* if `_highBound` is specified and the value is greater than *arg2*. This is useful when dealing with parameters representing values that must be between 0 and 1.
- Any distribution can also specify `_updateZero=1` to indicate that zero default values should be updated; otherwise zero values are left unchanged. That is, by default a value of zero will not be replaced by the random value, nor (in the case of `_apply=add`) have the random value added to it.
- Discrete distributions can specify `_tolerance=`*arg1* and/or `_precision=`*arg1*. The `_tolerance` modifier set the amount by which the sum of the probabilities can differ from 1. The default tolerance is 0.01. The `_precision` modifier sets the number of bins into which the discrete values are sorted, thus the resulting probability values will be accurate within 1/precision. The default precision is 100.

S3.3.3 Correlations

Correlations within a single matrix parameter, or between two parameters can be specified as:

```
Correlation Param1 [Param2] value
```

If only 1 parameter is named, this defines a correlation among the RVs for the vector or matrix defined for the named parameter. If 2 parameters are named, both must matrices with identical dimensions, in which case each cell of the first matrix is correlated with the cell at the same `address` in the second matrix.

S3.4 Parameter distributions used in simulations

For the Cropland Land Use Factor, the IPCC suggests the following uncertainty values shown in table S4.

Table S4: IPCC uncertainty ($\pm 2\sigma$) ranges for cropland land-use factors.

Regime	Factor	Error (95% CI)
Dry temp/boreal	0.80	±9%
Moist temp/boreal	0.69	±12%
Dry tropical	0.58	±61%
Moist tropical	0.48	±46%
Tropical montane	0.64	±50%

Table S5: Parameter distributions for the AEZ-EF model.

Parameter name	Target	Distribution	Parameters
croplandLandUseFactor	[AEZ-1]	UniformFactor	factor=0.61
croplandLandUseFactor	[AEZ-2]	UniformFactor	factor=0.61

Table S5 Continued:

Parameter name	Target	Distribution	Parameters
croplandLandUseFactor	[AEZ-3]	UniformFactor	factor=0.61
croplandLandUseFactor	[AEZ-4]	UniformFactor	factor=0.46
croplandLandUseFactor	[AEZ-5]	UniformFactor	factor=0.46
croplandLandUseFactor	[AEZ-6]	UniformFactor	factor=0.46
croplandLandUseFactor	[AEZ-7]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-8]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-9]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-10]	UniformFactor	factor=0.12
croplandLandUseFactor	[AEZ-11]	UniformFactor	factor=0.12
croplandLandUseFactor	[AEZ-12]	UniformFactor	factor=0.12
croplandLandUseFactor	[AEZ-13]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-14]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-15]	UniformFactor	factor=0.09
croplandLandUseFactor	[AEZ-16]	UniformFactor	factor=0.12
croplandLandUseFactor	[AEZ-17]	UniformFactor	factor=0.12
croplandLandUseFactor	[AEZ-18]	UniformFactor	factor=0.12
grassCarbonFraction	Single	UniformFactor	factor=0.05
woodyCarbonFraction	Single	UniformFactor	factor=0.05
oilPalmBiomassC	Single	Normal	mean=35 std=5.5
N2O-N-EF	Single	Lognormal	low95=0.004 high95=0.04
carbonNitrogenRatio	Single	Lognormal	mean=15 std=5.8
cropCarbonAnnualizationFactor	Single	Triangle	min=0.45 mode=0.5 max=0.55
croplandPastureEmissionRatio	Single	Triangle	min=0.0 mode=0.5 max=1.0
croplandSoil-C	Single	UniformFactor	factor=0.50
croplandSubsoil-C	Single	UniformFactor	factor=0.50
deadwoodByLatitude-C	Single	UniformFactor	factor=0.75
deadwoodByRegion-C	Single	UniformFactor	factor=0.75
deforestedFraction	Single	UniformFactor	factor=0.50 highBound=1
deforestedFraction	[Mala-Indo]	UniformFactor	min=0.55 max=1.00
excludedLitterFraction	Single	UniformFactor	factor=0.25 highBound=1
ipccCroplandLandUseFactor	Single	UniformFactor	factor=0.25
ipccForestLandUseFactor	Single	UniformFactor	factor=0.25
fireClearingFraction	Single	UniformFactor	factor=0.50 highBound=1
foregoneGrowthRate	Single	UniformFactor	factor=0.50
forestBurningEF	Single	UniformFactor	factor=0.25
forestCombustionFactor	Single	UniformFactor	factor=0.50 highBound=1
forestDefaultRootShootRatio	Single	Triangle	min=0.20 mode=0.25 max=0.30
forestLandUseFactor	Single	UniformFactor	factor=0.25
forestLitter-C	Single	UniformFactor	factor=0.50
forestRootShootRatio	Single	UniformFactor	factor=0.23
forestSoilLossFraction	Single	UniformFactor	factor=0.25 highBound=1
forestSubsoilLossFraction	Single	UniformFactor	factor=0.50 highBound=1
forestSoil-C	Single	UniformFactor	factor=0.50
forestSubsoil-C	Single	UniformFactor	factor=0.50
GWP-CH4	Single	Normal	mean=25 std=4.35
GWP-N2O	Single	Normal	mean=298 std=52.15
hwpFraction	Single	UniformFactor	factor=0.25
MalaIndoPeatEF	Single	UniformFactor	factor=0.25
MalaIndoPeatFraction	Single	UniformFactor	factor=0.25 highBound=1
pastureAgb	Single	UniformFactor	factor=0.80

Table S5 Continued:

Parameter name	Target	Distribution	Parameters
pastureLitter-C	Single	Triangle	min=0.05 mode=0.40 max=0.50
pastureBurningEF	Single	UniformFactor	factor=0.25
pastureCombustionFactor	Single	UniformFactor	factor=0.75 highBound=1
pastureSubsoilLossFraction	Single	UniformFactor	factor=0.25 highBound=1
pastureSoil-C	Single	UniformFactor	factor=0.25
pastureSubsoil-C	Single	UniformFactor	factor=0.50
totalTree-C	Single	UniformFactor	factor=0.25
totalTree-C	[*,Canada]	UniformFactor	factor=0.80
totalTree-C	[*,ME-N-Afr]	UniformFactor	factor=0.80
totalTree-C	[*,EU27]	UniformFactor	factor=0.80
totalTree-C	[*,ChiHkg]	UniformFactor	factor=0.80
tropicalForestRootShootRatio	Single	UniformFactor	factor=0.25
regrowth-C	Single	UniformFactor	factor=0.50
Correlation	foregoneGrowthRate regrowth-C		0.75

Table S6: Parameter distributions for the GTAP model.

Parameter name	Target	Distribution	Parameters
CDDG	Single	Uniform	min=10 max=20
CDGC	Single	Uniform	min=10 max=30
CDGS	Single	Uniform	min=10 max=30
CRFD	Single	LogFactor	factor=1.5
EFED	Single	Triangle	min=0.15 mode=0.50 max=0.85
ELEG	Rows	UniformFactor	factor=0.5
ELEN	Rows	LogFactor	factor=2
ELHB	Single	UniformFactor	factor=0.50
ELHL	Single	LogFactor	factor=2
ELKE	Rows	LogFactor	factor=1.5
ELNC	Rows	LogFactor	factor=1.5
ELNE	Rows	LogFactor	factor=1.5
ELVL	Single	LogFactor	factor=1.5
EPSR	Single	UniformFactor	factor=0.5
ESBM	Single	LogFactor	factor=2
ESBV	Rows	LogFactor	factor=1.5
ETA	Single	UniformFactor	factor=0.20 highBound=1.0
ETL1	Single	TriangleFactor	width=0.2
ETL2	Single	TriangleFactor	width=0.2
LVFD	Single	LogFactor	factor=1.5
OBCD	Single	Uniform	min=0.14 max=0.3
OBDO	Single	Uniform	min=10 max=20
OBDP	Single	Uniform	min=10 max=20
OBDR	Single	Uniform	min=10 max=20
OBDS	Single	Uniform	min=10 max=20
PAEL	[USA]	Uniform	min=0.1 max=0.6
PAEL	[Brazil]	Uniform	min=0.1 max=0.3
YDEL	Single	Uniform	min=0.03 max=0.25

S4 Model Results

Figure S2 shows the frequency distributions for 3 model outputs: ILUC Emission Factor, Non-CO_2 Emission Factor, and Total Emission Factor, which is the sum of the prior two quantities on a trial-by-trial basis. For each model output, 2 distributions are shown for each of the three fuel pathways examined. The items labeled “FF” (food fixed) were simulated with food consumption fixed in non-Annex-I countries; those labeled “FNF” (food not fixed) were run without this constraint. Constraining food consumption removes a degree of freedom for the model, causing other modeled behavior (e.g., extensification) to take up the slack, and resulting in ILUC emissions that were consistently about 10 g CO_2 MJ^{-1} higher than without the constraint.

S4.1 Non-CO_2 emissions

The GTAP non-CO_2 version 7 database (Rose et al., 2010) includes nitrous oxide (N_2O), methane (CH_4) and fourteen fluorinated gases (F-gases). In each region, non-CO_2 emissions are provided for each economic sector and driver, and regional household. To track changes in non-CO_2 emissions within the GTAP-BIO-ADV model, emissions are tied to specific drivers within each sector: factor inputs, intermediate inputs, or output. For example, emissions from fertilizer application in crop production are proportional to fertilizer use in crops. In livestock sectors, emissions from enteric fermentation and manure management are proportional to livestock capital. Household non-CO_2 emissions are tied to energy use.

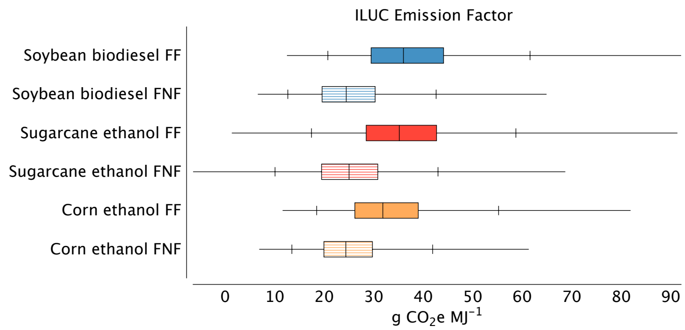
Tables S7 and S8 show the mean and bounds of the central 95% of the distribution for simulations with the three fuels, with food consumption fixed in non-Annex I countries (FF) and not fixed (FNF), both excluding (table S7) and including (table S8) NonCO_2 emissions. Note that for cane ethanol, including non-CO_2 emissions *reduces* the total emissions.

Table S7: Summary of results for ILUC emissions (g CO_2e MJ^{-1}), not including changes in emissions of methane (CH_4) or nitrous oxide (N_2O). FNF=food consumption not fixed anywhere; FF=food consumption is fixed in non-Annex I countries.

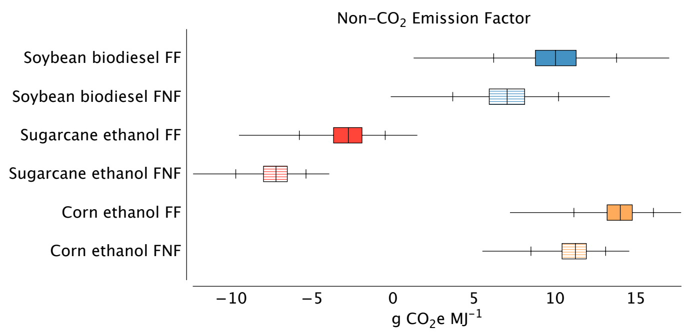
Experiment	Mean	2.5 percentile	97.5 percentile
Corn ethanol, FNF	25	13	42
Corn ethanol, FF	33	18	55
Cane ethanol, FNF	25	10	43
Cane ethanol, FF	36	17	59
Soybean biodiesel, FNF	25	13	43
Soybean biodiesel, FF	38	21	62

Table S8: As described in Table S7, except *including* changes in emissions of methane (CH_4) and nitrous oxide (N_2O).

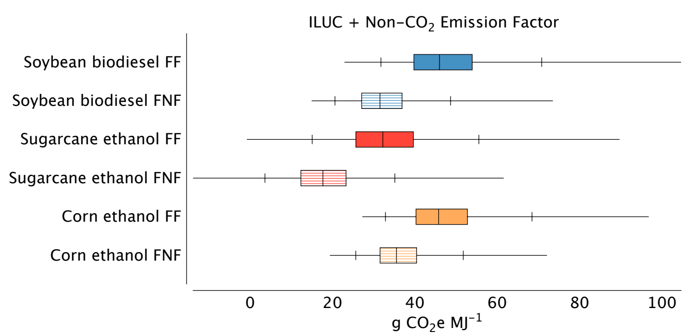
Experiment	Mean	2.5 percentile	97.5 percentile
Corn ethanol, FNF	36	26	52
Corn ethanol, FF	46	33	68
Cane ethanol, FNF	18	4	35
Cane ethanol, FF	33	15	56
Soybean biodiesel, FNF	32	21	49
Soybean biodiesel, FF	48	32	71



(a) ILUC emission factor



(b) Non-CO_2 emission factor, i.e., N_2O emissions from changes in fertilizer and manure application and in CH_4 emissions from changes in rice cultivation and livestock production

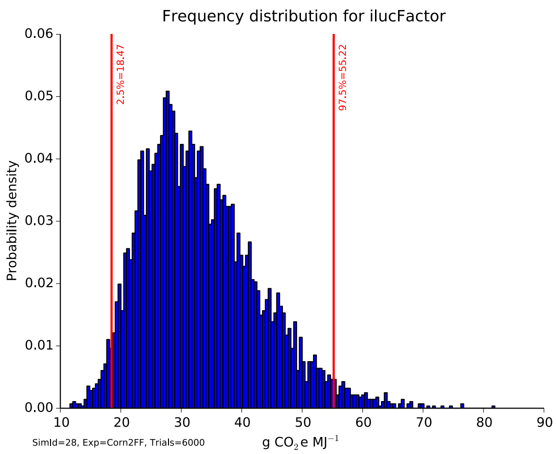


(c) Total emission factor (ILUC emissions + Non-CO_2 emissions)

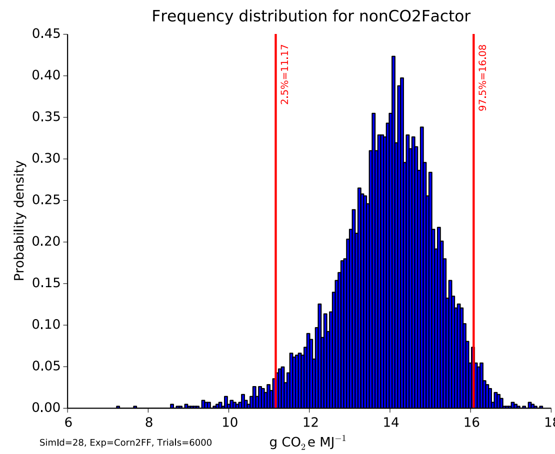
Figure S2: Comparison of ILUC, nonCO_2 and total emission factors for three fuel systems, both with food fixed (FF) and food not fixed (FNF).

Figures S3 through S5 show the frequency distributions for corn ethanol, sugarcane ethanol, and soybean biodiesel, for 3 model outputs: ILUC emissions, non-CO_2 emissions, and total emissions, which is simply the sum of the first two. In these model runs, food consumption has been held fixed in non-Annex I countries.

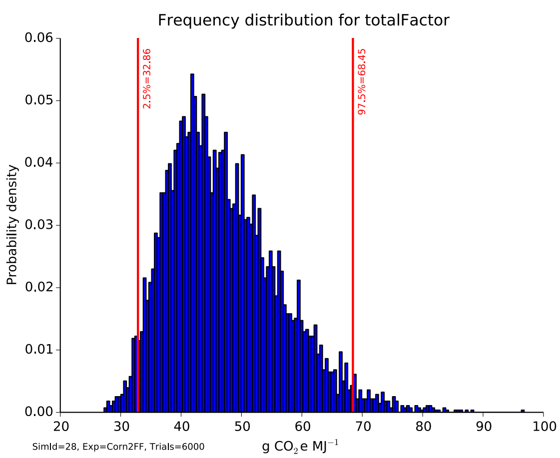
Figures S6 through S8 show the same results but for model runs in which food consumption was not held fixed anywhere.



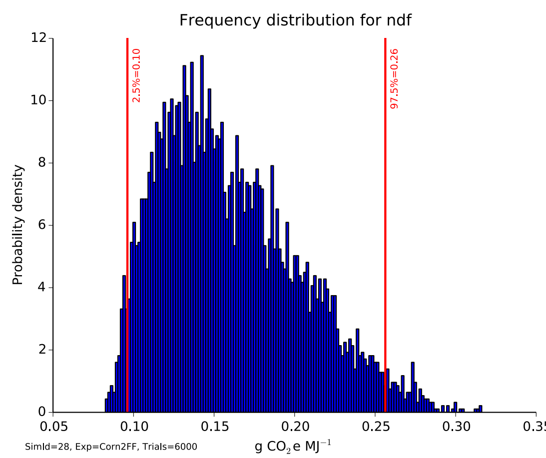
(a) Corn ethanol ILUC factor (food fixed)



(b) Corn ethanol Non-CO_2 Factor (food fixed)

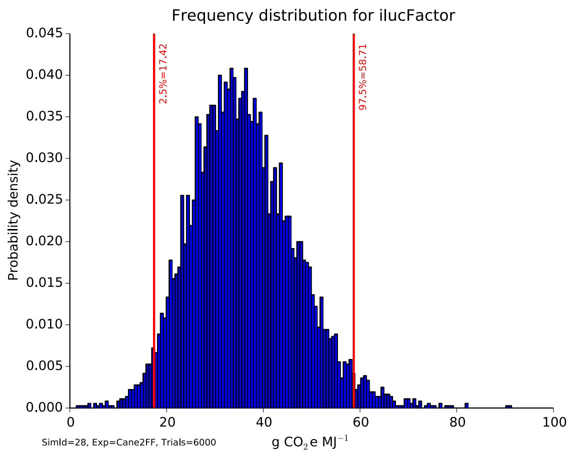


(c) Corn ethanol Total (ILUC+Non-CO_2) Factor, (food fixed)

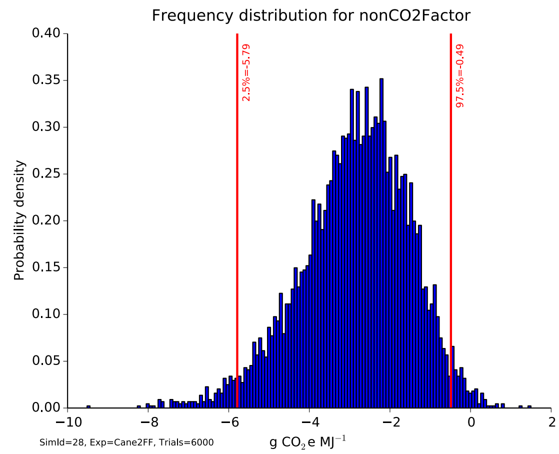


(d) Corn ethanol land Net Displacement Factor (food fixed)

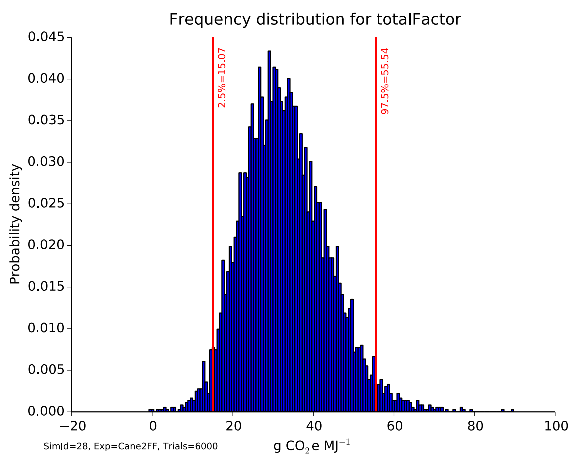
Figure S3: Key model output distributions for corn ethanol, holding food consumption fixed in developing countries.



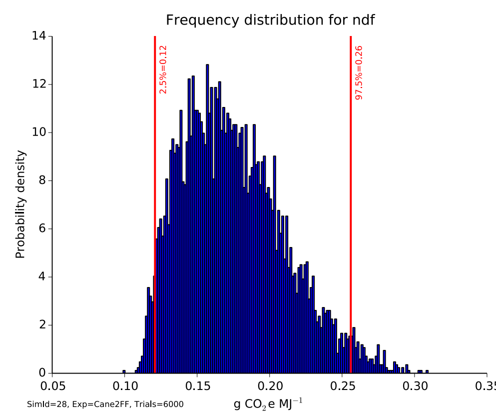
(a) Sugarcane ethanol ILUC factor (food fixed)



(b) Sugarcane ethanol Non-CO_2 Factor (food fixed)

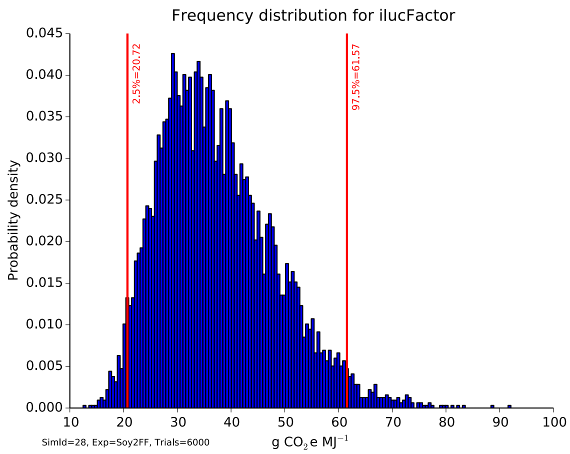


(c) Sugarcane ethanol Total (ILUC+Non-CO_2) Factor, (food fixed)

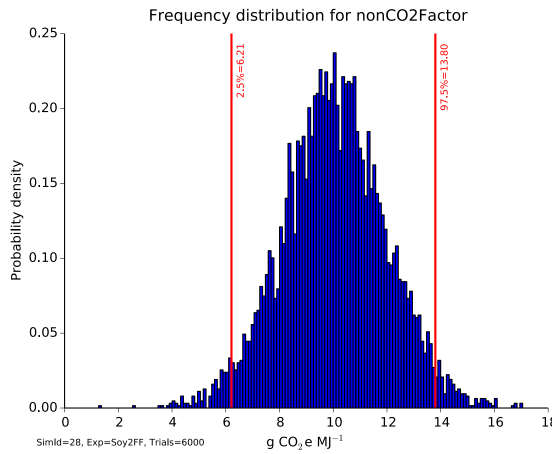


(d) Sugarcane ethanol land Net Displacement Factor (food fixed)

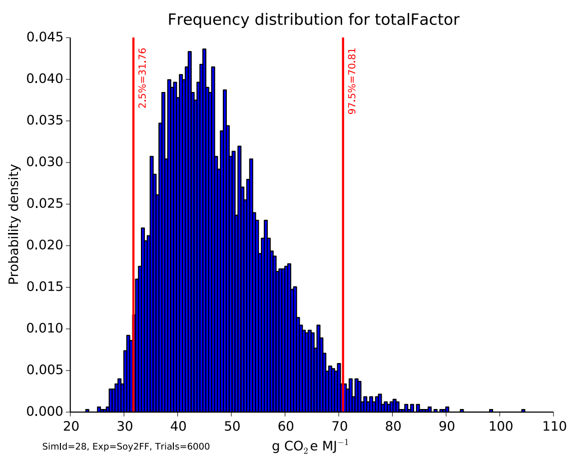
Figure S4: Key model output distributions for sugarcane ethanol, holding food consumption fixed in developing countries.



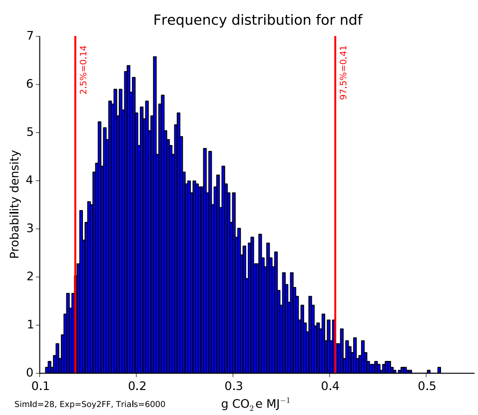
(a) Soybean biodiesel ILUC factor (food fixed)



(b) Soybean biodiesel Non-CO_2 Factor (food fixed)

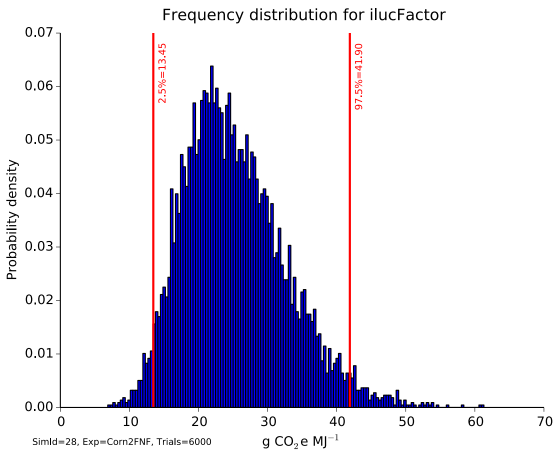


(c) Soybean biodiesel Total (ILUC+Non-CO_2) Factor, (food fixed)

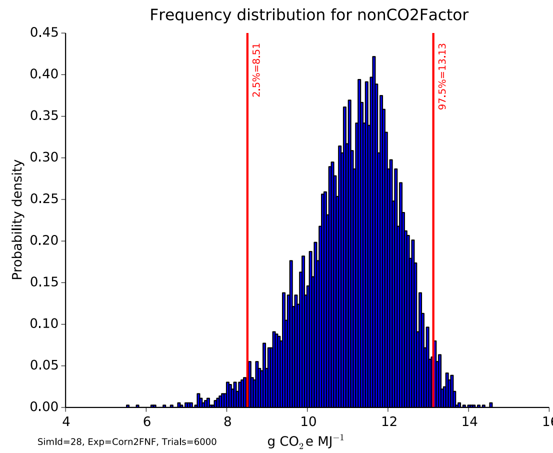


(d) Soybean biodiesel land Net Displacement Factor (food fixed)

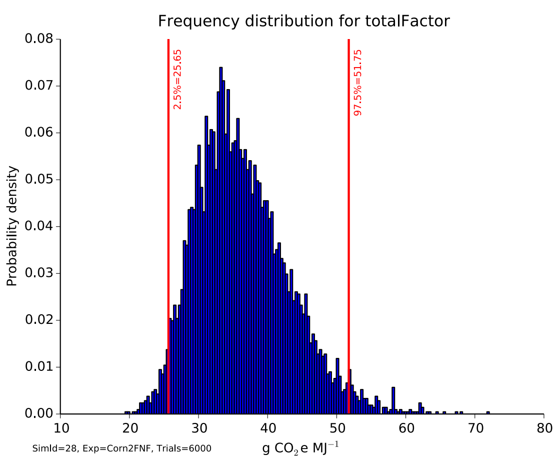
Figure S5: Key model output distributions for soybean biodiesel, holding food consumption fixed in developing countries.



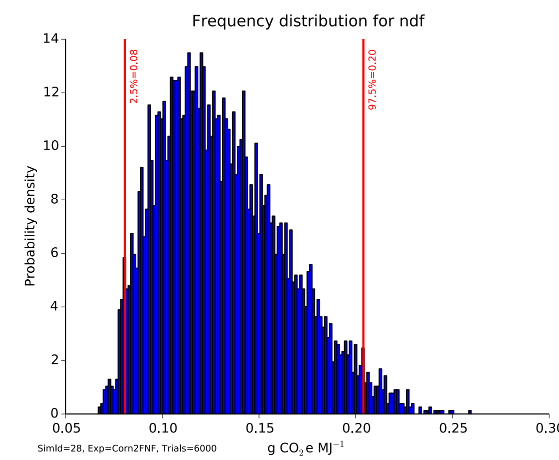
(a) Corn ethanol ILUC factor (food not fixed)



(b) Corn ethanol Non-CO_2 Factor (food not fixed)

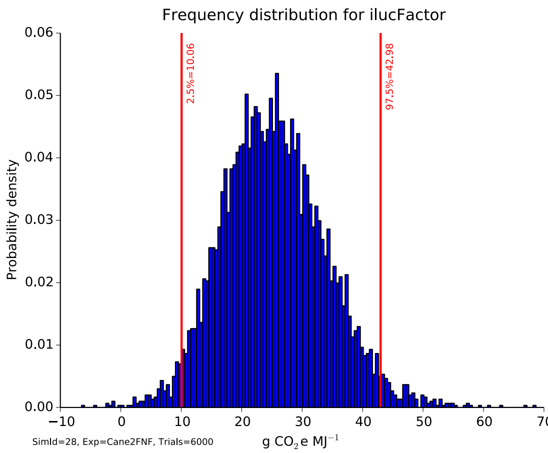


(c) Corn ethanol Total (ILUC+Non-CO_2) Factor, (food not fixed)

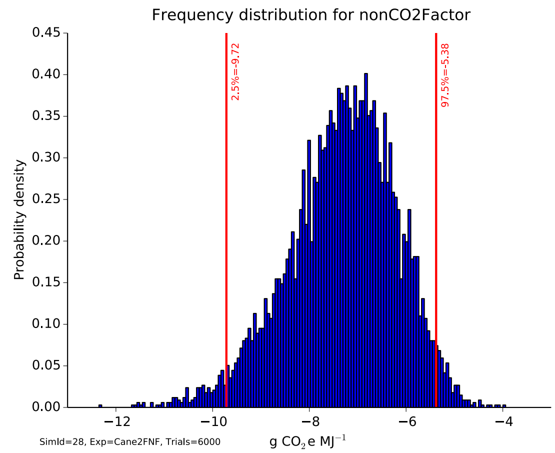


(d) Corn ethanol land Net Displacement Factor (food not fixed)

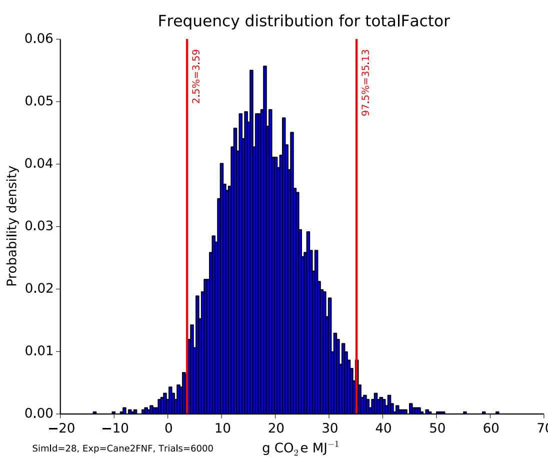
Figure S6: Key model output distributions for corn ethanol, without holding food consumption fixed.



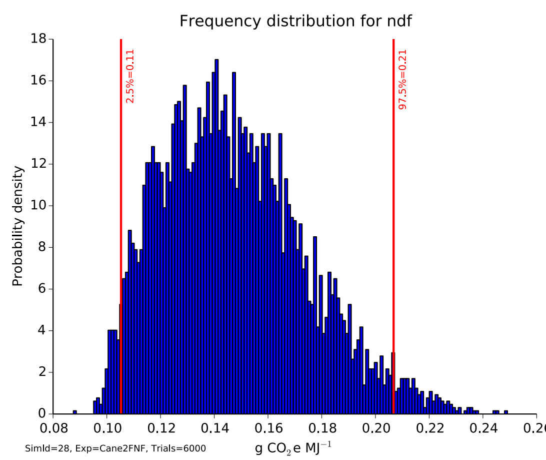
(a) Sugarcane ethanol ILUC factor (food not fixed)



(b) Sugarcane ethanol Non-CO_2 Factor (food not fixed)

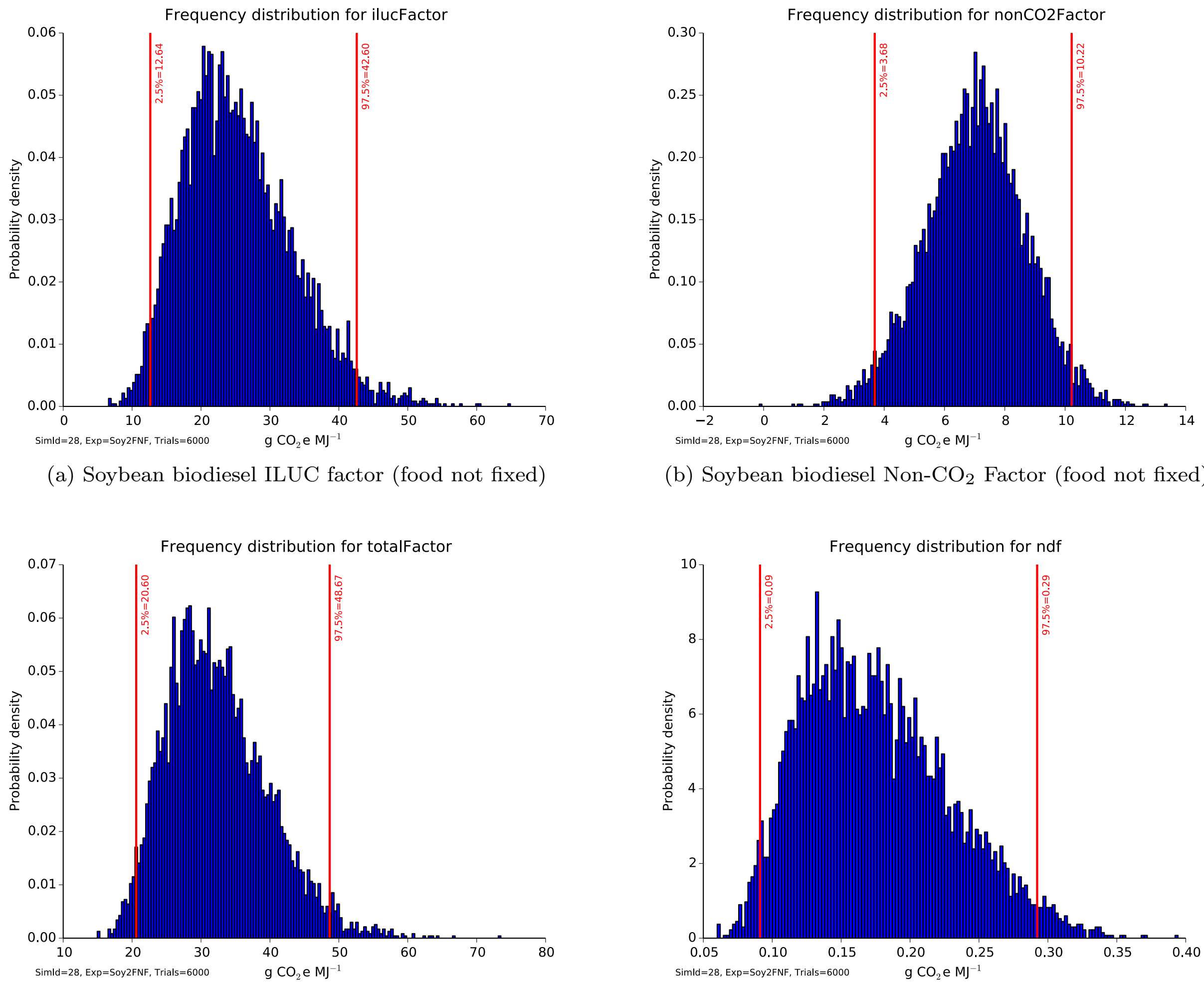


(c) Sugarcane ethanol Total (ILUC+Non-CO_2) Factor, (food not fixed)



(d) Sugarcane ethanol land Net Displacement Factor (food not fixed)

Figure S7: Key model output distributions for sugarcane ethanol, without holding food consumption fixed.



(a) Soybean biodiesel ILUC factor (food not fixed)

(b) Soybean biodiesel Non-CO_2 Factor (food not fixed)

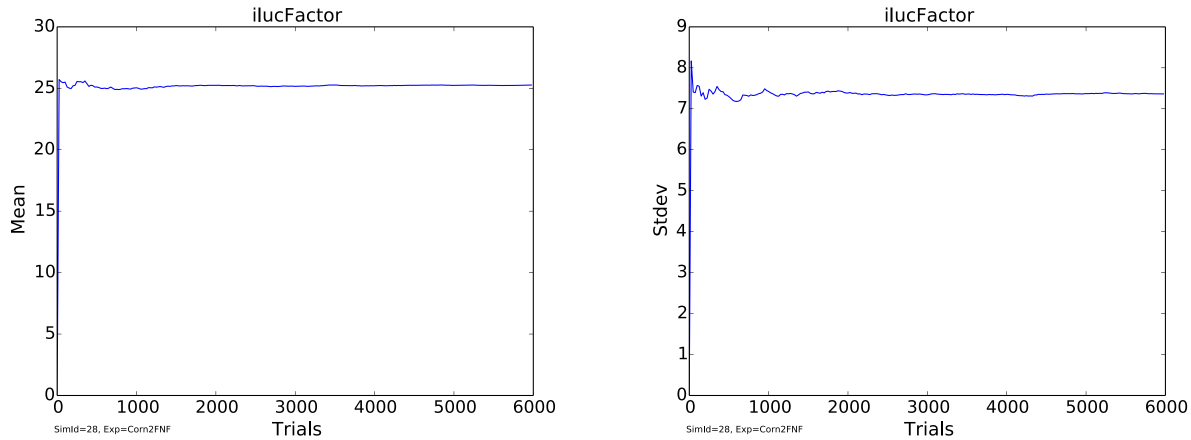
(c) Soybean biodiesel Total (ILUC+Non-CO_2) Factor, (food not fixed)

(d) Soybean biodiesel land Net Displacement Factor (food not fixed)

Figure S8: Key model output distributions for soybean biodiesel, without holding food consumption fixed.

S4.2 Statistical Convergence

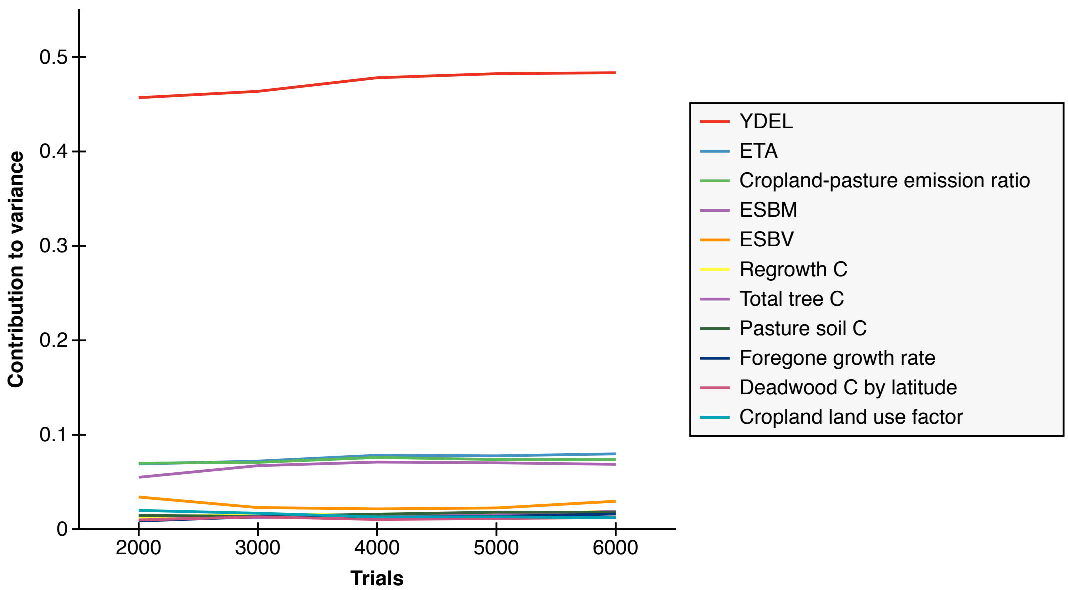
Figures S9a and S9b show that the mean value for ILUC emissions intensity for corn ethanol converges within about 500 trials, and standard deviation by about 1,500 trials. The corresponding plots for other output variables and biofuel pathways are quite similar.



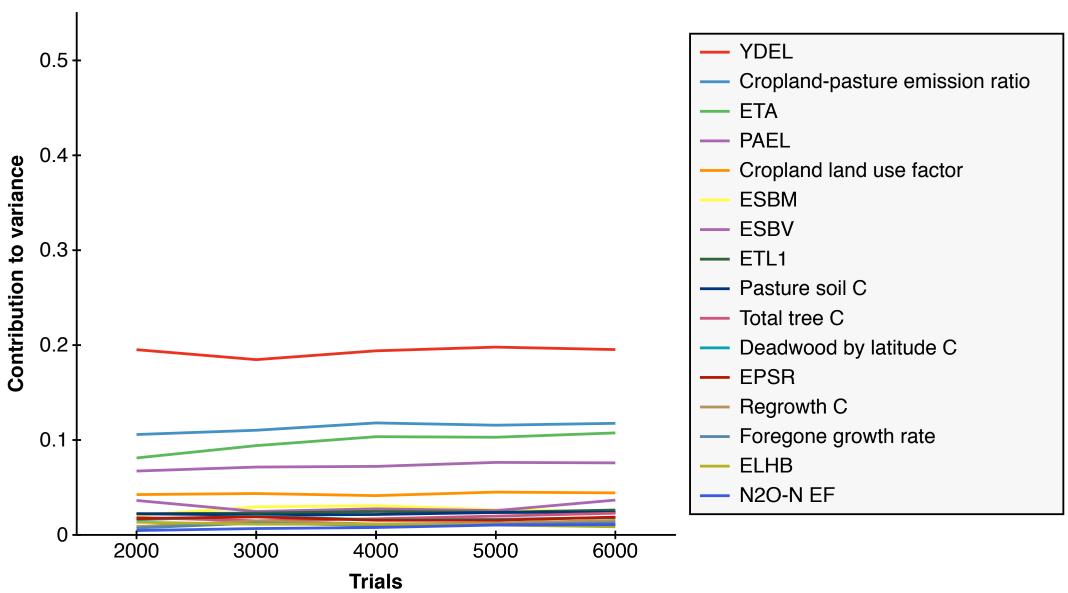
(a) Convergence of the mean value for ILUC emissions, corn ethanol.

(b) Convergence of the standard deviation for ILUC emissions, corn ethanol.

Figure S9: Convergence plots for the mean and standard deviation for the ILUC emissions associated with corn ethanol (food not fixed).



(a) Convergence of contribution to variance for corn ethanol over 6,000 trials (food not fixed).



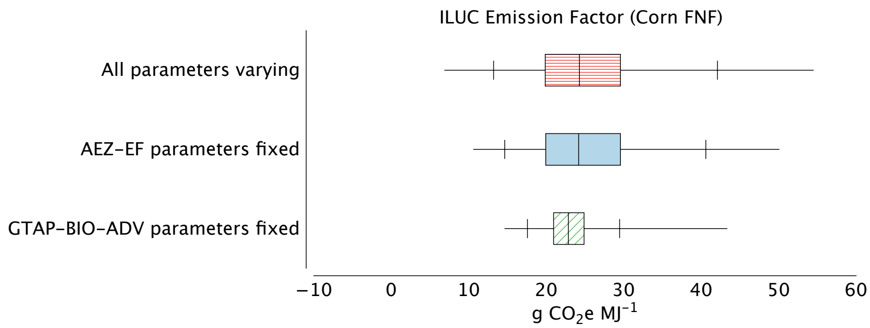
(b) Convergence of contribution to variance for sugarcane ethanol over 6,000 trials (food not fixed).

Figure S10: Convergence of contribution to variance as a function of the number of trials examined.

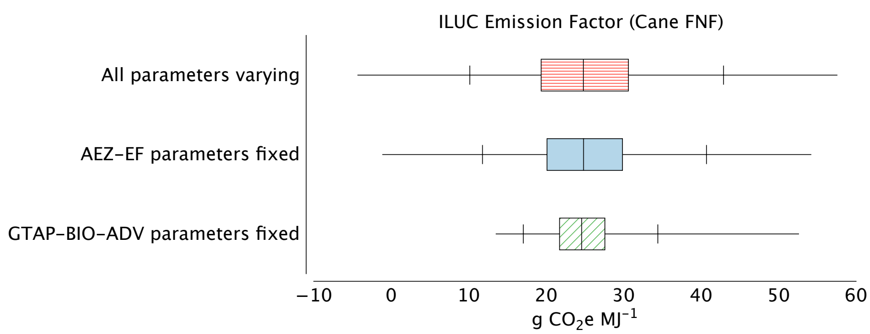
S4.3 Contribution to variance

We estimate contribution to variance using normalized rank (Spearman) correlations. For each input parameter, we compute the rank correlation with various output parameters across all trials. The rank correlations are squared and normalized to a percentage by dividing each by the sum of the squared correlation values. We restore the original sign to indicate directionality. Figures S12 through S17 show the percentage contribution to variance of the most influential input parameters to ILUC emissions.

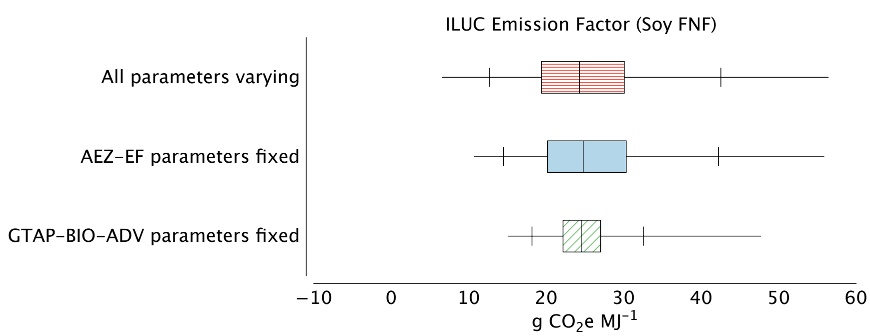
Parameters contributing 1% or more to total variance (Table S9) were included; others were considered unimportant contributors individually, though they together accounted for 20% of the total variance. Reducing the number of parameters to the "most important" 16 results in a reduction in the number of random variables from 538 in the "broader" stochastic scenarios to 37. (Several matrix or vector parameters have individual random value for rows and/or columns, thus the larger number of random variables than model parameters.) Simulation with this reduced number of parameters does not change results much. Predictably, the right tail is slightly less extreme, but for the purposes of, say, identifying parameters to include in an SSA, or for running numerous alternative MC simulations with fewer trials, this is a good approximation.



(a) Corn ethanol



(b) Sugarcane ethanol

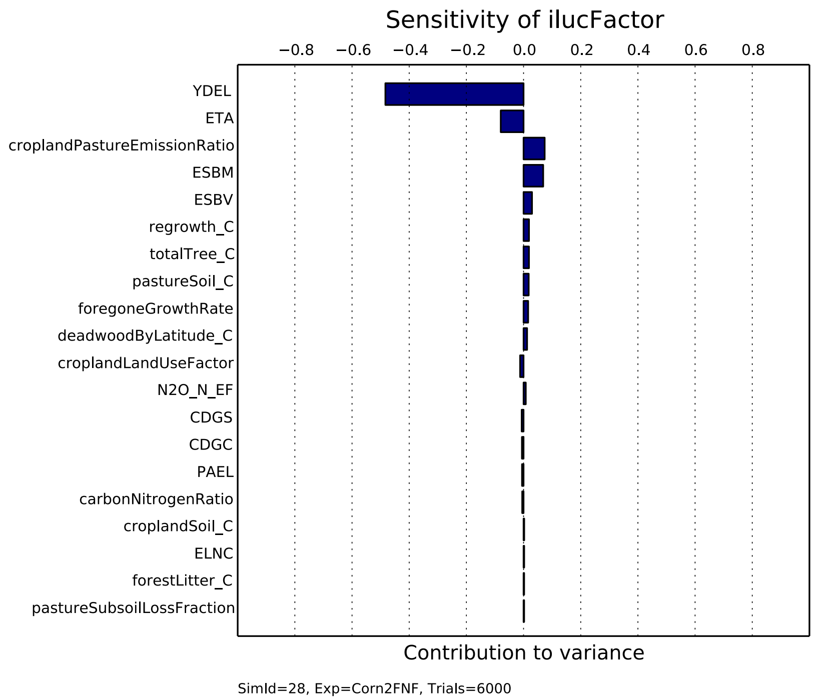


(c) Soybean biodiesel

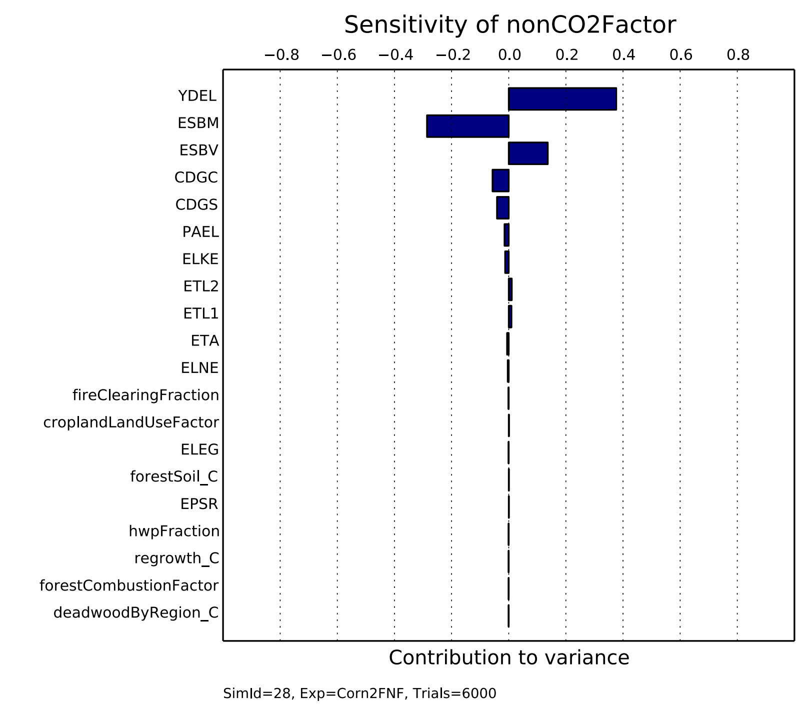
Figure S11: Frequency distributions for ILUC emission intensity showing the relative contributions to variance of the GTAP-BIO-ADV and AEZ-EF models for corn ethanol (a), sugarcane ethanol (b), and soybean biodiesel (c), in all cases with food consumption not fixed. In each plot, the bottom boxplot shows the results when GTAP-BIO-ADV parameters were fixed and AEZ-EF parameters varying. The middle boxplot shows the results with parameters from GTAP-BIO-ADV varying and those from AEZ-EF fixed. The top boxplot shows the results with all parameters varying. The simulations each used 3000 trials.

Table S9: Parameters (in alphabetical order) contributing at least 1% of the variance in ILUC emissions for the CornFNF or CaneFNF experiments.

Parameter Name	Description
	GTAP-BIO-ADV model
ELHB	Elasticity of substitution in biofuel subconsumption
EPSR	Elasticity of substitution in pasturecrop and pasturecover
ESBM	Armington elasticity of substitution within composite import bundle
ESBV	Elasticity of substitution in value-added-energy sub-production
ETA	Relative productivity of newly converted cropland, by Region-AEZ
ETL1	Elasticity of transformation between forest, cropland, and pasture
PAEL	Scalar yield elasticity target for cropland pasture
YDEL	Elasticity of yield with respect to price
	AEZ-EF model
Cropland land use factor	A parameter used in IPCCs method to compute soil carbon change
Cropland-pasture emission ratio	The fraction of emissions from pasture conversion assumed to be emitted upon conversion of cropland-pasture
Deadwood by latitude C	Carbon content of deadwood in boreal, temperate, and tropical AEZs
Foregone growth rate	The rate of tree growth (Mg C ha^{-1} y^{-1}) that would have occurred absent land use change
N_2O-N emission rate	The fraction of applied N released in the form of N_2O
Pasture soil C	The carbon content of pasture soil to 30 cm
Regrowth C	Tree growth for reforestation over 30 years (correlation with Foregone growth rate=.75)
Total tree C	The total amount of carbon in trees

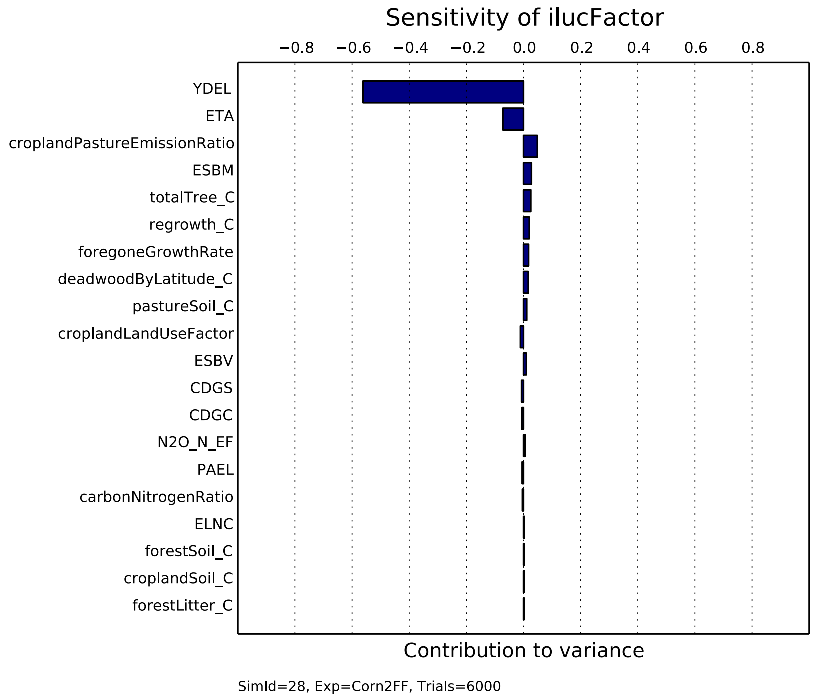


(a) Uncertainty importance for ILUC emissions, corn ethanol (food not fixed).

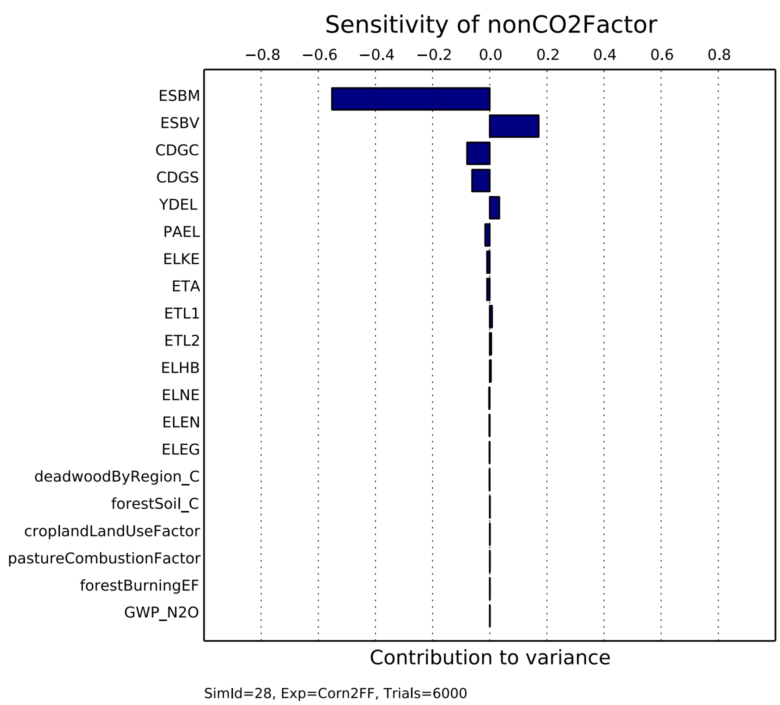


(b) Uncertainty importance for non-CO_2 emissions, corn ethanol (food not fixed).

Figure S12: Contribution to variance in ILUC factor and non-CO_2 emissions (corn ethanol; food not fixed).

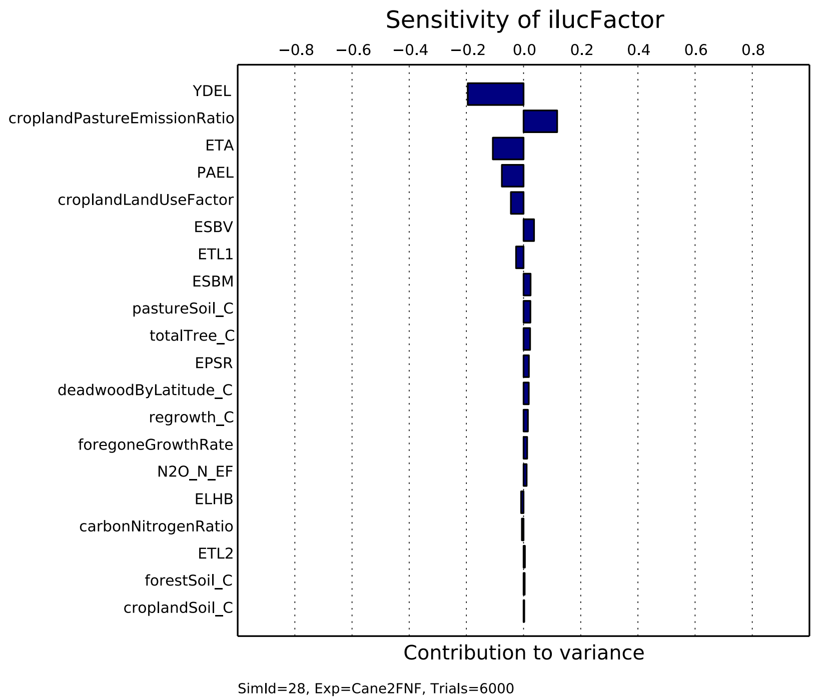


(a) Uncertainty importance for ILUC emissions, corn ethanol (food fixed).

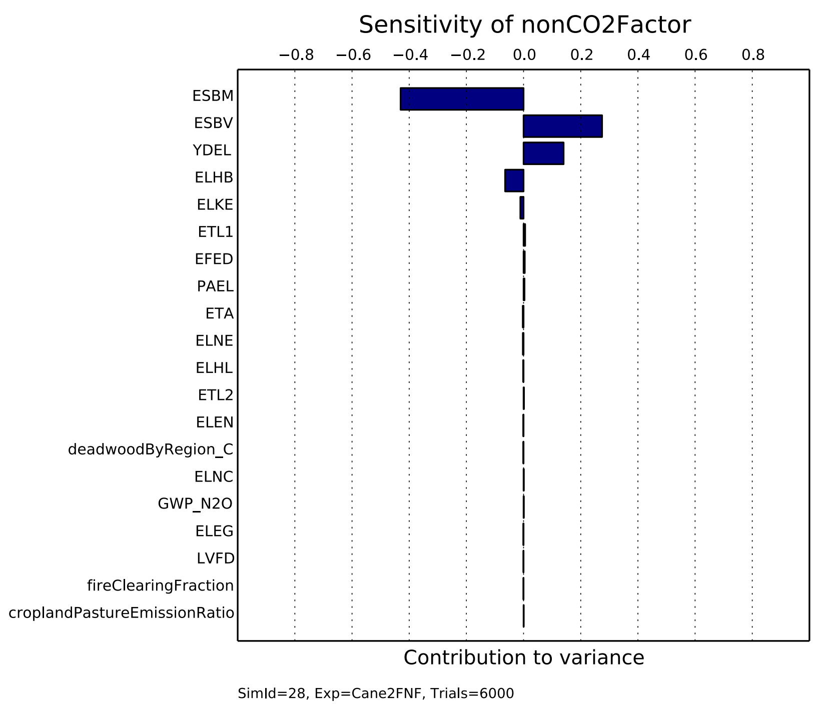


(b) Uncertainty importance for non-CO_2 emissions, corn ethanol (food fixed).

Figure S13: Contribution to variance in ILUC factor and non-CO_2 emissions (corn ethanol; food fixed).

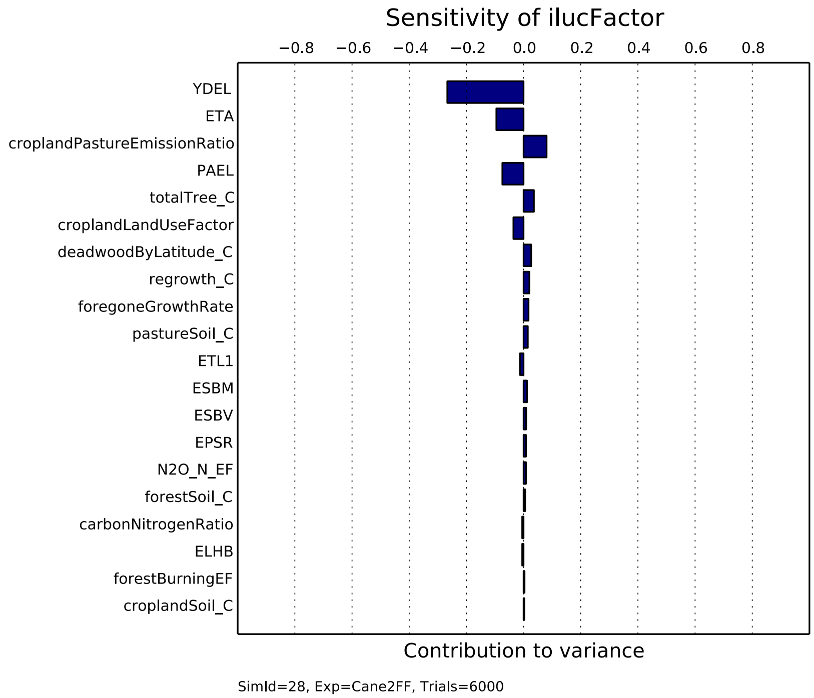


(a) Uncertainty importance for ILUC emissions, sugarcane ethanol (food not fixed).

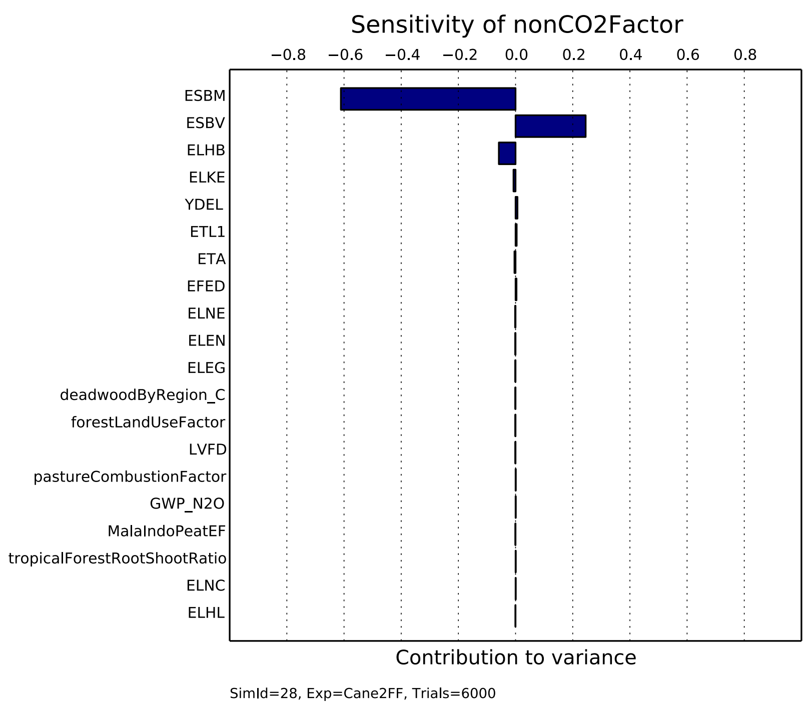


(b) Uncertainty importance for non-CO_2 emissions, sugarcane ethanol (food not fixed).

Figure S14: Contribution to variance in ILUC factor and non-CO_2 emissions (sugarcane ethanol; food not fixed).

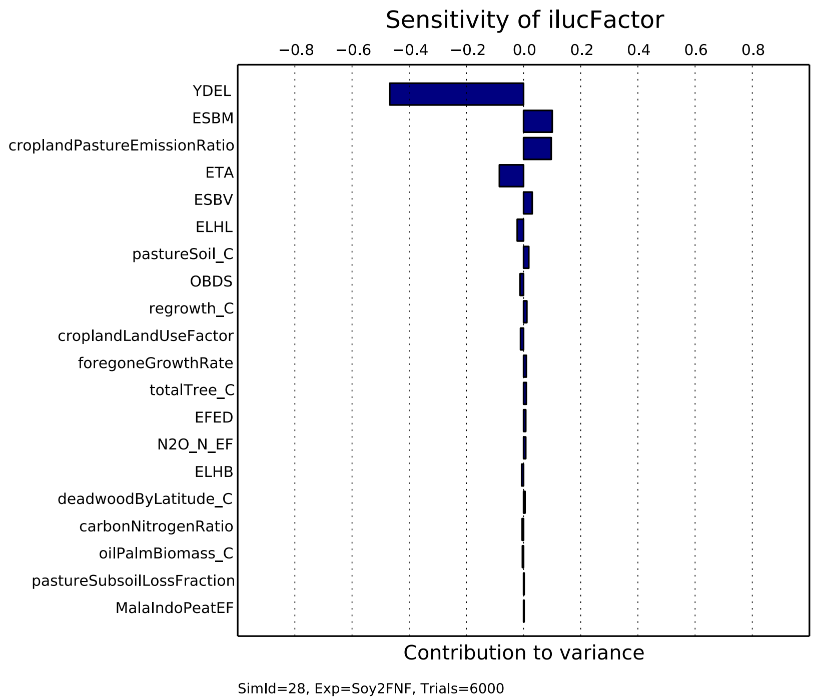


(a) Uncertainty importance for ILUC emissions, sugarcane ethanol (food fixed).

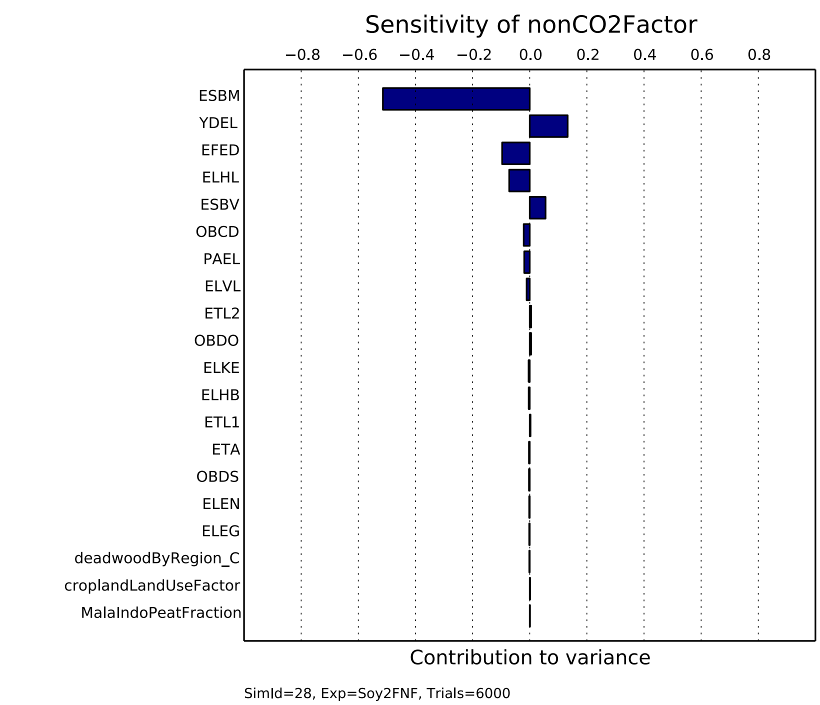


(b) Uncertainty importance for non-CO_2 emissions, sugarcane ethanol (food fixed).

Figure S15: Contribution to variance in ILUC factor and non-CO_2 emissions (sugarcane ethanol; food fixed).

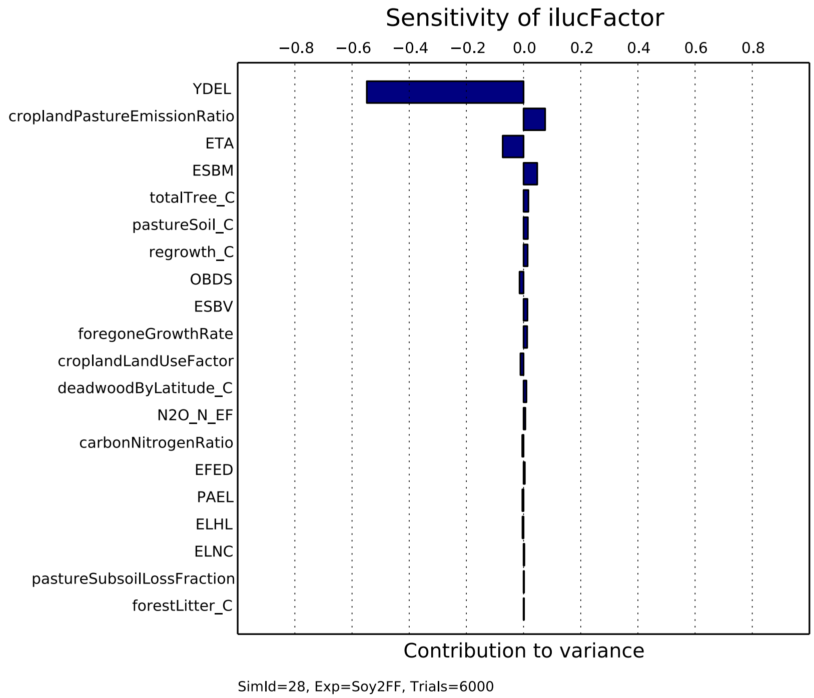


(a) Uncertainty importance for ILUC emissions, soybean biodiesel (food not fixed).

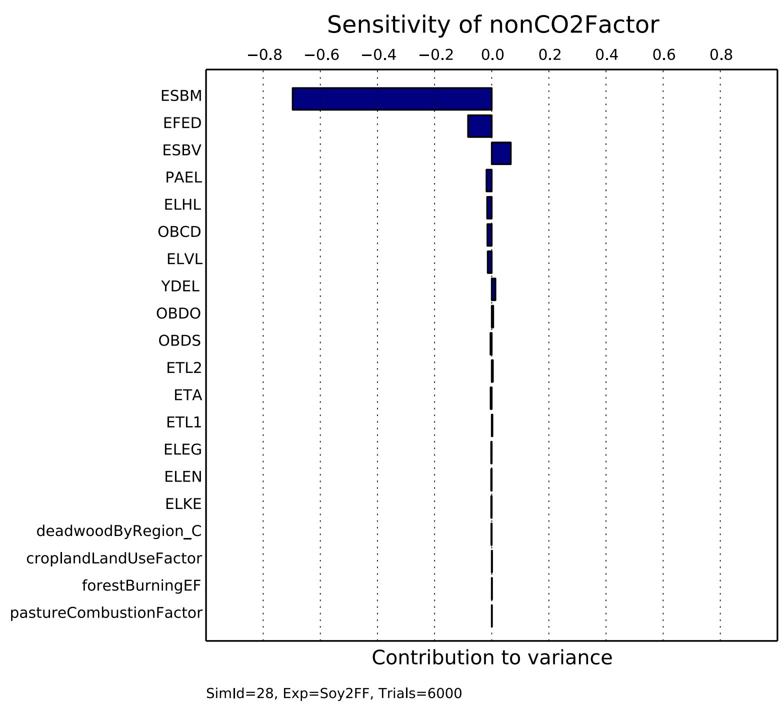


(b) Uncertainty importance for non-CO_2 emissions, soybean biodiesel (food not fixed).

Figure S16: Contribution to variance in ILUC factor and non-CO_2 emissions (soybean biodiesel; food not fixed).



(a) Uncertainty importance for ILUC emissions, soybean biodiesel (food fixed).



(b) Uncertainty importance for non-CO_2 emissions, soybean biodiesel (food fixed).

Figure S17: Contribution to variance in ILUC factor and non-CO_2 emissions (soybean biodiesel; food fixed).

S5 Comparison with other studies

Table 1 compares results for corn ethanol uncertainty analysis from this paper and with those from other studies, indicating which type of model parameters (economic or GHG accounting) were incorporated in the uncertainty analysis.

Below, we briefly discuss uncertainty analysis for the two studies less described in the main text (USEPA, 2010; Laborde and Valin, 2011). For the Plevin (2010) entry, the values presented are those generated using uniform distributions on all parameters. The values shown for Hertel et al. (2010) were generated using the RunGTAP Systematic Sensitivity Analysis feature, which is based on a Gaussian Quadrature approach. The remaining analyses used Monte Carlo simulation. The values from Laborde and Valin (2011) were multiplied by 2/3 to convert from 20-year to 30-year amortization as was used in the other studies listed. ILUC-MCS (A) shows results without fixing food consumption in developing countries, while (B) shows results with fixing food consumption. ILUC-MCS (C) shows results varying only GTAP parameters, while (D) shows results varying only AEZ-EF parameters. Note that the evaluation years for USEPA and Laborde studies were hypothetical worlds in 2022 and 2020, respectively, whereas the Hertel et al. study and ILUC-MCS assumed medium-term adjustment to a shock imposed on the global economy in 2001 and 2004, respectively. All studies targeted US corn ethanol shocks, except for Laborde and Valin (2011), where the amount and location of corn production to satisfy the EU RED policy was endogenously determined (alongside the rest of the biofuel mix, given an exogenously determined ethanol/biodiesel ratio).

Table S10: Uncertainty ranges estimated for indirect land-use change emission intensity from expanding corn ethanol production. See text for detailed explanation.

	Parameters varied		ILUC emission factor (g CO_2e MJ^{-1})		
Model	Economic	GHG Accounting	2.5% value	Mean	97.5% value
ILUC-MCS (A)	✓	✓	13	25	42
ILUC-MCS (B)	✓	✓	18	33	55
Hertel et al. (2010)[a]	✓	✓	2	27	52
Plevin (2010)[b]	✓	✓	21	62	142
ILUC-MCS (C)	✓	–	15	25	41
Laborde and Valin (2011)	✓	–	4[d]	7	8.8[e]
ILUC-MCS (D)	–	✓	18	23	29
USEPA (2010)[c]	–	✓	22	30	40

[a] Examining the variation of the most controversial yield parameters yielded a range of 15 to 90 g CO_2e MJ^{-1}.
[b] Based on the results using uniform distributions.
[c] International (outside US) LUC emissions only, for year 2022.
[d] 5% value
[e] 95% value

S5.1 Laborde (2011)

This study included a Monte Carlo analysis on seven economic parameters, over 1000 trials, assuming a log-uniform distribution centered on the default value. The approach assumes perfect correlation across sectors/countries or regions for a given parameter, but independent draws for each parameter. To establish parameter ranges, they extended initial parameter ranges drawn from studies in the literature, dividing the lower bound by 2 and multiplying the upper bound by 2, except as noted below.

Economic factors incorporated in this analysis overlapped partially with our analysis, although the parameter list differed somewhat because of the differences between the GTAP-BIO-ADV and MIRAGE-Biof model structures and assumptions. Overlapping factors included (default values and ranges for developed and developing countries —sometimes different—are in the report):

- Endogenous yield response (YDEL in GTAP). In MIRAGE-BIof, this effect is incorporated in two separate parameters, due to that models splitting out of key production inputs (feedstuff, fertilizer) from primary factors (e.g., capital).
- Land substitution among crops (ETL2 in GTAP). In MIRAGE-Biof, the land use nesting structure includes a different nest (and elasticity) for substitution among highly substitutable crops (e.g., grains and oilseeds), and between other crops.
- Land expansion into other covers (ETL1 in GTAP). In MIRAGE-Biof, this parameter is used to characterize ease of land transformation between used and available land for cropping. Thus, new pasture and forest land are both considered potentially available for cropping. Although they were not distinguished from one another in the MCS analysis, a shifter to a variable indicating the share of new land coming from primary forest (based on work by Winrock International for the US EPA), was also included in the Monte Carlo analysis.[4]
- Marginal yield return on new cultivated land (ETA in GTAP). For this parameter, the lower bound and upper bound were set (at 0.5 and 1, respectively), rather than determined by dividing and multiplying identified ranges by a factor of 2.
- Shifter in demand elasticity for use of agricultural commodities as intermediate inputs (changes how easily processing sectors substitute away from biofuel crops and oils, in response to the modeled shock) (not in our MCS analysis using GTAP).

Several findings are worthy of note. The MCS found that the amount of newly converted land due to the biofuel shock was more uncertain (widely dispersed) than changes in land already in production, highlighting the impact of uncertainty about competition among forest, pasture, and cropland. The study also used MCS results to analyze correlations of LUC effects across feedstocks, with a preliminary recommendation to consider diversification of feedstock portfolio between tropical and non-tropical sources (as feedstocks within these geographical areas were correlated with each other).

S5.2 US EPA (2010)

The study applied Monte Carlo analysis only to international (not domestic) land use change emissions, based on output from the FAPRI-CARD international trade economic model on changes in area in particular crops by region. The analysis first applied heuristic rules to translate economic model output into changes in several land cover types "agriculture"—annual, perennial, and pasture—or "natural (unmanaged) land. The CI analysis required estimating emission consequences of conversion of various types of unmanaged land—savanna, forest, shrubland, wetlands, and mixed (cropland and natural vegetation). In contrast to the GTAP treatment of forest land (accessible for economic activity, in particular forestry), all forest for the EPA analysis was considered "natural." The method was to apply proportional conversion rates of natural land estimated from historical satellite imagery.

The uncertainty analysis then focused on estimates of types of unmanaged land that would be likely to undergo conversion, and their associated emissions, using:

[4]Other assumptions on competition between productively used noncrop land were examined in sensitivity analysis supplemental to the MCS analysis.

(a) classification of land covers from satellite imagery that were used to derive proportional allocations for expansion of cropland into unmanaged territory (MODISv5 images for 2001and 2007); and

(b) errors in parameters used to estimate emission factors for conversion from one land cover type to another.

For (a), a stochastic model based on estimated standard errors for the process used to adjust land cover classifications relying on number of sampled validation training sites and the aggregation of land cover classes to categories used by the EPA, and generated 95% confidence intervals for each of 54 international regions. The stochastic model assumed normally distributed classification errors, and generated 300 alternative realities of land covers based on the standard errors, each of which was used to calculate the pool of land conversion shares for each region.

For (b), the uncertainty in emission factors, Monte Carlo analysis was performed to generate 95% confidence intervals for administrative units/countries, combining uncertainty in sources of emissions (input parameters) derived from data or expert opinion, assuming normality in parameter distributions, and imposing perfect cross-variable correlation in cases using common data source, geographic location, or data interpolation process.

A Monte Carlo analysis was run combining uncertainty from (a) and (b), generating 300 land use change trials by the method used in (a), and 50 emission factor draws by the method used in (b) for each of these 300 trials, for a total of 15,000 iterations. Mean and 95% CI of emissions were calculated for each region and across regions using weighted average emissions across the iterations. The EPA emphasized that the uncertainty surrounding the use of historical patterns to predict future land use change share allocations for unmanaged land was not part of the MCS.

S6 Model limitations

This analysis examined only a small subset of the uncertainties associated with the GTAP-BIO-ADV and AEZ-EF models. Out of necessity, most model parameter probability distributions were based on our subjective judgment. In addition to parameter uncertainty, both GTAP-BIO-ADV and AEZ-EF involve model uncertainties that are difficult to quantify, such as choices of functional forms for production and demand functions and for soil carbon loss, uncertainties in base year data, biases or inaccuracies introduced by aggregating sectors and regions, and omissions such as irrigation constraints on agricultural expansion and the inability to convert non-commercial land into commercial use.

Like all models, the two models used here gain tractability by simplifying a more complex reality. Although the models are useful for illuminating relationships among key parameters and sub-systems, as noted at the outset of the paper, their results should not be interpreted as a prediction of real world outcomes. We discuss model uncertainties and limitations in more detail below.

S6.1 GTAP

Some GTAP parameters are econometrically estimated, however many are based on expert opinion, i.e., educated guesses. Even where parameters are estimated, owing to a paucity of data, many regions and sectors are assigned a single value based on literature describing a small number of regions. Given the lack of data for point estimates, it is not surprising that there is generally inadequate information from which to develop distributions for model inputs. For this reason, some studies assign a simple stylized distribution to all or most parameters such as normal distributions with a coefficient of variation of 20% (Elliott et al., 2011), or uniform distributions from 50% to 200% of the parameters point estimate (Laborde and Valin, 2012).

The GTAP-BIO-ADV model employed in this paper is a static rather than dynamic model; the experiments presented in this paper do not capture changes in population, labor force, preferences and technology over time. Thus, the model results therefore portray the effects of an instantaneous increase in biofuel production in the assumed circumstances and year. This version of the GTAP model represents only land in current economic use for forestry, livestock grazing, and cropping. Unlike some other CGE models (e.g., MITs EPPA and IFPRIs MIRAGE) and partial equilibrium models (e.g., GCAM), this version of GTAP cannot project conversion to economic use of land not currently in economic use. For the purposes of estimating ILUC emissions, it would be helpful if GTAP were modified to include this capability.

In addition to parameter uncertainty, CGE models involve model uncertainties stemming from modeling choices that are difficult to quantify, such as the effects of the choice of functional forms for production and demand functions, the level of sectoral and regional aggregation, the choice of baseline year, and the calibration of model parameters to that year. In addition, the national input-output data used to produce the core social accounting matrix (SAM) is of varying accuracy and the SAM must be manipulated into an initial equilibrium state that didn't exist in the real world. The procedure for adjusting the SAM is inevitably somewhat subjective. These uncertainties are not generally included in uncertainty analyses of CGE models, yet these choices can substantively affect model outcomes (Jansen, 1994; Roberts, 1994; McKitrick, 1998; Abler et al., 1999). Model uncertainty is particularly challenging to quantify because we cannot compare results to the real world to gauge the models accuracy. Though, with respect to the GTAP model, several studies did validate the model (Liu et al., 2004; Valenzuela et al., 2007; Beckman et al., 2011). More generally, all complex, open systems (including CGE and ecosystem carbon accounting models) in which processes are incompletely understood, and input data incompletely known, are fundamentally unverifiable (Oreskes et al., 1994).

With time, as more data become available, additional aspects of the modeling exercise (behavioral parameters, expected correlations, outcomes) may be verifiable empirically using statistical analyses.

Similar uncertainties arise with respect to ecosystem carbon accounting models: functional forms, choice of the parameters, and assumptions required to fill in missing values. These are discussed further in section S6.2.

Beyond uncertainties associated with model construction and data manipulation, estimating ILUC emissions requires several additional assumptions or modeling choices that substantively affect model results, including:

- Assumption that ILUC can be estimated through economic modeling alone, i.e., that economic model parameters—primarily elasticities—and constraints can be adjusted to reflect important economic or non-economic factors, e.g., if land that is not used productively is subject to expropriation
- Choice of model type: CGE vs PE (trading off the strength of capturing complex economy-wide feedback effects (in CGE) against important sectoral bottom-up detail)
- Choice of, and consistency in timeframe examined
- Policy choices about which features to include in the model (e.g., whether reduction in food consumption should receive GHG reduction credit), and which real-world factors are important enough to include (e.g., irrigation constraints)

Other limitations particular to the version of GTAP we've used include:

- Disagreement among experts about correct values for model parameters
- Forest that is not currently in economic use cannot be brought into production.

S6.1.1 Estimating ETA: the relative productivity of newly converted cropland

The GTAP-BIO-ADV model estimates the relative productivity of land converted to cropland using the ratio of (i) the average net primary productivity (NPP) of land not in crop production at in the initial equilibrium state, to (ii) the average NPP of land in crop production in the initial equilibrium (Taheripour and Tyner, 2012). These values are computed per Region-AEZ combination using the Terrestrial Ecosystem Model by modeling the NPP of a C4 crop (calibrated to corn grown in Iowa in 1996).

To account for the increased productivity resulting from irrigation of currently cropped land, the ratios are reduced by 10%. Based on the assumption that new cropland would not be more productive than existing cropland, on average, the ratios are then truncated to 1. While this approach is a conceptual improvement over applying a single value for ETA globally (e.g., Hertel et al., 2010), the method used requires several critical assumptions:

1. **TEMs estimates of NPP are reasonably accurate.**
   Pan et al. (1996) performed a sensitivity analysis on the TEM model (version 4.0), showing that estimated NPP is sensitive to different assumptions about soil texture, temperature, precipitation, and radiation. These factors vary over space and time.

2. **The ratio of average NPP of non-cropped land to cropped land is a good proxy for the relative yield of land actually brought into production.**
   For this to be true, either the variance around yield values in a given region must be small, or the selection of land must be random. If land selection is based on assumed yield potential, using the average would underestimate the yield, whereas if land is selected by proximity to existing cropland, its unclear whether the average under- or overestimates the yield. As the authors indicate, a single Region-AEZ can contain land with widely varying productivity (Taheripour and Tyner, 2012). In addition, differences in management practices can produce large differences is yield, regardless of potential NPP. Note that if land selection were indeed random, there should be no difference in productivity between cropped and non-cropped landand this analysis wouldnt be necessary.

3. **Reducing the NPP ratios by 10% is a good proxy for the effects of irrigation.**
   Irrigation is only one of the management practices that affects actual productivity, and its unclear that a 10% correction accounts for these differences.

4. **Truncating the ratios to 1 produces a more accurate result.**
   If the basic approach of using the NPP ratio to estimate relative productivity is correct, its unclear why a correction should be required. Nor is it clear why 1 is the best value: why not 0.9, 1.1, or some other value? Should truncation to 1 precede reduction by 10% for irrigation?

   We hasten to note that these factors do not invalidate the method of estimating ETA, but the cascade of uncertainties represented by these assumptions does suggest treating the resulting ETA values as coarse approximations. In the end, its difficult to judge whether this approach produces a more accurate result than was achieved using a single global value for ETA.

S6.2 AEZ-EF

The report on the AEZ-EF model documents numerous uncertainties and limitations associated with that model (Plevin et al., 2014). We briefly summarize them here.

- Forest carbon stocks represent the area-weighted average for all forested land in each Region-AEZ, while GTAP represents only (economically) accessible forest.

- Wetlands are assumed to not be cropped; a carbon density threshold is applied to identify and filter out wetlands.
- Estimates of forgone sequestration depend on the unknowable future state of a forest.
- Estimates of carbon in long-lived wood products are very coarse.
- Estimates of below-ground carbon are estimated based on allometric equations.
- Estimates of the carbon stored in litter, understory plants, and harvested wood products are based on coarse estimates.
- CO2-equivalence is summed for only CO2, CH4, and N2O. Other known climate forcing effects (e.g., albedo change, emissions of aerosols and GHG-precursors) are excluded from the analysis.
- GTAP does not project specific land cover transitions; it provides only projected net changes in area for each land cover class. Heuristics are applied to identify plausible land transition sequences.
- Up-front emissions resulting from LUC are linearly amortized over 30 years; the atmospheric residence time and decay of GHGs is not accounted for.
- All emissions from above and below-ground carbon are assumed to be released immediately.

S6.2.1 Cropland-pasture emission ratio

To represent the emission from conversion of cropland-pasture (C-P), the AEZ-EF model multiplies the emissions computed (by region and AEZ) for pasture conversion by 50% to estimate the emissions from cropland-pasture conversion. We note that in the Monte Carlo analyses, we represented this value with a triangular distribution bounded by 0 and 1 with a mode of 0.5.

S6.2.1.1 Treatment of Cropland-Pasture in the CCLUB model

Here we compare the approach taken in the CCLUB model, released by Argonne National Laboratory (Dunn et al., 2013).

To assess changes in soil carbon in the U.S., CCLUB uses a "surrogate" Century model (results of saved Century model runs), at the county level, using each counties dominant soil textures, as well as yield and weather history.

CCLUB estimates emissions only for the conversion of cropland-pasture, forest, and pasture to biofuel feedstock production. That is, when modeling biofuels from corn, miscanthus, switchgrass or corn with stover removal, CCLUB assumes these lands are converted to the modeled biofuel feedstock. CCLUB averages emissions factors across counties in an AEZ to produce a single, average AEZ value, which is then applied to area projected to change by the GTAP model. We note that the emission factors are not weighted to account for the different land area in each county. For land-use changes outside, the model incorporates emission factors developed by Winrock International for the U.S. Renewable Fuel Standard (Harris et al., 2008; Harris, 2011).

The CCLUB model authors created a young forest-shrub category within 'accessible' forest to reconcile GTAP forest data with other data sources. This assumption, however, is applied to land-use change estimates for which GTAP-BIO-ADV considered this land to be commercial forest.

The accuracy of results using the CCLUB method depends on these assumptions:

1. **The dominant (majority or plurality) soil type in each county is assumed to be a good proxy for the average soil type (and C stock or conversion emissions) in the county.**

2. **The simple (i.e., not area-weighted) average C stock by county in an AEZ is assumed to be a good proxy for the average C stock in the AEZ.**

   One value is used to represent the C stock in each county in an AEZ, and the resulting values are averaged without regard to relative land area: an area-weighted average would be more appropriate since the size of counties is highly variable. According to data downloaded from the US Census website, the maximum county area in the US is 145,505 sq mi, with an average of 1,124 sq. mi. and a standard deviation of 3,611 sq. mi. From our carbon database, its clear that C stocks are also highly variable spatially. It's unclear how the use of simple averaging biases the results: if the extremes of area line up with the extremes of C, using the average could be highly distorting. Of course, we might be lucky and it all just averages out despite the high variance.

3. **The Century model is assumed to accurately represent actual land conversion emissions.**

   Century represents changes in soil C to a depth of about 20 cm, while recent research suggests that studies that sampling to this level misses important changes in soil C occurring in the full top meter of soil as a result of different tillage practices. The point here is that a model such as Century is only as accurate as the data used to calibrate it, and if methods used to produce that data introduce biases, the modeled results will be similarly biased.

   To produce the data used in the surrogate model, the authors first spin up Century to represent current soil C stocks, based on an assumed land-use history. Specifically, the authors assumed that all C-P was in crops from 1880-1950, in pasture/hay/grasslands from 1950-2010, and then in corn-corn or miscanthus/switchgrass from 2011-2040. Even if Century models this land-use history perfectly, if the land-use history of the land converted deviates from these assumptions, the Century projection will misrepresent the actual state of the land.

   The actual land-use history of the converted cropland-pasture strongly determines conversion emissions: land recently in crops will have very low emissions, while lands taken out of crop production long ago will have high emissions. Simply assuming a single land-use history across all land does not address this key information gap.

4. **All converted C-P is assumed to be replaced by the biofuel feedstock being examined in GTAP-BIO-ADV.**

   GTAP-BIO-ADV, however, offers no indication of which specific crop is grown on converted C-P, nor does it indicate how many ha were converted from cropland-pasture to cropland overall; it merely provides the net change in each land use type, by region and AEZ.

5. **Treating GTAP-BIO-ADV results as applying to a young forest-shrub category is assumed to not bias the results.**

   Even if the new category represents land more accurately, this assumption is at odds with assumptions underlying the economic logic. For example, if the GTAP model projects conversion of forestry land to cropland, the supply of timber is reduced, which increases price and induces afforestation in other regions. If this land is actually young forest-shrub, timber supply would be unaffected and thus the afforestation would not be induced.

6. **The average carbon stock in an AEZ is assumed to be a good proxy for carbon on the land actually converted.**

   This assumption is reasonable if one further assumes either low variance of C stocks across the AEZ, or that the land converted is randomly selected across the AEZ. The point is that if there is wide variability and some non-random approach is used to select C-P land for conversion, the C stock on land actually converted could be biased toward one extreme or the other. Of course it also requires that all the preceding assumptions are reasonable.

Given all of the assumptions required in this more complex procedure, there is little basis for calling the result obtained more accurate than a simple assumption with a wide variance, and the apparently greater precision imparted by excluding uncertainty is specious. We agree that the approach of assigning cropland-pasture conversion half the emissions of pasture conversion is a coarse simplification.

However, since the real value is unknown, we assigned this parameter a broad distribution (uniform with minimum of 0 and maximum of 1) in the Monte Carlo simulation. The USDA definition of cropland-pasture admits everything from cropland to pasture[5].

In addition to not knowing the actual carbon stock on actual cropland-pasture, the modeling framework cannot identify which plot of cropland-pasture is converted, other than placing it within a given Region-AEZ. High variance in C stock, and probably land-use history, therefore translates into broad uncertainty about actual emissions.

The primary difference between the CCLUB approach and the AEZ-EF approach is that CCLUB employs more finely-resolved data, not that it requires fewer assumptions. The CCLUB result appears more scientific, but given the reliance on a number of assumptions without a strong empirical basis, e.g, computing average AEZ carbon stocks using unweighted county-based averages, assuming that C-P transitions exclusively to biofuel feedstocks, and assuming that all C-P has a single, known, land-use history—there's no basis for concluding that CCLUBs approach is more accurate. Both approaches are limited by the assumptions required to bridge low-resolution CGE model results—which are not spatially-explicit and do not identify specific land transitions—to the spatial resolution and land-transition specificity required to estimate carbon changes.

S6.3 Limitations of the Monte Carlo simulation and analysis

In their analysis of ILUC using a CGE model of Brazil, Ferreira Filho and Horridge (2014) note:

> A CGE model like that used here builds on a host of assumptions; about functional forms; about assumed elasticity values; and about initial data. Rarely do we have a probability distribution which measures the uncertainty of estimates that are fed in—so we cannot in general compute probability distributions for model outputs. We can however merely report how results depend on input values.

For example, in the GTAP-BIO-ADV model used in the present analysis, the land nesting structure is very simple (cropland, pasture and forests compete in the same nest), potentially leading to overestimation of conversion from forests to cropland (Babcock and Carriquiry, 2010); other CGE models employ a more complex structure (Ahammad and Mi, 2005; Golub and Hertel, 2008). However, a more complex nested structure requires additional transformation parameters, by AEZ and region, which should be calibrated to land supply elasticities for which econometric estimates are not currently available. Given this issue, Laborde and Valin (2012) conducted sensitivity analysis on the nesting structure of non-cropland.

For these and other reasons, a Monte Carlo simulation with the GTAP-BIO-ADV and AEZ-EF models should likewise not be interpreted as a prediction. The MCS does, however, allow us to interrogate the relationships among input and output parameters given the present model structure and data.

[5]See http://www.ers.usda.gov/data/majorlanduses/glossary.htm#cropforpasture

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