

# Greenhouse Gas Emissions from Biofuels' Indirect Land Use Change Are Uncertain but May Be Much Greater than Previously Estimated

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The life cycle greenhouse gas (GHG) emissions induced by increased biofuel consumption are highly uncertain: individual estimates vary from each other and each has a wide intrinsic error band. Using a reduced-form model, we estimated that the bounding range for emissions from indirect land-use change (ILUC) from US corn ethanol expansion was 10 to 340 g CO<sub>2</sub> MJ<sup>-1</sup>. Considering various probability distributions to model parameters, the broadest 95% central interval, i.e., between the 2.5 and 97.5%ile values, ranged from 21 to 142 g CO<sub>2</sub>e MJ<sup>-1</sup>. ILUC emissions from US corn ethanol expansion thus range from small, but not negligible, to several times greater than the life cycle emissions of gasoline. The ILUC emissions estimates of 30 g CO<sub>2</sub> MJ<sup>-1</sup> for the California Air Resources Board and 34 g CO<sub>2</sub>e MJ<sup>-1</sup> by USEPA (for 2022) are at the low end of the plausible range. The lack of data and understanding (epistemic uncertainty) prevents convergence of judgment on a central value for ILUC emissions. The complexity of the global system being modeled suggests that this range is unlikely to narrow substantially in the near future. Fuel policies that require narrow bounds around point estimates of life cycle GHG emissions are thus incompatible with current and anticipated modeling capabilities. Alternative policies that address the risks associated with uncertainty are more likely to achieve GHG reductions.

## 1. Introduction

To mitigate climate change from the transportation sector, new policies are being implemented in the US and Europe to reduce the global warming effect of road transportation fuels, presently dominated by petroleum-based gasoline and

diesel. These regulations, including the US Energy Independence and Security Act (EISA) of 2007, California's Low-Carbon Fuel Standard (LCFS) (1, 2), and Europe's Renewable Energy Directive (RED) (3), promote greenhouse gas (GHG) reductions based on estimates of the life cycle GHG emissions from various transportation fuels. Twelve US states have committed to implementing low-carbon fuel standards similar to California's (4).

EISA defined life cycle GHG emissions to include "significant indirect emissions such as significant emissions from land use changes" (5); the definition was subsequently adopted verbatim into the California LCFS (6). Indirect land use change (ILUC) emissions occur when grassland and forest are converted to cropland somewhere on the globe to meet the demand for commodities displaced by the production of biofuel feedstocks. Direct land use change, in contrast, occurs when a previous land use is converted to bioenergy crop production. ILUC emissions are potentially large compared to the direct global warming effects of processes in the biofuel supply chain, for any biofuel whose feedstock competes with food for land. Indeed, these emissions may more than negate the climate benefits otherwise estimated for some biofuels (1, 7–10). (We note that other activities that compete with food for land, including roads and development, also cause ILUC emissions. Our purpose here is to improve methodology for estimating the marginal ILUC caused by biofuels production.)

Existing policies demand that each fuel be assigned a measure of the contribution to global warming associated with the production and use of the fuel. This is generally defined as the life cycle emissions of CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O, weighted by their 100-year global warming potentials and summed into CO<sub>2</sub>-equivalent emissions (11). In this study, we refer to this measure as *global warming intensity* (GWI). The challenge faced by regulators is that GWI is unobservable: estimates must be produced by modeling the global economy and land conversion processes. Any model of ILUC emissions—and therefore, of the GWI of biofuels—is approximate at best (12–15).

ILUC is the most uncertain component of the GWI for biofuels. The following sequence of modeling steps are typical of studies that estimate the ILUC emissions induced by the expansion of corn ethanol production in the US [e.g., refs 1, 7, 8, and 10] or the EU (9):

1. An economic equilibrium model (e.g., FASOM, FAPRI, GTAP, MIRAGE) is used to project the effects of increased US or EU biofuel production on global land and commodity markets, including (i) how much additional land will be brought into production to compensate for land removed from other uses to produce biofuels and (ii) the approximate location of this land.

2. Land use changes projected by the economic model are mapped to specific land cover types based on historical patterns of land use change.

3. For each category of land cover conversion, the quantity and time profile of GHG emissions from land use conversion are estimated.

4. To calculate the GWI measure (e.g., grams of CO<sub>2</sub>-equivalent per MJ of biofuel), the emissions induced by the expanded biofuel production are attributed to a quantity of fuel, usually defined with reference to a time period of fuel production.

There is uncertainty inherent in each of these modeling steps, as described in Table S3, following a typology (Figure S1) based on Krupnick et al. (16). *Stochastic uncertainty*, or more simply *variability*, involves inherent heterogeneity

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among individuals or across space and time. These uncertainties are often visible in empirical data and thus relatively easy to characterize probabilistically and to propagate through a model. In contrast, *epistemic uncertainty* captures our lack of knowledge, and inconsistency of different experts' knowledge and judgment, of the correct values for model parameters, of the functional relationships among the processes being modeled, and about the efficacy of our models at representing these processes. *Decision uncertainty* involves subjective choices by a modeler or decision-maker including baseline year, analytic horizon, weighting factors, discount rate, and so on. Our ignorance of the most representative values for model parameters, functional forms, and subjective choices is difficult to quantify probabilistically; this uncertainty is better modeled by examining alternative scenarios (16, 17).

**1.1. Prior Estimates of ILUC Emissions.** Several studies have examined the ILUC emissions induced by expanding production in the US of corn ethanol, the most-used and most-studied biofuel, which we use as an example in the present study. Other biofuel feedstocks, such as sugar cane, palm oil, and cellulosic crops, cause some amount of ILUC and estimating their GWIs will require a similar analysis. To compare corn-ethanol analyses, Tables S1 and S2 describe the model, data, region, and results including the ranges estimated (using various methods) for five studies. In the five prior studies of the GHG emissions from ILUC induced by US or EU corn ethanol, sensitivity analyses produced ranges of 20–200 (8), 15–90 (10), 25–104 (1), and 36–53 (9), and 21–118 (7) g CO<sub>2</sub>e MJ<sup>-1</sup>.

The range of results demonstrates the substantial uncertainty any decision-maker should have about ILUC emissions. Moreover, none of these studies examined the full range of uncertainties in the economic modeling, land cover detection, carbon accounting, and the treatment of emissions over time (Table S3). Where sensitivity analysis was performed in these studies, it was almost exclusively local, one-at-a-time analysis, describing changes in model results caused by perturbations in individual parameters while fixing all other parameters at their default value. In general, a *global* sensitivity analysis, i.e., one that allows for simultaneous changes in multiple parameters, is called for unless a model is linear (18, 19). The range in results outlined by a global sensitivity analysis will generally be broader than that of a local sensitivity analysis.

**1.2. Estimating a Plausible Range for ILUC Emissions.** In the present article, we characterize plausible boundaries around ILUC emissions using a simple and transparent model parametrized from the literature, assigning subjective probability distributions to all parameters and propagating these uncertainties through the model using Monte Carlo simulation. We employ several alternative sets of probability distributions to examine the possible size and shape of the frequency distribution for ILUC emissions and examine the contribution of each model parameter to the uncertainty in the result. Our aim is thus not to determine the most accurate probability distribution around ILUC emissions or claim that one distribution is better than another but to characterize a plausible range of ILUC emissions that is robust to assumptions about the underlying distributions of key parameters and to consider how this information can inform fuel GHG regulations.

## 2. Methods

**2.1. Reduced-Form Model.** To explore the range of ILUC emission estimates that can result from alternative model parametrizations, we use a *reduced-form model of ILUC* (hereafter, RFMI) based on the nine parameters described in Table 1. The *NDF* is the net displacement factor for land, defined in section 2.2.2. The average emission factor (*Avg-*

**TABLE 1. Parameters and Ranges Explored Using the Reduced-Form Model for US Corn Ethanol**

parameter	units	low	high
fuel yield	L ha <sup>-1</sup> y <sup>-1</sup>	3500	4500
net displacement factor		25%	80%
emission factor <sub>forest</sub>	Mg CO <sub>2</sub> ha <sup>-1</sup>	350	650
emission factor <sub>grassland</sub>	Mg CO <sub>2</sub> ha <sup>-1</sup>	75	200
emission factor <sub>wetland</sub>	Mg CO <sub>2</sub> ha <sup>-1</sup>	1000	3000
fraction <sub>forest</sub>		15%	50%
fraction <sub>grassland</sub>		1 – (forest + wetland)	
fraction <sub>wetland</sub>		0%	2%
production period	y	15	45

*EmissionFactor*) is the average mass of CO<sub>2</sub> emitted per unit area for land converted to cropping. For the purposes of this model, we apply straight-line amortization of the ILUC emissions over the total biofuel production occurring over a presumed production period (*ProductionPeriod* × *AddedCapacity*) assumed to begin with the initial ILUC emissions, although we caution that this approach underestimates the relative warming caused by ILUC (20). Table 1 lists the parameters that are subjected to bounding analysis in the reduced-form model.

The CO<sub>2</sub> emissions resulting from land use conversion can be represented by the following equations; the individual parameters are discussed at length in section 2.2.

$$ILUC(MgCO_2MJ^{-1}) = \frac{GrossLandRequired(ha) \times NDF \times AvgEmissionFactor(Mg CO_2 ha^{-1})}{ProductionPeriod(y) \times AddedCapacity(MJ y^{-1})} \quad (1)$$

where

$$GrossLandRequired(ha) = \frac{AddedCapacity(MJ y^{-1})}{FuelYield(MJ ha^{-1} y^{-1})} \quad (2)$$

$$AvgEmissionFactor(Mg CO_2 ha^{-1}) = \sum_{i=Forest, grassland, wetland} EmissionFactor_i(Mg CO_2 ha^{-1}) \times Fraction_i \quad (3)$$

Canceling *AddedCapacity* from the numerator and denominator allows us to simplify to

$$ILUC(g CO_2 MJ^{-1}) = \frac{NDF \times AvgEmissionFactor(Mg CO_2 ha^{-1}) \times \frac{10^6 g}{Mg}}{ProductionPeriod(y) \times FuelYield(MJ ha^{-1} y^{-1})} \quad (4)$$

From the form of eq 1 we can see that if the terms in the numerator have wide error bars, and those in the denominator have relatively narrow error bars, the multiplicative form of the numerator will result in a right-skewed bounding range: the high bounding value will be further from the point estimate than is the lower bounding value. This is indeed the case, as demonstrated below.

RFMI is implemented in Microsoft Excel. We use the Crystal Ball Monte Carlo simulation add-in for Excel to examine alternative probability distributions for model parameters and to support uncertainty importance analysis. Lacking an empirical basis for assigning probability distributions to the model parameters, we explored the sensitivity of RFMI results to different probability distributions: uniform, triangular, betaPERT (21), and log-normal. (Like a triangular distribution, a betaPERT distribution has fixed minimum

and maximum values and a most probable value. However the betaPERT distribution has a bell shape (a rescaling and translation of the beta distribution on the unit interval) which, relative to a triangular distribution, has more probability density in the center and less at the extremes.) For the uniform, triangular, and betaPERT distributions, the maximum and minimum values were set to those shown in Table 1, with the central value for the triangular and betaPERT set to the midpoint of the range. For the log-normal case, log-normal distributions were assigned to the production period, average fuel yield, and three emission factors by setting the 2.5% and 97.5% values of the distribution to the ranges as shown in Table 1; the remaining parameters were assigned betaPERT distributions as described previously.

To evaluate the relative contribution of each RFMI parameter to variance, we assigned each parameter a uniform probability distribution ranging from their corresponding low and high values indicated in Table 1 and ran a 10,000-trial simulation, using Latin Hypercube Sampling. While the precise statistics of the output distribution are not meaningful, this approach allows us to estimate the contribution to variance for each parameter based on the normalized rank correlation of each parameter to the final amortized ILUC emissions value.

**2.2. Parameter Ranges.** Table 1 lists the bounding values assumed for each parameter in the present exercise, which apply to ethanol from US corn. In the following sections we explain the rationale and evidentiary basis for these ranges.

**2.2.1. Average Fuel Yield.** Initial ILUC emissions are a function of the areal biofuel yield ( $\text{L ha}^{-1} \text{y}^{-1}$ ) at the time of expansion. Searchinger et al. assumed a corn ethanol yield of  $3766 \text{ L ha}^{-1} \text{y}^{-1}$ ; Hertel et al. assumed  $3598 \text{ L ha}^{-1} \text{y}^{-1}$ . In its final rulemaking for RFS2, the USEPA (1) assumed that corn ethanol yield will reach nearly  $4423 \text{ L ha}^{-1} \text{y}^{-1}$  in 2017 and  $4692 \text{ L ha}^{-1} \text{y}^{-1}$  in 2022. Our analysis uses a range of 3500 to  $4500 \text{ L ha}^{-1} \text{y}^{-1}$  for average fuel yield over the modeled time horizon.

**2.2.2. Net Displacement Factor.** Land net displacement factor (NDF) is the ratio of (a) hectares of land brought into crop (not pasture) production anywhere in the world to replace agricultural land used by biofuel feedstocks, to (b) the hectares dedicated directly to additional biofuel feedstocks. The NDF includes the combined effects of (i) price-induced yield increases, (ii) relative productivity of land converted to cropping, (iii) price-induced reductions in food consumption, and (iv) substitution of crop products by biofuel coproducts, such as distillers' grains replacing corn as animal feed.

The NDF is perhaps the most challenging parameter to estimate since it is a result of a system of globally linked economic markets and thus depends on many uncertain parameters and subjective choices in the economic models used. NDF is also the most influential parameter in the RFMI because the range of values from prior studies is broad. The NDF is calculated for a specific time period, using crop yields for that period.

Values imputed for NDF vary from 28% of land used to meet the modeled increase in biofuels production in the Hertel et al. analysis (22), to 72% in the Searchinger analysis, and higher in the USEPA analysis where the published results for corn ethanol ranged from 89% in 2012, to 55% in 2017, and 29% 2022. Our analysis uses a low value of 25% and a high value of 80% for NDF. This range reflects significant model uncertainty as well as parametric uncertainty in each model. These uncertainties and the USEPA NDF values are discussed further in Supporting Information sections 3.1 and 4, respectively.

**2.2.3. Ecosystem Conversion Fractions.** The GHG emissions resulting from conversion to cropland vary with prior land cover type, cropping system, and region. The GTAP

model predicts changes in area dedicated to pasture, forestry, and cropland within various agroecological zones and trade regions, whereas the FAPRI model predicts changes in cropland within political regions. Because these models are not spatially explicit at the ecosystem level (for instance, there are many kinds of forest within a particular region that might be converted to agriculture), the studies reviewed here employ historical land conversion data to estimate both the broad category of land converted (e.g., forest and grassland in the case of FAPRI) and the specific ecosystems converted within those categories (in the case of both GTAP and FAPRI).

However, key weaknesses afflict the available land conversion data. For example, most land cover studies have focused on locations of net changes in forest cover and cropland area but not on the full land use transitions that identify the conversion of one land cover type to another (23). Those studies that do capture land sources for new agricultural lands are often limited to local and regional scales rather than entire countries or AEZ, further limiting our ability to predict land use change processes triggered by biofuel expansion (24). This approach assumes that LUC induced through commodity markets today has the same patterns and land sources as historical LUC, which may or may not have been induced through a globalized economic system. In fact, the drivers of deforestation have shifted from clearing for subsistence agriculture, local markets, and beef production to larger-scale, industrial agriculture for local to global markets, particularly in Brazil and Indonesia (25). While the predominance of forest conversion for agricultural expansion continues, the displacement of small-scale farmers and cattle pasture by industrialized agriculture is more frequent today (24). Despite the fact that current and future LUC patterns may be different than those in the past, no better approach than using historical LUC information has been established, making this a highly uncertain component of estimating ILUC emissions.

Searchinger et al. estimate that 52% of the LUC resulting from corn ethanol expansion occurs on forested land and 48% in grassland. Hertel et al. estimate that 19% of the net conversion to cropland comes from forest and 81% from pasture. We were unable to derive a corresponding division from the USEPA analysis.

We assume that the forest conversion fraction ranges from 15% to 50% of the total LUC induced by biofuels expansion. Given the high emission factor for wetland conversion, but sparse empirical data on the fraction of conversion from wetlands, we use a conservative fraction ranging from 0% to 2%. The grassland fraction is computed as 100% minus the sum of the forest and wetland fractions and thus ranges from 48% to 85%.

**2.2.4. Land Conversion  $\text{CO}_2$  Emission Factors.** We define a parameter representing the average  $\text{CO}_2$  emissions associated with the conversion to cropland for each of three coarse land cover classes: forest, grassland, and wetland. The models used by CARB and USEPA use more land classes, with differentiated emission factors for forest and grassland subtypes. The coarse values used here for the three broad land cover classes represent area-weighted averages of emissions from these subtypes and thus depend on assumptions of the occurrence of conversion for each of these subtypes. Thus the ranges assigned to the emission factors represent both variability in carbon emissions for conversion of specific land cover types and model and parameter uncertainty expressed as differing projections of the location and magnitude of land conversions.

Several challenges make it difficult to accurately estimate  $\text{CO}_2$  emissions from land use changes across large regions. First, the carbon stocks in the original ecosystem (i.e., before conversion) have not been systematically studied or well quantified, particularly in the tropics (26). Forest inventories



are often used to estimate carbon stocks, but as pointed out by Houghton (27), inventories remain outdated and incomplete across much of the developing world. In regions where estimates do exist, there can be a wide range in estimates of total biomass and soil carbon stocks as well as in the locations of more and less carbon-dense forests. In addition, Houghton notes that existing estimates are largely for undisturbed forests. Natural disturbances, human activities, and underlying environmental conditions add further variability to these estimates. Consequently, it is not clear that the carbon stock estimate for an ecosystem is representative of the carbon stock of the land affected by LUC, which could be higher or lower (27). However, moving beyond a single carbon stock value would require spatially explicit information on the locations of LUC as well as dramatic improvements and increases in biomass data collection and mapping.

Estimating the carbon fluxes from land use conversion requires estimates of the above- and below-ground biomass and soil carbon stocks before the conversion as well as (1) the stocks after conversion or (2) a method of predicting carbon loss as a function of conversion practice and the productivity of the new crop planted. The total ecosystem carbon stock (and its estimates) are uncertain for any location and are variable from place to place (26, 28, 29). Below-ground biomass is usually estimated using a “shoots-to-roots” ratio based on estimates of above-ground biomass.

Gibbs et al. (30) estimated CO<sub>2</sub> emissions for conversion of various tropical land cover types to biofuel feedstocks, assuming an eventual loss of all aboveground and below-ground biomass, and 25% of soil carbon for conversion to cropland and 10% for conversion to plantations. They estimated a loss of 334 to 897 Mg CO<sub>2</sub> ha<sup>-1</sup> for tropical forest conversion across all regions, with a range of 538 to 793 Mg CO<sub>2</sub> ha<sup>-1</sup> for the Americas, 202 to 482 Mg CO<sub>2</sub> ha<sup>-1</sup> for disturbed tropical forests across all regions, and 307 to 437 Mg CO<sub>2</sub> ha<sup>-1</sup> in the Americas. Fargione et al. (31) estimated the change in above- and below-ground carbon stocks 50 years after conversion associated with the conversion of several land cover types to biofuel feedstock production, including forgone sequestration. They estimated a loss of 702 Mg CO<sub>2</sub> ha<sup>-1</sup> for lowland tropical rainforest in Southeast Asia and 737 Mg CO<sub>2</sub> ha<sup>-1</sup> for Amazonian rainforest. Based on different economic models, but using essentially the same emission factors, Searchinger et al. (8) and Hertel et al. (10) estimated average emissions for forest conversion of 533 and 607 Mg CO<sub>2</sub> ha<sup>-1</sup>, respectively; these values include 30 years of foregone sequestration that would have occurred in the absence of land conversion. We note that although the Searchinger et al. and Hertel et al. studies used essentially the same emission factors, their average emissions for conversion of forest and grassland differ because the economic models used predicted different locations and quantities of LUC. For the average emission factor for forest conversion, we use a range from 350 to 650 Mg CO<sub>2</sub> ha<sup>-1</sup>.

For conversion of US central grasslands to cropland, Fargione et al. (31) estimated a loss of 134 Mg CO<sub>2</sub> ha<sup>-1</sup>. Searchinger et al. (32) estimate the emissions for conversion of temperate grasslands to be 199 Mg CO<sub>2</sub> ha<sup>-1</sup>; for tropical grasslands, they estimate 104 Mg CO<sub>2</sub> ha<sup>-1</sup>. Gibbs et al. (30) estimate a loss of 52 to 103 Mg CO<sub>2</sub> ha<sup>-1</sup> for tropical grassland and 126 to 348 Mg CO<sub>2</sub> ha<sup>-1</sup> for tropical shrubland and savanna. The average values estimated by Searchinger et al. (8) and Hertel et al. (10) for grassland to cropland were 142 and 105 Mg CO<sub>2</sub> ha<sup>-1</sup>, respectively. For the average emission factor for conversion of grassland to cropland, we use a range from 75 to 200 Mg CO<sub>2</sub> ha<sup>-1</sup>.

The emission factor for conversion of moist tropical Southeast Asian forests from the Woods Hole Research Center data set is 1146 Mg CO<sub>2</sub> ha<sup>-1</sup> (32). For peatland tropical rainforest in Southeast Asia, Fargione et al. (31) estimated a

loss of 3452 Mg CO<sub>2</sub> ha<sup>-1</sup>, noting that this would be an underestimate if drainage were sustained for more than 50 years. Gibbs et al. (30) estimate the total loss of 5867 Mg CO<sub>2</sub> ha<sup>-1</sup> over 120 years for the conversion of peat soils. For wetlands, we assume emissions range from 1000 to 3000 Mg CO<sub>2</sub> ha<sup>-1</sup>.

**2.2.5. Production Period.** The RFMI treats all ILUC emissions associated with biofuels expansion as occurring instantaneously at the start of biofuel expansion. We recognize this is a simplification of the actual emission profile and have written separately on this subject (20). However, for simplicity in the exposition of the present bounding analysis, we have ignored these complexities. The effect of this omission is to somewhat underestimate the GHG effects of biofuels relative to those of gasoline, but this effect is small relative to the uncertainty ranges examined here. To include these emissions in fuel regulations that assign a GHG rating to each unit of fuel, the emissions must be attributed to each unit of fuel associated with the expansion, which requires an estimate of the duration of production. The simplest approach uses straight-line amortization to distribute the emissions evenly over the years of biofuels production. Searchinger et al. (8) assumed 30 years of biofuel production, a value which has subsequently been adopted by both CARB and USEPA in their respective rulemakings (1, 2). However, the 30-year assumption was not based on empirical data or modeling but rather was chosen conservatively to avoid being too low (33). In contrast, the EU Renewable Energy Directive requires that land use change emissions be distributed evenly over 20 years of production [ref 3, Annex V]. Note that changing the assumed production period from 30 to 20 years increases the unit ILUC emissions value by 50%.

Some biofuels, especially those cheap or efficient to produce such as Brazilian cane ethanol, may be produced for longer than the 30 year value. Although the value for this parameter has been a model choice in practice, it can be treated as a variable whose most representative value is uncertain. We allow a range of 15 to 45 years.

### 3. Results

Assuming parameter independence, plausible (in the range-of-possibilities sense used here) values for the ILUC factor based on interval analysis ranged from about 10 to 340 g CO<sub>2</sub>e MJ<sup>-1</sup>, as shown in Figure 1. (The assumption of parameter independence is discussed further in the Supporting Information, section 2.1.3.)

**3.1. Plausible Frequency Distributions.** The shapes of the probability distributions used to represent model parameters in the Monte Carlo analyses had a relatively small effect on shape of the output frequency distribution: in all cases, the output distributions were approximately log-normal, with a prominent right tail. Figure 2 shows the output distributions from simulations based on four alternative parameter distribution forms. Median values ranged from 55 to 59 g CO<sub>2</sub>e MJ<sup>-1</sup>. The widest 95% central interval (21 to 142 g CO<sub>2</sub>e MJ<sup>-1</sup>) resulted from using uniform parameter distributions; the narrowest (30 to 103 g CO<sub>2</sub>e MJ<sup>-1</sup>) resulted from using betaPERT distributions.

The parameter ranges used in this model result from many underlying uncertainties that, in many cases, are poorly characterized. Therefore, it is difficult to place great confidence in the specific ranges used here. However, if we believe that values within the chosen ranges are plausible given the uncertainties, and we assume the values are independent, then the extreme values possible from the model (10 to 340 g CO<sub>2</sub>e MJ<sup>-1</sup>) are also plausible. Likelihood is addressed below.

The uncertainty ranges here are wider than those presented by the cited studies because we combined ranges of input parameters derived from those studies, and the ranges reported by the studies were generally based on one-at-a-

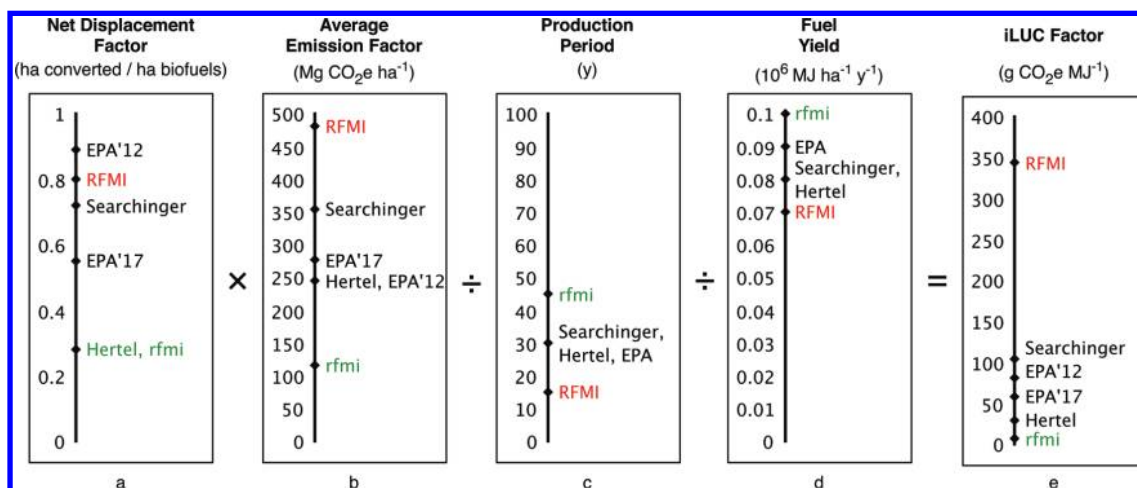


FIGURE 1. Parameter (panels a-d) and result (panel e) ranges for ILUC factor. Values in panels a-d identified as RFMI combine to produce the highest result; values identified as rfmi produce the lowest result. RFMI = highest values in Reduced Form Model of ILUC, rfmi are lowest values therefrom; EPA'12 = USEPA results for year 2012; EPA'17 = USEPA results for year 2017.

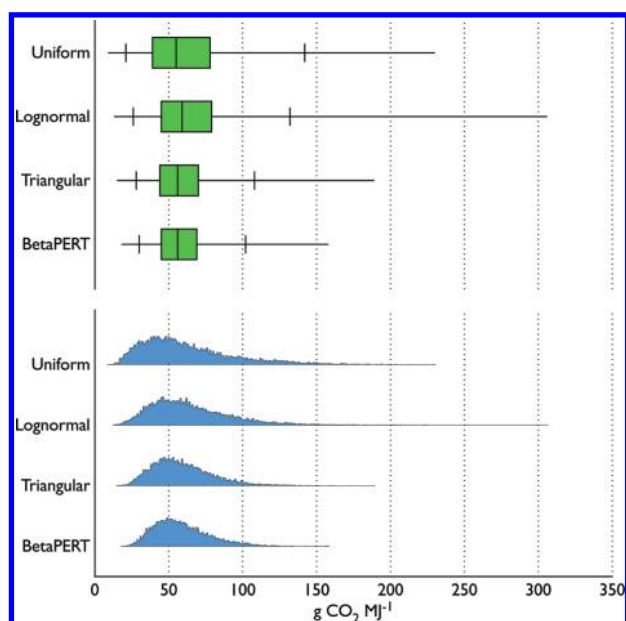


FIGURE 2. Frequency distributions for four Monte Carlo simulations of ILUC emissions for US corn ethanol using (i) betaPERT, (ii) triangular, (iii) log-normal, and (iv) uniform distributions for model parameters. The green boxes in the upper half show the interquartile range; the line across the box indicates the median. The ends of the whiskers show the maximum and minimum values, and the crossbars identify the 95% central interval, i.e., the 2.5 and 97.5%ile values. The blue curves in the lower half show the shape of the same frequency distributions.

time sensitivity analyses that considered a small set of parameters. The bounding range produced by probabilistic combination of even the uniform distribution (Figure 2) is narrower than that produced using interval calculations (compare the X axis of Figure 2 with the Y axis of Figure 1) because the likelihood of all input parameters achieving their bounding values simultaneously in the Monte Carlo simulation is very low. While we chose to define the “plausible” range as the central 95% interval, it is important to recognize that the further right tails of these distributions represent nonzero risk of very high ILUC emissions if fossil fuel is displaced by biofuels, and the left tail offers no such corresponding prospect of very large emissions reductions.

**3.2. Uncertainty Importance Analysis.** The NDF accounts for about half the variance in the ILUC emission factor

when the production period is allowed to vary from 15 to 45 years; the production period itself accounts for about 40% of the total variance. With the production period fixed at 30 years, the NDF accounts for about 70% of the variance in the ILUC emission factor. (Figure S2 shows the contribution to variance for each parameter under these two assumptions about production period.) The NDF, while represented as a single parameter in RFMI, is a derived result of economic models such as FAPRI and GTAP. As discussed earlier, it is unlikely that modelers will be able to greatly reduce the uncertainty in this parameter.

#### 4. Discussion

The variation in parameter values and model results for ILUC has been interpreted by some as a sign that the ILUC modeling process is not yet mature or sufficiently advanced to be used in policy making [e.g., see refs 34 and 35]. Our study challenges this interpretation on three grounds. First, much of the variance in estimates of ILUC stems from decision uncertainty in modeling choices and stochasticity in the underlying processes, both ecological and human. We believe it will not be possible to reduce these uncertainties soon. Nor is it likely that the large contribution from epistemic uncertainties will be reduced soon: the complexity of the real global economy precludes accurate prediction (12, 36). Second, even when allowing for the full range of current uncertainty, the probability distributions for ILUC estimates had a right tail indicating a significant likelihood of large positive values, and third, none of the distributions included zero or negative values.

Omitting ILUC emissions from the analysis is equivalent to assigning a value of zero to this effect. If estimates of ILUC emissions were (i) centered symmetrically (ii) at zero—that is, if the *most likely* and *expected* values were zero—and (iii) if the costs to society of under- or overestimating the value were symmetrical across zero, it might be reasonable to ignore ILUC emissions in this sense. However, our analysis and the modeling studies discussed herein suggest that ILUC emissions for corn ethanol are *not* best approximated by zero, whatever estimator is used, and the presence of a long right tail argues strongly against using a value of zero. Several studies have also projected significant ILUC emissions associated with other food-competitive feedstocks such as soybeans, rapeseed, sunflower, wheat, palm oil, and switchgrass (1, 2, 9). We are not aware of any peer-reviewed model of ILUC emissions that predicts small or negative ILUC values for any biofuel. The estimates of ILUC emissions for corn ethanol of 30 g CO<sub>2</sub> MJ<sup>-1</sup> by CARB and 34 g CO<sub>2</sub>e MJ<sup>-1</sup> by

USEPA (for 2022) are at the low end of the range estimated here; a value at least five times as large is also plausible. Excluding ILUC from these regulatory efforts provides only specious precision and could result in perverse policy outcomes.

In a forthcoming paper, we examine the implications for policymaking of different possible cost functions, especially including the case where overestimating and underestimating the global warming intensity of a given fuel by the same amount do not have the same social cost, together with asymmetric probability distributions for GWI.

The broad uncertainty in estimates of ILUC emissions (and life cycle GHG emissions more generally) has created challenges for regulators tasked with developing performance-based regulations of biofuels. While some stakeholders focus on the low end of the plausible range of ILUC emissions, others focus on the high end. Unfortunately, neither of these perspectives can be proved incorrect. However, given the range of estimates generated by the plausible parameters used in this study, a value much higher than the values estimated by CARB and USEPA appears more likely than a value below those estimates. Policies that deal explicitly with the risk posed by potentially high ILUC emissions might be more appropriate. Indeed, some are calling for slowing or halting biofuel expansion until these risks can be reduced (14, 37). One way to narrow the uncertainty and reduce the risk of large ILUC emissions would be to discourage biofuel feedstocks that compete with food for land, for example, by targeting degraded land for agricultural expansion, and to encourage use of other feedstocks such as wastes, residues, and certain algae production systems that do not involve displacing production of other commodities. However, production of even these feedstocks can have indirect climate effects that must be considered (38).

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## Supporting Information Available

Treatment of uncertainty, details of prior studies of ILUC emissions, and additional tables and figures. This material is available free of charge via the Internet at <http://pubs.acs.org>.

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