Reply to Comment on ‘Carbon intensity of corn ethanol in the United States: state of the science’

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Keywords: land use change, agroeconomic models, land intensification, corn ethanol life cycle analysis, yield price elasticity, CCLUB, empirical land use change analysis

Abstract

Spawn-Lee et al published a comment on our recent paper, ‘Carbon intensity of corn ethanol in the United States: state of the science.’ Their commentary is critical of our methodology and conclusions regarding greenhouse gas (GHG) life cycle analyses (LCAs) for corn starch ethanol and gives particular attention to the estimation of emissions from land use change (LUC). Several of the concerns stated by Spawn-Lee et al were raised in prior publications and are addressed in the recently published literature, thus, we respond to those points in brief and refer readers to those papers for more information. In response to their remaining concerns, we present detailed information in support of our approach for assessing LCAs of corn starch ethanol and our findings. Our original paper and the corroborating information provided here demonstrate that our methods are robust and our results are credible. Further, we hope this response contributes to constructive discussion and research on estimation of GHG emissions and LUC linked to corn starch ethanol.

1. Introduction

Our paper ‘Carbon intensity of corn ethanol in the United States: state of the science’ is a topical review of greenhouse gas (GHG) life cycle analyses (LCAs) for corn starch ethanol. Therein, we assess the strengths and weaknesses of commonly relied upon LCAs and derive a central best estimate and credible range of carbon intensity (CI) for feedstock production, co-product production, ethanol production, land use change (LUC) associated with demand for corn feedstock, and four smaller components of the corn starch ethanol system.

A recent comment on our publication makes several points that are critical of our methodology and conclusions [1]. The authors give particular attention to the topic of LUC. Spawn-Lee et al point out, and we agree, that LUC is an important component of LCAs for biofuels. We welcome the attention given to our paper by Spawn-Lee et al and prepared this reply to ensure readers have the information needed to fully evaluate their critiques of our topical review.

In this response, we address the comments of Spawn-Lee et al point-by-point. We first reply to their comments on our approach to evaluating the overall CI for corn starch ethanol. Next, we reply to Spawn-Lee et al comments on our evaluation criteria for LUC estimates and provide detail on (a) agroeconomic models; (b) economic data year; (c) yield price elasticity (YDEL); and (d) land intensification. That section is followed by our response to their comments on our calculation of an estimate for domestic LUC (dLUC). In the final section, we address their comments on trends in LUC modeling results and empirical analyses of LUC. We provide additional analysis, where feasible, throughout the reply.
2. Overall CI of corn starch ethanol

As described in our paper, we examined LCAs for corn starch ethanol in the United States published between 2010 and 2020, assessed their reliability according to clearly stated criteria, and filtered the studies to produce a set of the most current and reliable LCA results [2]. Our assessment criteria favored more recent LCAs that incorporate the latest relevant data and tools for calculating energy input and GHG emissions for corn starch ethanol production. We drew upon those LCAs to derive a central best estimate for the CI of eight elements that comprise the corn starch ethanol system. We summed the component-specific CI values to obtain a central best estimate for the total CI of the overall system.

Spawn-Lee et al appear to disapprove of the general approach we used to derive a central best estimate for the CI of corn ethanol from existing LCAs. They state that ‘deconstructing and recombining elements of disparate LCAs belies the scientific intent of LCA and may ultimately miscount emissions’ [1], but provide no evidence to support this comment. Notably though, the general approach we used has been employed and published by others who analyzed the CI of corn starch ethanol [3].

Similarly, Spawn-Lee et al state that our central best estimate for the CI of corn starch ethanol is ‘considerably smaller than all of the prior estimates’ [1]. This assertion is not supported by the facts. Figure 1 of our paper shows that our findings are consistent with the latest and most reliable LCAs [2]. Our central best estimate of 51.4 gCO₂e MJ⁻¹ is 1 gCO₂e MJ⁻¹ (2%) lower than the CI for 2019 published recently by Lee et al [6]; 3 gCO₂e MJ⁻¹ (6%) lower than the CI published by Argonne National Laboratory (ANL) in 2020 and 2019; 6 gCO₂e MJ⁻¹ (12%) lower than the CI published by United States Department of Agriculture (USDA)/ICF in 2018; and 1 gCO₂e MJ⁻¹ (2%) lower than the CI forecasted for 2022 and published by USDA/ICF in 2018 [4–7]. This consistency is a necessary result of our methodology and the CI estimates from those analyses all lie within the range of credible CI values described in our original paper.

3. Estimated carbon intensity of LUC

Spawn-Lee et al are correct that our central best estimate for LUC is one reason why our conclusion about the overall CI for corn starch ethanol is modestly lower than other recent estimates. Furthermore, we agree that LUC is one of the most uncertain components of LCAs for biofuels as well as for other uses of large tracts of land [8–11]. The literature is replete with recommendations for advances in modeling and data on land use, productivity, rent, and carbon stock needed to refine estimates of GHG impacts from LUC [12–18].

Spawn-Lee et al characterize the criteria we used to evaluate prior LUC estimates as ‘unjustified’ and state that we provide ‘no statistical evidence’ for the criteria [1]. While our rationale is described in Scully et al [2], we use this opportunity to reiterate the portions of our approach that are relevant to the concerns raised by Spawn-Lee et al. First, we discuss the development of our evaluation criteria and assessment of agroeconomic models used in prior LCAs (sections 3.1 and 3.2) and then specific parameters of those models (sections 3.3–3.5). In section 3.6, we reply to the comments on our calculation of dLUC using the latest version of the Carbon Calculator for LUC from Biofuels Production (CCLUB) (2020) with an updated version of GTAP-BIO (hereafter ‘GTAP’).

3.1. Evaluation criteria

As described in our paper, we developed evaluation criteria for LUC analyses in existing LCAs after: (a) an in-depth review of the literature on methods used to estimate LUC in corn starch ethanol LCAs and (b) discussions with field-leading experts in the biofuel LCA community. We interviewed researchers and analysts at the U.S. Department of Energy ANL and Oak Ridge National Laboratory, USDA, Purdue University, University of Illinois, and Ohio State University and others to develop the framework for our analysis of LUC. In addition, we received independent reviews of our LUC work product from scientists and analysts outside of our research team and organizations. We also reviewed papers that discuss the differences between major agroeconomic models [19, 20], a recent paper that discusses the significance of economic data year and model tuning to account for land intensification [21], and 20 studies from 1976 to 2017 on corn YDEL [22–33]. These considerations are described in the context of the comments from Spawn-Lee et al in the remainder of this section. To further address their comments, we also present additional analyses that support our assessment of prior LUC estimates and our calculation of a dLUC value.

3.2. Agroeconomic model

Spawn-Lee et al challenged our finding that GTAP is currently the most reliable means of estimating LUC for corn starch ethanol even though several lines of evidence indicate that GTAP is the field-leading agroeconomic model.

GTAP is a computable general equilibrium (CGE) model that addresses land intensification and expansion on regional and national scales globally. The model predicts LUC for specific land types based on both economic and physical data. In 2010, EPA stated that ‘since its inception in 1993, GTAP has rapidly become a common “language” for many of those conducting global economic analysis’ [34]. GTAP is used by the major corn ethanol LCA modeling groups such as ANL and California Air Resources Board (CARB). Moreover, the model is generally accepted...
as evidenced by the numerous peer-reviewed publications that use it in evaluations of the global implications of biofuel production and policy and other environmental and trade topics [6, 21, 35–39].

A distinguishing advantage of GTAP is its ability to account for linkages of the biofuel industry with all other economic activities on a global scale [40]. In contrast, the Food and Agricultural Policy Research Institute (FAPRI) model, which was used in three of the 15 LUC studies we reviewed, is a partial equilibrium (PE) model which by definition only covers selected markets and does not account for links to non-agricultural sectors [40]. PE models generally have less well developed treatment of land markets than CGE models such as GTAP, which is a significant limitation since competition for alternative uses of land is the crux of LUC and analyses for biofuels [40].

In addition to being widely used and generally accepted, GTAP is regularly updated to generate more refined and accurate estimates of LUC, including those associated with biofuels [21, 41]. Briefly, since 2010 GTAP has been updated to include: market mediated factors; co-products of biofuel refining such as animal feed (distillers’ dried grains with solubles), regional extensive margins by agroeconomic zone (AEZ); 2004, 2007, and 2011 economic databases; land transformation elasticities on a regional scale; region-specific multiple cropping; and land cover nesting structure that includes idled cropland [42]. Meanwhile, since 2008 FAPRI has been refined to include: market mediated factors with and without yield response, as well as multiple cropping and pasture area in Brazil [42]. Notably, these advancements have resulted in a downward trend of LUC estimates from both models [21, 42].

Spawn-Lee et al called out a limitation of GTAP, specifically, that unmanaged land was unavailable for conversion to agricultural land [43]. We agree that the absence of unmanaged lands is a limitation to GTAP. However, GTAP does account for accessible forest area, which includes managed forests and some unmanaged, where accessibility is a function of distance to infrastructure [44]. It is important to acknowledge that even if GTAP were to account for unmanaged forest, the LUC modeling would still be limited since emissions factors that distinguish between managed and unmanaged forest have yet to be developed [45, 46]. As a result, it is not possible to complete a quantitative analysis to assess the impact of including or omitting unmanaged lands in GTAP. As noted in our original paper, additional research on emission factors (EFs) for land conversion, as well as standardization of EFs, should be a priority for developers and users of LUC modeling.

Spawn-Lee et al also critique our evaluation of the FAPRI model. As stated above, FAPRI was used to estimate LUC in three analyses of corn starch ethanol that we reviewed (see supplemental materials for Scully et al [2]). They correctly note that our reference [47] regarding limitations of satellite images for LUC analysis does not mention Moderate Resolution Imaging Spectroradiometer (MODIS) specifically, the source of imagery used in the EPA 2010 LUC analysis [19]. However, our point was that estimation of LUC from analysis of satellite imagery can contain substantial errors that limit the utility of this approach even for data sources with greater resolution than MODIS [48–50] (table 1). Recent analyses of this issue have recommended development of best practices and standard methods for handling key aspects of satellite imagery data including classification of land cover, aggregation of land classes, and changes in land classification schema over time [48, 49]. We believe that continued advances in the use of satellite imagery data is an important area of development for LUC analyses of biofuels.

3.3. Economic data year

Spawn-Lee et al criticize our selection of 2004 economic data and state ‘Taheripour et al expressly renounced this [2004-derived] estimate as outdated and instead favor a larger value’ [1]. Spawn-Lee et al’s interpretation of Taheripour et al’s statements regarding 2004 data is inaccurate and taken out of context. The 2011 economic data in Taheripour et al does not supplant the 2004 economic data but instead provides another global economic state for which LUC associated with a specific change in biofuel demand can be simulated.

In GTAP, the economic data year defines numerous state conditions that influence estimates of land intensification and extensification in response to an increase or decrease in demand for a biofuel. Examples of these conditions include: volume of biofuel production; national and regional shares of global production of goods and services; commodity-level changes in production and export shares by country and region; and land cover, harvested area, and crop production by region [21]. Of course, many of these conditions vary over time. As a result, the CI associated with LUC is a dynamic component of LCA modeling for corn starch ethanol because the estimated CI depends on the baseline economic year, change in ethanol production, and location of the changed production.

Analyses reported by Taheripour et al (2017) illustrate the sensitivity of CI estimates for LUC to the state variables contained in the GTAP using the 2004 and 2011 economic year databases [21]. An increase in U.S. corn starch ethanol production from 3.9 billion gallons (BG) in 2004 to 15 BG yielded an estimated LUC CI of 8.7 gCO₂e MJ⁻¹. In the corresponding case for 2011, increasing ethanol production to 15 BG from a starting point of 13.93 BG in 2011 resulted in an estimated LUC CI of 12 gCO₂e MJ⁻¹. The 2011 economic data year resulted in greater CI impacts than the 2004 economic data year despite a smaller increase in ethanol production. The authors attribute
Table 1. Key findings from studies of consistency of cropland area change estimated from satellite imagery data for the United States.

| Region                      | Database(s) and years | Findings                                                                 | References |
|-----------------------------|-----------------------|--------------------------------------------------------------------------|------------|
| Western corn belt           | USDA CDL and USGS NLCD, 2006–2011 | Aggregation of land classes for a single data source, CDL, resulted in transitions between corn/soy and grassland that that differed by more than 100% and opposite in direction | [50]       |
| Prairie Pothole Region of US and Canada | USDA CDL and NAIP, 2006–2014 | Estimates of forest to cropland conversion differ by more than 10-fold among data sources. For example, forest to cropland conversion in South Dakota was 94,000 ha according to the CDL; 2300 ha per a modified CDL; and 1200 ha per the NAIP | [49]       |
| United States               | USDA CDL, Census, NRI, and PCHA, 2007–2017 | Cropland acreage differed between the CDL satellite imagery and tabular databases but trends over time were strongly and positively correlated. Changes in cropland area over three time periods were weakly to moderately correlated among the four sources of cropland data. Cropland area change calculated from CDL data processed to reduce errors was weakly correlated with estimates from the Census, NRI, and PCHA. | [48]       |

CDL USDA cropland data layer satellite imagery
Census USDA census of agriculture database
NAIP USDA national agricultural imagery program
NLCD USGS national land cover database
NRI USDA national resources inventory database
PCHA USDA principal crops harvested acreage database
USDA United States department of agriculture
USGS United States geological survey

The larger impact in 2011 compared to 2004 to several factors including: less availability of cropland pasture in the US, less flexibility in US corn markets, smaller corn yield, more reductions in US crop exports, larger dried distillers grains soluble trade share, smaller capital share in corn ethanol cost structure, and larger marginal land use [21]. These results are an example of how LUC estimates and the associated CI are a function of the scenario being modeled rather than a direct, measurable source of GHG emissions.

The 2011 economic year analysis noted in the preceding paragraph is the only estimate of LUC identified by our literature review that was derived from the latest version of GTAP and 2011 economic year data [21]. Had we relied on that 2011 economic data year result rather than prior estimates of LUC CI for ethanol expansion from 2004 levels, our central estimate for the overall CI of corn starch ethanol would be 59.5 gCO₂e MJ⁻¹, a value that is within the credible range described in our original publication.

For the scope of our analysis, a review of major LCAs for corn starch ethanol, we determined that consideration of LUC analyses based on the 2004 economic year to be most appropriate. We examined 27 LUC estimates for corn starch ethanol, 23 of which required a baseline economic year, and 19 of those which used 2004 as the baseline economic year [2].

The 2004 economic data reflect market conditions at the outset of a four-fold (3.4–13.9 billions of gallons [BG]) expansion of U.S. ethanol output from 2004 to 2011 [51]. Ethanol production in the US has been relatively constant since 2011 at approximately 15 billion gallons annually [51]. These events provided model developers with an opportunity to (a) infer effects of increased demand for ethanol on land use and (b) calibrate LUC models to the observed changes in land use since 2004. As a result, GTAP developers tuned the model’s treatment of cropland intensification and expansion to observed changes in land use over this period of rapid growth in ethanol production (see sections 3.4–3.6). We consider this model calibration to be an important strength of LUC estimates derived for the years during which U.S. ethanol production increased substantially.

3.4. Yield price elasticity
Spawn-Lee et al criticise our selection of an acceptable YDEL range of 0.175–0.325, stating it is ‘relatively high’ and ‘likely double-counts intensification responses to bioenergy demand’ [1]. These authors...
also claim that our range was solely based on ‘one study’ (Taheripour et al [21]) in which it was proposed on an essentially arbitrary basis’ and that we disregard the calculated average from our literature review of YDEL values [43]. We address the potential for double counting in section 3.5 and expand upon our prior finding for YDEL here.

With respect to our YDEL literature review, Spawn-Lee et al state that we ignore the context presented in Berry, which estimated YDEL to be zero or negligible, and not higher than 0.1 [52], when in fact we did consider that publication in our analysis (see supplemental materials for Scully et al). We also note that the ‘CARB expert working group that reviewed the existing research in this area did not find Berry’s conclusions credible on yield to price response, instead concurring that farmers undertake intensification in response to crop prices’ [41].

Spawn-Lee et al state that our YDEL range is based solely on one study and has an ‘arbitrary basis’ [43]. That characterization is not accurate. We conducted a literature review to identify raw YDEL values, calculated the average of those values (0.23), and compared that average to the commonly used YDEL of 0.25. The default value for YDEL in GTAP is 0.25 [35]. This value appears to be commonly used as our analysis showed that 17 of the 27 LUC estimates we considered were derived using a YDEL of 0.25 (see supplemental materials for Scully et al [2]). Separately, the CARB expert work group on elasticity values also recommended a YDEL of 0.25 [53]. The CARB expert group also opined on when a range of YDEL values, in consideration of multiple cropping, may be appropriate: ‘If differentiation [in YDEL] can occur by country, then setting the price elasticity to 0.175 for countries with no double cropping, 0.25 for the U.S. and 0.3 for Brazil and Argentina [with higher rate of double cropping] will provide a more reasonable approximation to reality’ [42, 53]. Subsequently, Taheripour et al expanded upon the CARB expert work group’s recommendation by analyzing global, regionally-specific land use data to develop ‘a full set of regional YDEL values based on the observed regional yields obtained from the FAO data set from 2003 to 2013’ [42]. Based on these considerations, we concluded that the current most credible YDEL range is 0.175–0.325, since it was supported by CARB’s expert group, is inclusive of the commonly used value of 0.25, and is corroborated by the average YDEL calculated from 20 relevant studies on corn YDEL dating from 1976 to 2017.

3.5. Land intensification
According to Spawn-Lee et al, ‘requiring explicit treatment of “land intensification” in addition to a relatively high yield price elasticity that implicitly accounts for some of the process likely double-counts intensification responses to bioenergy demand and thus underestimates rates of LUC’ [1]. This assertion only applies to the LUC values that were calculated by Taheripour et al (2017) which applied regional land intensification parameters in addition to regional YDELs [21]. This concern was raised and addressed in previous publications; therefore, we conducted no new analysis on this matter and encourage readers to review those papers for details on this topic [18, 21, 42]. Briefly, GTAP was updated with a land intensification parameter to ‘represent improvement in harvest frequency due to multiple cropping and/or conversion of idled cropland to crop production’ [41]. The land intensification parameter is empirically-based and calculated using regional ‘FAO data based on actual observations on regional harvested area and cropland area’ [21, 41]. The region-specific land intensification parameter in addition to region-specific YDELs allows GTAP to account for observed corn yield response, harvest frequency, and conversion of idled cropland to crop production, informed by empirical data [21].

Spawn-Lee et al also assert that by incorporating land intensification, we fail to account for ‘additional fertilizer and amendments that would increase emissions from the “farming” sector’ [1]. We acknowledge this is a limitation of our methodology, since running a complete LCA was outside the scope of our review. New analyses should be performed to quantitatively characterize the impact of LUC-related intensification on farming emissions.

To address Spawn-Lee et al’s comment on our analysis of USDA corn farming irrigation data, we present the data in table 2. As we noted, the Ecoinvent water use estimate was traced through Ecoinvent documentation to an old report which assumed full irrigation, an assumption that the USDA data clearly and transparently contradicts [54, 55]. As displayed in table 2 and described in our original paper, only 11.5% to 15.7% of corn planted acres are irrigated [55].

3.6. Domestic LUC calculation
Spawn-Lee et al comment on our method for calculating an updated dLUC value. First, they criticize the feedstock pathway (i.e. GTAP scenario) we selected

| Year | Planted acres (1000 acres) | Irrigated acres (1000 acres) | Percent irrigated |
|------|--------------------------|----------------------------|-----------------|
| 1996 | 70 255                   | 8716                       | 12.4%           |
| 1997 | 62 149                   | 7851                       | 12.6%           |
| 1998 | 71 388                   | 9848                       | 13.8%           |
| 1999 | 68 299                   | 10 697                     | 15.7%           |
| 2000 | 73 772                   | 11 039                     | 15.0%           |
| 2001 | 70 744                   | 9761                       | 13.8%           |
| 2005 | 76 470                   | 9540                       | 12.5%           |
| 2010 | 81 740                   | 9422                       | 11.5%           |

Table 2. Corn farming irrigation practices in the United States from 1996 to 2010.

Reference: [55]
in CCLUB. As described in our paper, we selected the ‘Corn Ethanol 2013’ GTAP scenario over ‘Corn Ethanol 2011’ because it was calibrated with regionally-specific land transformation elasticities and land specific costs of converting pasture or forest to cropland [2]. The land transformation elasticity is significant to include in modeling, since it ‘reflects the ease of land transition from one state to another’ [46]. GTAP 2011 applied a single land transformation elasticity value for the globe, whereas GTAP 2013 used two ‘United Nations FAO land cover data sets [from 1990 to 2010] to develop region-specific land transformation elasticities’ [37, 46]. Additionally, GTAP 2011 assumed the costs for converting pasture and forest to cropland were identical, while ‘often the opportunity costs of converting forest to cropland is higher than the economic costs of converting pastureland to cropland’ [37]. Taheripour and Tyner updated GTAP to categorize regions as having a low, medium, or high land transformation elasticity and reflect the greater cost of converting forest to cropland than converting pastures based on empirical data and real world observations [37, 46]. Given these updates, we determined ‘Corn Ethanol 2013’ to be a valid source for estimating dLUC in our review.

Second, Spawn-Lee et al criticize our use of CENTURY-based EFs for characterizing soil organic carbon (SOC), since ‘unlike the other two sets of EFs, which are based on summaries of empirical data, the CENTURY-based EFs are based on the predictions of a biophysical model—a variant of the popular CENTURY model- that simulates SOC stocks and their responses to LUCs’ [1]. We calculated dLUC using CENTURY EFs because they are the default in CCLUB [46]. Additionally, we accepted CENTURY EFs since ‘the approaches used in CENTURY modeling is consistent with the technique of the Intergovernmental Panel on Climate Change of continuously updating carbon stock change factors based on such factors as management activities and various yield scenarios’ [41]. An advantage of CENTURY modeling is its potential to account for a broad range of soil characteristics, climate, and management conditions [41].

Third, Spawn-Lee et al challenge how the CENTURY EFs in CCLUB treat emissions associated with transitioning cropland pasture to cropland. This concern has been raised and addressed in previous publications and we encourage readers to review those papers for more detailed information [18, 41]. In contrast to CENTURY, the Winrock and AEZ EF models determine ‘cropland pasture emissions as simply one-half the estimate generated using the corresponding pasture/grassland EFs’ [1]. While our objective was not to conduct a thorough review of various EFs, the treatment of cropland pasture in CENTURY appears to be more evidence-based since it is informed by USDA statistics, than the method utilized by Winrock and AEZ EFs [41].

| Emission factor modeling scenario | Domestic LUC Value gCO₂e MJ⁻¹ |
|----------------------------------|-------------------------------|
| Century                          | −2.3                          |
| Woods Hole                       | 1.7                           |
| Winrock                          | 8.6                           |
| gCO₂e/MJ                         | grams of carbon dioxide equiva- |
|                                  | lent emissions per megajoule  |

Here we calculate dLUC values using various EFs, to address Spawn-Lee et al’s criticism that we only rely on results that applied the CENTURY emissions. As displayed in table 3 the dLUC value ranges from −2.3 to 8.6 gCO₂e MJ⁻¹ when using CENTURY, Woods Hole, and Winrock emissions factor models. If we were to incorporate these values in our methodology for determining overall LUC estimates, the range would be −1.0 to 16.7 gCO₂e MJ⁻¹, with a central estimate of 7.9 gCO₂e MJ⁻¹. This central estimate differs by only 4 gCO₂e MJ⁻¹ from our original central estimate of 3.9 gCO₂e MJ⁻¹ and is within our original credible range for LUC.

4. LUC modeling and empirical analysis

4.1. LUC modeling

Spawn-Lee et al critique our observation that LUC ‘estimates have decreased through time and are “converging” on a lower consensus estimate’. They provide a statistical analysis of modeled LUC estimates in support of that statement; however, the application of a statistical test is not appropriate since the sampling set is from modeled results and not a population [43]. Moreover, nowhere in our paper did we describe the downward trend of modeled LUC values to be statistically significant [2]. The concept of an observed downward trend in corn ethanol LUC modeling is not novel and we are not the first to acknowledge it. In fact, numerous publications in the primary literature recognize this trend [6, 18, 38, 42], Lewandrowski et al clearly state that ‘across studies, estimates of corn ethanol-driven iLUC emissions trend down over time’ [3]. Further, Malins et al acknowledge a downward trend in LUC estimates, stating that ‘various academic and working papers have, however, tended to decrease iLUC emissions compared to previous estimates’ [18]. In addition, Lee et al (2019) state ‘the downturn in simulated LUC emissions is a result of better developed and calibrated economic models and better modeling of GHG emissions from LUC’ [6]. Moreover, Taheripour et al (2021) display the advancements in modeling over time of both the GTAP and FAPRI model and demonstrate that there is a ‘reduction in land use emissions due to model and data improvements,’ which ‘is not limited to the GTAP-BIO model but is a common finding of the literature’ [42].
4.2. LUC empirical analysis

Spawn-Lee et al refute our assertion that cropland area declined by 38 million (M) acres from 2002 to 2017 and state that "using those same USDA data, Lark et al showed instead that cropland underwent a net expansion after implementation of the RFS by as much as 13.9 M acres (between 2007 and 2017)" [1, 56]. To address this claim, we reviewed USDA's Census of Agriculture (CoA) data from 2002 to 2017 and reproduced the analyses of Taheripour et al (2021) and Lark et al (2020) [42, 56–60].

We identified two differences between their analyses that explain the apparently conflicting results: (a) different definitions of cropland and (b) different time periods. Taheripour et al (2021) relied upon the definition of cropland developed and reported by USDA in the CoA. According to USDA, cropland is the sum of harvested area, cropland pasture, and unused cropland which includes idle land, failed cropland, and cropland in summer fallow [42]. In contrast, Lark et al (2020) defined cropland as the sum of harvested, failed, and fallow cropland, thus excluding cropland-pasture and idle land [61]. Regarding time period, Taheripour compared total cropland in 2017 to that in 2002, whereas Lark used the same ending year (2017) but a different starting year (2007) than Taheripour et al [42, 56].

Table 4 displays the results of the Taheripour et al (2021) and Lark et al (2020) analyses according to their cropland definitions for both time periods. As shown in the table, when both definitions are applied to 2002 and 2017, the CoA data show a reduction of 10.3–37.7 million acres of cropland. Similarly, the USDA definition of cropland shows a decrease in cropland of 37.7 million acres for the period 2002–2017 and a decrease of 10.0 million acres for the period of 2007–2017. The only instance where there is an apparent expansion in cropland is when cropland pasture and idle cropland are excluded from the cropland definition and the analysis compares data for 2007–2017. These conflicting results are not surprising considering that the literature clearly demonstrates that empirical approaches to LUC are sensitive to the analysis technique, including definitions of land use categories and time periods [50]. Spawn-Lee et al did not mention this literature in their comment on our paper.

Spawn-Lee et al also commented on our empirical LUC data reference; however, the analysis has since undergone peer-review and has been published [42, 62]. Furthermore, we were able to replicate Taheripour et al's analysis by relying upon USDA's CoA [57–60].

We acknowledge that there are uncertainties in existing sources of data for assessing LUC [48, 63]. As we mention in our paper, we encourage researchers to continue to expand upon empirical LUC analysis to characterize changes in land use more accurately.

5. Conclusion

We are grateful for the comments we have received and the opportunity to provide more information about our prior work. We recognize that LCA, like other environmental modeling, is an uncertain science. For that reason, we aimed to be transparent in our approach and clear about the results in our original paper. We prepared this reply to address the comments raised in Spawn-Lee et al. We hope the information presented is useful to other readers of our work and this journal. Upon careful consideration of the comments received and as described here, we remain confident in the reliability of our methods and findings.

Acknowledgements

The authors are thankful to Dr. Steffen Mueller and developers of GREET from ANL for their valuable insights and suggestions.

Funding

This topical review was conducted by scientists and engineers at Environmental Health & Engineering, Inc. with financial support from POET, LLC.

References

[1] Spawn-Lee S A, Lark T J, Gibbs H K, Houghton R A, Kucharik C J, Malins C, Pelton R and Robertson G P 2021 Comment on 'Carbon intensity of corn ethanol in the United States: state of the science'
[2] Scully M J, Norris G A, Alarcon Falconi T M and MacIntosh D L 2021 Carbon intensity of corn ethanol in the United States: state of the science Environ. Res. Lett. 16 043001
[3] Lewandrowski J, Rosenfeld J, Pape D, Hendrickson T, Jaglo K and Moffroid K 2019 The greenhouse gas benefits of corn ethanol–assessing recent evidence Biofuels 11 361–75
[4] Argonne National Laboratory 2019 GREET 1 2019 (Argonne National Laboratory)
[5] Argonne National Laboratory 2020 GREET 2020. GREET 1 Series (Fuel-Cycle Model) (Argonne National Laboratory)
[6] Lee U, Kwon H, Wu M and Wang M 2021 Retrospective analysis of the U.S. corn ethanol industry for 2005–2019: implications for greenhouse gas emission reductions Biofuels, Bioprod. Biorefin. 15 1318–31

[7] Rosenfeld J, Lewandrowski J, Hendrickson T, Jaglo K, Moffroid K and Pape D 2018 A life-cycle analysis of the greenhouse gas emissions from corn-based ethanol Report prepared by ICF under USDA Contract No. AG-3142-D-17-0161 (Accessed 5 September 2018)

[8] Zhao Q, Wen Z, Chen S, Ding S and Zhang M 2019 Quantifying land use/land cover and landscape pattern changes and impacts on ecosystem services Int. J. Environ. Res. Public Health 17 126

[9] Dadashpoo H, Azizi P and Moghadasi M 2019 Land use change, urbanization, and change in landscape pattern in a metropolitan area Sci. Total Environ. 655 707–19

[10] Somer L J, Moran C J, Barrett D J and Soares-Filho B S 2014 Processes of land use change in mining regions J. Clean. Prod. 84 494–501

[11] Phelps L N and Kaplan J O 2017 Land use for animal production in global change studies: defining and characterizing a framework Glob. Change Biol. 23 4457–71

[12] Babcock B A and Iqbal Z 2014 Using recent land use changes to validate land use change models Land Use Policy 37 319–30

[13] Chen X and Khanna M 2018 Effect of corn ethanol production on conservation reserve program acres in the US Appl. Energy 225 124–34

[14] Efroymson R A, Kline K L, Angelsen A, Verburg P H, Dale V H, Langeveld J W and McBride A 2016 A causal analysis framework for land-use change and the potential role of bioenergy policy Land Use Policy 59 516–27

[15] Kline K L, Oladou G A, Dale V H and McBride A C 2011 Scientific analysis is essential to assess biofuel policy effects: in response to the paper by Kim and Dale on 'Indirect land change for biofuels: testing predictions and improving analytical methodologies' Biomass Bioenergy 35 4488–91

[16] Klaverprij J H and Mueller S 2012 Baseline time accounting: considering global land use dynamics when estimating the climate impact of indirect land use change caused by biofuels Int. J. Life Cycle Assess. 18 319–30

[17] Li Y, Miao R and Khanna M 2018 Effects of ethanol plant proximity and crop prices on land-use change in the United States Am. J. Agric. Econ. 101 467–91

[18] Malins C, Plevin R and Edwards R 2020 How robust are reductions in modeled estimates from GTAP-BIO of the indirect land use change induced by conventional biofuels? J. Clean. Prod. 258 120716

[19] US Environmental Protection Agency, Assessment and Standards Division Office of Transportation and Air Quality 2010 Renewable fuel standard program (RFS2) regulatory impact analysis EPA-420-R-10-006 U.S. Environmental Protection Agency

[20] Coordinating Research Council Inc 2011 CRC Report No. E-88 review of transportation fuel life cycle analysis

[21] Taheripour F, Zhao X and Tyner W E 2017 The impact of considering land intensification and updated data on biofuels land use change and emissions estimates Biotechnol. Biofuels 10 191

[22] California Air Resources Board 2009 Proposed Regulation to Implement the Low Carbon Fuel Standard California Environmental Protection Agency

[23] California Air Resources Board 2015 Staff report: calculating carbon intensity values from indirect land use change of crop-based biofuels

[24] Houck J P and Gallagher P W 1976 The price responsiveness of US corn yields Am. J. Agric. Econ. 58 731–4

[25] Lyons D C and Thompson R L 1981 The effect of distortions in relative prices on corn productivity and exports: a cross-country study J. Rural Dev./Nongchon-Gyenge 4 83–102

[26] Menz K M and Pardy P 1983 Technology and US corn yields: plateaus and price responsiveness Am. J. Agric. Econ. 65 558–62

[27] Choi J-S and Helmerger P G 1993 How sensitive are crop yields to price changes and farm programs? J. Agric. Appl. Econ. 25 237–44

[28] Huang H and Khanna M 2010 An econometric analysis of U.S. crop yield and cropland acreage: implications for the impact of the carbon price change Agricultural & Applied Economics Association 2010 (Denver, Colorado, 25–27 July 2010) (https://doi.org/10.2139/ssrn.1700707)

[29] Berry S and Schlenker W 2011 Technical Report for the ICCT: Empirical Evidence On Crop Yield Elasticities (Accessed 5 August 2011)

[30] Smith A and Summer D 2011 Estimating the crop yield response to price: implications for the environmental impact of biofuel production (University of California Davis)

[31] Goodwin B K, Marra M C, Piggott N E and Mueller S 2012 Is yield endogenous to price? An empirical evaluation of inter-and intra-seasonal corn yield response

[32] Rosas J F 2012 Essays on the environmental effects of agricultural production Iowa State University

[33] Miao R, Khanna M and Huang H 2015 Responsiveness of crop yield and acreage to prices and climate Am. J. Agric. Econ. 98 191–211

[34] US Environmental Protection Agency 2005 Renewable fuel standard (RFS1): final rule

[35] Hertel T W, Golub A A, Jones A D, O’Hare M, Plevin R J and Kammen D M 2010 Effects of US maize ethanol on global land use and greenhouse gas emissions: estimating market-mediated responses Bioscience 60 223–31

[36] Tyner W E, Taheripour F, Zhuang Q, Birur D and Baldos U 2010 Land use changes and consequent CO2 emissions due to US corn ethanol production: a comprehensive analysis final report revisited Purdue University

[37] Taheripour F and Tyner W 2013 Biofuels and land use change: applying recent evidence to model estimates Appl. Sci. 3 14–38

[38] Dunn J B, Mueller S, Kwon H-Y and Wang M Q 2013 Land-use change and greenhouse gas emissions from corn and cellulosic ethanol Biotechnol. Biofuels 6 51

[39] Wang M, Han J, Dunn J B, Cai H and Elgowainy A 2012 Well-to-wheels energy use and greenhouse gas emissions of ethanol from corn, sugarcane and cellulosic biomass for US use Environ. Res. Lett. 7 045905

[40] Kretzschmer B and Peterson S 2010 Integrating bioenergy into computable general equilibrium models—a survey Energy Econ. 32 673–86

[41] Taheripour F, Mueller S and Kwon H 2021 Response to ‘How robust are reductions in modeled estimates from GTAP-BIO of the indirect land use change induced by conventional biofuels?’ J. Clean. Prod. 310 127431

[42] Taheripour F, Mueller S and Kwon H 2021 Appendix A: supplementary information to response to ‘How robust are reductions in modeled estimates from GTAP-BIO of the indirect land use change induced by conventional biofuels’ J. Clean. Prod. 310 127431

[43]Spawn-Lee S A et al. 2021 Supplementary materials for comment on ‘Carbon intensity of corn ethanol in the United States: state of the science’

[44] Hertel T, Golub A, Jones A, O’Hare M, Plevin R and Kammen D 2009 Supporting online materials for: global implications for greenhouse gas emission reductions in modeled estimates from GTAP-BIO of the indirect land use change induced by conventional biofuels’ J. Clean. Prod. 310 127431
management change from biofuels production (CCLUB)
Argonne National Library, Division ES September 2020
[47] Shrestha D S, Staab B D and Duffield J A 2019 Biofuel impact on food prices index and land use change Biomass Bioenergy 124 43–53
[48] Copenhaver K, Hamada Y, Mueller S and Dunn J B 2021 Examining the characteristics of the cropland data layer in the context of estimating land cover change ISPRS Int. J. Geo-Inf. 10 281
[49] Dunn J B, Merz D, Copenhaver K I. and Mueller S 2017 Measured extent of agricultural expansion depends on analysis technique Biofuels, Bioprod. Biorefin. 11 247–57
[50] Singh N, Kline K L, Efroymson R A, Bhaduri B and O’Banion B 2017 Uncertainty in estimates of bioenergy-induced land use change: the impact of inconsistent land cover data sets and land class definitions Bioenergy Land Use Change 231 143
[51] U.S. Energy Information Administration 2020 U.S. Production, Consumption, and Trade of Ethanol
[52] Berry S T 2011 Biofuels policy and empirical inputs to GTAP models (Accessed 4 January 2011)
[53] Babcock B, Gurgel A and Stowers M 2011 Final recommendations from elasticity values subgroup (ARB LCFS Expert Workgroup)
[54] Ecoinvent Database 2020 Database (available at: www.ecoinvent.org/) (Accessed 4 April 2020)
[55] U.S. Department of Agriculture Economic Research Service Crop production practices for corn: all survey states 2019 (available at: https://data.ers.usda.gov/reports.aspx?ID=17883) (Accessed 20 August 2019)
[56] Lark T J, Spawn S A, Bougie M and Gibbs H K 2020 Cropland expansion in the United States produces marginal yields at high costs to wildlife Nat. Commun. 11 1–11
[57] USDA National Agricultural Statistics Service 2002 Census of agriculture (No. AC-02-A-51) USDA2004
[58] USDA National Agricultural Statistics Service 2007 Census of agriculture (No. AC-07-A-51) USDA2009
[59] USDA National Agricultural Statistics Service 2012 Census of agriculture (No. AC-12-A-51) USDA2014
[60] USDA National Agricultural Statistics Service 2017 Census of agriculture (No. AC-17-A-51) USDA2019
[61] Lark T J, Spawn S A, Bougie M and Gibbs H K 2020 Supplementary information for cropland expansion in the United States produces marginal yields at high costs to wildlife Nat. Commun. 11 1–11
[62] Hoekman S K 2019 6th CRC workshop on life cycle analysis of transportation fuels Coordinating Research Council Special Panel Exploring Key Issues in LUC Modeling (Argonne National Laboratory) (Accessed 15–17 October 2019)
[63] Pearson K, Pritsolas J, Copenhaver K and Mueller S 2020 Assessment of the National Resources Inventory (NRI), the census of agriculture, the Cropland Data Layer (CDL), and demand drivers for quantifying land cover/use change (Accessed 25 March 2020)