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A review of domestic land use change attributable to U.S. biofuel policy

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Abstract

Estimates of land use change (LUC) attributable to the U.S. Renewable Fuel Standard (RFS) are critical for evaluation of the program's impacts on air and water quality, biodiversity, and soil quality. To improve our understanding of the range of published estimates, we reviewed 29 studies published since 2008 attributing domestic LUC to the RFS, updating previous comparisons and adding a growing number of empirical approaches to estimating biofuel-induced LUC. To identify principal reasons underlying differences in reported effects, we documented key attributes of studies' methods including spatial extent, time period, baseline scenario, policy influence, and LUC definitions. Across computable general equilibrium (CGE) and partial equilibrium (PE) economic simulation model studies we found a range of 0.01–2.45 million acres of net cropland expansion per billion-gallon increase in biofuels. Empirical approaches reporting national-scale estimates fall within this range, reporting 0.38–0.66 million acres per billion-gallon increase. Empirical studies had a much smaller range of estimates and were closer to PE approaches than CGE. Studies generally did not represent all the potential drivers of biofuel production, and instead reported projections reflecting a combination of RFS impacts and other influences. Additional refinements to the modeling and empirical approaches reviewed in this study can further improve our understanding of the land use change driven by biofuels and the RFS Program.

Keywords

Biofuels; Land use change; Policy impact evaluation; Renewable fuel standard; Ethanol

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Declaration of competing interest
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1. Introduction

Since the 1978 National Energy Conservation Policy Act [1], the U.S. has encouraged the production of biofuels to promote energy security and rural development, while simultaneously mitigating the negative impacts of carbon pollution on the global climate. In 2005, the Energy Policy Act established the first renewable fuel standard (RFS1), which was subsequently updated under the 2007 Energy Independence and Security Act (EISA) to become the RFS2 [2,3] (Fig. 1). The RFS2 requires that transportation fuel consumed in the U.S. contains a minimum volume of renewable fuels, increasing from 12.95 billion gallons (BG) of renewable fuels in 2010 to 36 billion gallons per year in 2022. EISA also limited the contribution of conventional biofuels, largely comprised of corn-based ethanol, to 15 BG/yr. The U.S. Environmental Protection Agency (EPA) has additionally adjusted the total required volume under the RFS2 downward each year 2014–2020 due mostly to limitations on the supply of advanced biofuels such as cellulosic ethanol, which was anticipated to grow considerably under EISA.

Policies stimulating biofuel production are predicated on the assumption that biofuels can provide environmental and societal benefits greater than those of conventional transportation fuels [4]. A growing body of research has refined the accounting of environmental impacts of biofuel policies, in particular by incorporating estimates of indirect price effects, which are generally not captured by traditional life cycle assessments. Increasing demand for biofuel feedstocks will lead, ceteris paribus, to an increase in the price of such feedstocks, and, due to land scarcity, in an increase in price of other crops [5]. These price effects can encourage producers to intensify production via inputs such as fertilizer and energy, bring non-cropland into feedstock production, and shift existing cropland toward biofuel feedstock production [6]. The latter can result in the displacement of the original crop to new areas, potentially resulting in indirect land use change domestically or abroad [5,7]. Changing crop types (e.g. cotton or wheat to corn) may also have detrimental effects on some environmental end points (e.g. water quality, because corn receives higher chemical inputs per acre) but not others (e.g. soil carbon, because corn has higher root biomass), depending on management practices.

The predominant approach to isolating the effects of the RFS program on land use from all other potential influences is the use of economic models that simulate market behavior [8]. Economic simulation models can be used to estimate the effects of biofuel policies by first constructing a baseline in which the policy is not present and comparing it to a counterfactual scenario in which the policy is in place. In assessments of a policy which is already in place, economic simulation models compare the observed baseline to a counterfactual in which the policy had not been put in place. These models project land use change due to a given policy based on agriculture and forestry market dynamics, biophysical characteristics, crop production technologies, and trade patterns [9]. The difference in projected land use change between a baseline and the policy scenario is an estimate of the attributional effect of the policy. These models often vary widely in their temporal resolution (e.g., annual, 5-year), spatial resolution (e.g., county, state, country, region), and degree of market detail (e.g., Computable General Equilibrium (CGE) models with less detail but more market scope versus Partial Equilibrium (PE) models with less market

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scope but more detail). More recent studies increasingly acknowledge that the corn ethanol industry is affected by many market and non-market factors, including the RFS Program, the Volumetric Ethanol Excise Tax Credit (VEETC), the phaseout of Methyl Tertiary Butyl Ether (MTBE), EPA's regulation of gasoline Reid vapor pressure, state policies, logistical infrastructure, relative prices of oil and corn, and trade, among other factors (Duffield, Johansson, and Meyer 2015). Models also vary in the extent to which they are able to isolate the RFS Program impacts from these other influences on biofuel production and consumption.

As biofuels policies have been in place for longer periods, and land cover data generated via remotely sensed imagery have become more sophisticated and accessible, it is increasingly possible to estimate the effects of biofuel policies using historical observations. Empirical studies derive a statistical relationship between an observed land use conversion response (e.g., non-crop to crop conversion) and a treatment (e.g., ethanol refinery location or capacity). These approaches often rely on quasi-experimental methods to control for confounding influences on land use change, to isolate the effect of a given biofuel policy influence. Like economic simulation models, empirical approaches generally do not disentangle the influence of a specific biofuel policy (e.g., the RFS Program) from other factors that influence biofuel production such as state biofuel policies, oil prices, or international biofuel demand. Instead, they aim to isolate the effect of biofuel production increases on land conversion, leveraging historical observations. Empirical studies often have much higher spatial resolution than economic simulation models (e.g., 30-m) [10,11], and inform whether estimates of effects from the simulation models are supported by observations.

The objective of this paper is to provide an up-to-date synthesis of the current state of knowledge regarding estimated land use change (LUC) in the U.S. estimated attributable to the RFS Program (RFS1 and 2) and corn ethanol production. Here we define LUC as a transformation in the way humans use or manage land. We review studies published since 2008 linking the RFS Program or domestic corn ethanol production, to LUC in the U.S. Where possible, we identify underlying methodological reasons for differences in reported estimates. This review updates previous comparisons of economic simulation modelling approaches to estimating biofuel-induced LUC [12,13]. In addition, this is the first review to examine the growing body of empirical approaches to estimating spatially refined biofuel-induced LUC in the U.S., which have not previously been synthesized. By comparing both economic simulation model and empirical approaches we were able to identify gaps or biases from a single method and compile findings across diverse methodological approaches [14].

2. Materials and methods

2.1. Literature review and screening

To conduct our assessment we collected an initial set of relevant reports and articles. In December 2019 we generated a database of 12,814 papers that cited any of the 365 references in the Second Triannual Report to Congress on Biofuels [6]. We used Sciome's SWIFT-Active Screener program to facilitate identification of those studies in the database

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which examined U.S. biofuels and land use change [15]. We then supplemented this with additional references identified by researchers and practitioners experienced in the field of biofuel policy evaluation which were not otherwise captured. Finally, we applied a snowball approach to gather additional papers that either cited, or were cited by, these studies [16]. The result of this approach yielded a list of 122 studies (Appendix), which we then manually screened to identify those which include a quantitative analysis attributing LUC in the U.S., or any U.S. subregion, to U.S. corn ethanol production or the RFS Program.

We excluded reports which evaluated the effects of non-U.S. based biofuel policies [17,18], or theoretical policies or scenarios rather than specific U.S. policies and/or the RFS Program [19]. We also excluded studies that focused on changes in land use or land cover without a concomitant evaluation of the role of biofuel policy in inducing this observed land use [20,21], and studies which improved estimates of greenhouse gas emissions from LUC, for example via modified emissions factors, using a previously published estimate of LUC [22,23]. While we evaluated studies that estimated effects of both conventional and advanced biofuels, we limited our assessment to those studies which included at least one estimate of the effects of conventional corn-based ethanol, excluding studies that focused on the role of cellulosic biofuel production [24,25]. Many of these studies also included estimates of international land use change. However, given that the purpose of this study is to examine the land use changes in the U.S., and compare those with empirical estimates which are predominantly from the U.S., we focus on the U.S. portion of these studies. Finally, in cases of a series of studies which presented incremental updates to a modelling approach we included the most recent papers in our review [26,27], and excluded the preceding refinements [28,29]. After applying these filters, we selected 15 economic simulation modelling studies and 14 empirical studies for more detailed assessment.

2.2. Assessment of the literature

For each study we extracted estimates of the area of LUC attributable to the treatment examined and, to the extent possible, harmonized reported units to facilitate comparability. Studies reported a wide range of LUC types, including for example changes in the acreage of specific crops, and transitions between various land cover types and crop categories. To facilitate comparison, we focused on reported net cropland change (not including cropland pasture), net expansion in corn cultivation, and impacts on Conservation Research Program (CRP) acreages, as these LUC metrics were the most common across all studies included in our review. Studies also examined the impacts of a range of different biofuels including corn ethanol, soy biodiesel, advanced biofuels, or the sum of all biofuels irrespective of type. We focused on those studies examining corn ethanol, which comprise the large majority of the increase in biofuel production in the U.S. However, studies that incorporated other biofuel types often did not disentangle the relative contribution of each, limiting direct comparison between reported results.

We documented five key attributes of each studies’ methodology, including: (1) the spatial extent and resolution of the analysis, (2) the time span and increment of the analysis, (3) the treatment examined by the study, (4) which biofuel feedstocks are represented in the model, and (5) the types of land cover changes examined. In the case of economic simulation models, we also identified the model used, the type of model (whether PE or CGE), how the baseline and scenarios are constructed, and the level of detail of key model elements including energy markets and the agricultural sector.

Across the economic simulation models there are hundreds of parameters that must be defined for each region and time period of analysis [30]. These include, for example, assumptions regarding trends in technological advancements and growth in crop productivity, input-output ratios, types of available inputs, responses to price signals, yield and price elasticities, land availability and conversion costs, and substitutability among products, all at varying levels of spatial and temporal aggregation [8]. The present evaluation does not compare all differences in model structure, internal constraints, and parameter selection, as the diversity of these model elements is vast and differences are obscured by interactions and non-linearities that prevent a direct comparison [31]. Instead, we focus on high-level reasons for differences in modelled projections and estimates of program effects.

3. Results

3.1. Study attributes

3.1.1. Geographic scope and resolution—Of the 15 economic simulation studies that we assessed, eight used global models to determine LUC attributable to biofuels, including GLOBIOM and ADAGE (Table 1, models defined in Table footnotes), where the U.S. is represented as a single geographic unit and GTAP and FAPRI, that divide the U.S. into regions. The remaining seven economic simulation modelling studies in our assessment used national scope models including FASOM, BEPAM, PEEL, and REAP. These national models have a more detailed representation of U.S. market activities and use a more refined spatial simulation unit such as county or state. Global simulation models generally projected lower U.S. cropland expansion per billion-gallon increase in biofuel, relative to domestic simulation models (reported range of 0.01–1.45 million acres, averaging 0.43 million acres for global studies versus a range of 0.14–2.45 million acres, averaging 0.99 million acres for national studies). This may be because international models capture global responses of commodity markets to price signals, allowing more production to occur in other regions than under the exogenous assumptions of national models and thus mitigating the pressure on U.S. domestic cropland. Additionally, global models incorporate biofuel production mandates and other policies around the globe, and assume these were unaffected by the U.S. RFS Program.

The geographic scope and spatial resolution of the 14 empirical studies that we assessed vary widely (Table 2, Fig. 2). Five of these studies analyzed land cover change attributable to biofuels across the entire continental US, six studies analyzed at least three states, and three studies analyzed just one state (Fig. 2). Across all of these empirical studies the spatial resolution was based on parcel, county, or grid cell level data on LUC (Table 2). This level of granularity refines estimates of where the effect of biofuels may have occurred on the landscape relative to economic simulations that report at regional or national scales.

3.1.2. Time period—The time frames over which each study in our assessment evaluated LUC is highly variable (Fig. 3). Economic simulation studies were more likely to estimate the effects of a policy scenario prospectively, to generate projections of likely future effects. Exceptions include Taheripour et al., 2020 [26], Bento et al., 2015 [32], and Chen & Khanna 2018 [33], which estimated effects retrospectively, but for different periods (i.e., 2004–2016, 2009–2015, and 2007–2012, respectively). On average, economic simulation studies evaluated 15-year time frames, while empirical studies' time period of interest was limited to available historical data and on average evaluated effects over a 7-year period.

Few studies reported effects over subsets of their aggregate period of interest. Li et al., 2019 [34] evaluated biofuel induced LUC over 2003–2014, but also in subsets of this period including 2003–2012, 2008–2012, and 2008–2014. Similarly, Taheripour et al., 2020 [26] reported effects from the CGE modeling separately over 2004–2011 and 2011–2016. This additional temporal disaggregation allowed these studies to evaluate the temporal variability of biofuel effects on LUC over their full study period. Differences in study time periods and level of disaggregation are important, as US. biofuel production has experienced a non-linear ramp-up, with rapid expansion from 2004 to 2011, followed by slower growth from 2011 to the present (Fig. 1). Indeed, Taheripour et al., 2020 [26] reported that net cropland expansion attributable to biofuel policy was higher over 2004–2011 (when they project 1.01 million acres of expansion) than over 2011–2016 (when they project 0.16 million acres of expansion) (Table 1).

For the purposes of evaluating the potential effects of the RFS Program, it is advantageous to cover the entire period of growth of the industry (e.g., 2002–2013), and especially of the growth during the enactment of the RFS Program (i.e., 2006–2013). Notably, only four empirical or economic simulation studies included the entire 2002–2013 time span, and only seven included the 2005–2013 time span (Fig. 3). We also acknowledge that since the RFS Program is applied to a dynamic market, there is little reason to expect the effect of the Program to be constant over time.

3.1.3. Scenarios and treatments—The economic simulation modelling studies we reviewed determined the effect of the RFS Program on LUC by comparing a baseline scenario in the absence of the policy to a scenario in which the RFS Program is in place (Table 1). Across the studies, the policy targets represented similar levels of biofuel production. Those studies that took a retrospective approach used policy scenarios based on actual RFS mandates or observed quantities of biofuel or ethanol production or consumption [26,33]. Studies which took a prospective approach generally estimated the effects of reaching 15 BGY of corn ethanol in 2015 and maintaining this level of production for the length of the study period.

Overall, there is variability in how economic simulation studies set their baselines. Most assumed that an observed level of ethanol or biofuel production in the recent past would stay constant through the simulation horizon, for example at 2001 levels [37,39], 2004 levels [41], 2006 levels [42], 2007 levels [33,43,44], or 2010 levels [40]. For these studies benchmarking production to an earlier year, when biofuel production was lower, resulted in a larger assumed biofuel shock over the study period. For example, Oladosu & Kline 2013 [39] compared a scenario where corn ethanol production stayed constant at 2001 levels to a scenario where production increased to 13.3 BGY (a difference of 11.6 BGY), while

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Cai et al., 2013 [40] compared a scenario where production stayed constant at 13.3 BGY to a scenario where production increased to 15 BGY (a difference of just 1.7 BGY). If no other treatment was included other than the RFS Program, then any increase relative to the baseline was attributed to the RFS.

Four studies simulated a baseline without the RFS Program, either parameterizing biofuel quantities based on external sources or simulating the conditions during that period [5,26,35,36]. EPA 2010 [36] relied on projected biofuel quantities released by the Energy Information Administration's 2007 Annual Energy Outlook (AEO) [45], which included ethanol and fuel policies prior to the RFS2. Similarly, Malcolm et al., 2009 [35] set baseline biofuel demand equal to the 2007 USDA Long-Term Projections, an analysis which also incorporated existing domestic and international biofuel policies, but which results in projections that are approximately constant [46]. USDA projected 13.3 BGY corn ethanol production in 2015, while AEO projected 11.1 BGY in the same year (Table 1). Taheripour et al., 2020 [26] used an approach to simulate baseline biofuel production in the absence of the RFS Program using factors expected to influence biofuel production, such as non-RFS federal biofuel programs, increasing oil prices, octane, and international biofuel demand. This allowed that study's scenario design to disentangle the estimated effects of the RFS Program from some of the other concurrent policies and influences on biofuel production and resulting LUC. Interestingly, simulated trends in U.S. cropland scenarios without biofuel expansion varied significantly, for example Chen and Khanna 2018 [33] assumed a 17 million acre increase from 2007 to 2012, in contrast to Taheripour et al., 2020 [26] who assumed cropland would decrease by 6.3 million acres from 2004 to 2011. Although simulating dynamic biofuel production levels for the baseline case still requires input assumptions of other macro- and technoeconomic parameters, it can help to improve consistency across the baseline and biofuel shock scenarios.

Of the empirical studies in our review, six estimated the effect of crop or corn prices on LUC (Table 2). Another nine empirical studies used a spatial approach and estimated the effect of ethanol plant proximity and/or capacity on LUC. Only one empirical study examined the effect of both corn/crop prices and ethanol refinery capacity simultaneously [34]. The studies which estimated the impact of crop or corn price increases on LUC do not disentangle price changes due to the RFS Program from price changes due to other concurrent influences on prices (e.g., other biofuel policies, oil prices, international demand). As with the simulation studies, empirical studies which only included one treatment (e.g., ethanol production or corn/crop price) are likely to associate any estimated effect to the treatment evaluated. It is possible to pair estimates of LUC price elasticity with previously derived estimates of the effect of the RFS Program on crop prices, to generate estimates of total RFS Program-induced LUC [47]. However, it is also worth noting that the estimated effects of U.S. corn ethanol policy on corn price changes span a large range [48].

3.1.4. Land use change outcomes—The economic simulation model studies in our review used a wide variety of land cover input data and tracked different types of LUC (Table 1). In addition to land cover resolution, land cover definitions varied widely by source, with some models focusing solely on changes to total cropland, others including specific crops, and still others including specific transitions from other cover types, such as forest, pasture, and cropland pasture. When detailed land cover change types were represented the simulation could account for differences in agricultural productivity and regional availability of inputs (e.g., labor, water, and suitable land). Also, there are considerable differences in what mechanisms are used to model land transitions ranging from conversion costs, logit functions, and various approaches that allow for land to transition to its highest economic use. Across all studies examined, most reported a change in overall crop area from of a biofuel shock, while several reported changes in corn acreage specifically, and four reported changes in land in the Conservation Reserve Program (CRP).

Of the empirical studies we reviewed, three estimated the effects of a given treatment on crop acreage in aggregate, six estimated effects on corn acreage specifically, and three estimated effects on both crop and corn acreage (Table 2). Three studies estimated the effects of biofuel policies on enrollment in the CRP. All of the empirical studies in our review used the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) data as a primary input for price estimates, relying either on the Cropland Data Layer (CDL) [60] or NASS reported county level statistics on corn acreage, crop acreage, and CRP enrollment. The degree to which these input data were modified also varied by study. For example, Motamed, McPhail, and Williams 2016 [57] summarized the area of crops and corn from the CDL pixels within 10 × 10 km grid cells, while Secchi et al., 2011 [58] manually modified continuous soybean rotations to soy-corn rotations to better reflect Iowan soy cultivation patterns, Stevens 2015 [59] mapped CDL data onto Common Land Units to better represent field-level dynamics, and Lark et al., 2021 [47] generated land cover trajectories categorizing temporal trends into stable, intermittent, and one-time converted cropland following [10]. The variety of differences among empirical studies suggests that comparisons at fine spatial scales may be inconclusive, although aggregated results at larger scales may be comparable. Large differences among these empirical studies has been noted in the literature [61], with recommended approaches beginning to emerge that would increase comparability among studies [62].

3.1.5 Biofuel types—All of the assessed economic simulation studies estimated the effects of the observed or expected increase in corn ethanol, and several studies explicitly included other biofuel types including soybean biodiesel (five studies) and advanced biofuels including various types of cellulosic ethanol (six studies) (Table 1). The inclusion of advanced biofuels is more common among those studies which examined effects of the RFS Program farther into the future, as in CARB 2014 [41], Cai et al., 2013 [40], and Chen et al., 2021 [44], when production of these biofuels are anticipated to increase. None of the studies explicitly included diesel from fats, oils, and grease, which currently make up roughly half the biodiesel pool in the U.S.

The empirical studies that focused on the effect of crop price increases on land use change implicitly considered the effects of all biofuels, as price increases can be attributed to the aggregate effect of all biofuels. The studies in our review that focused on the LUC effects surrounding ethanol refineries intended to examine the effects of corn ethanol on LUC. However, even the studies which focused on biorefineries did not decompose land use change attributable to the refinery – which could reasonably be assumed to be due to corn ethanol specifically – from those changes due to crop prices – which could be due to all factors that influence crop prices. The exception was Li et al., 2019 [34] which used instrument variables to separate the attributional effects from corn/crop price from the attributional effect of ethanol capacity, on corn and cropland acreages. This is advantageous from the perspective of attribution estimation but was uncommon among studies.

3.1.6. Economic simulation model type—Two broad classes of economic simulation models - partial equilibrium (PE) and computable general equilibrium (CGE) models - have been used to estimate the effect of biofuel policies [8]. PE models focus on the sectors of the economy relevant to biofuels including agriculture, forestry, and the energy sectors, and assume that conditions in the rest of the economy do not have feedback effects. PE models encompass detailed representations of the economic and biophysical relationships within modelled sectors, requiring influences from macroeconomic variables and sectors outside of the model scope to be exogenously determined. On the other hand, CGE models represent economy-wide dynamics and links between sectors, however they include less detail on land use by crop and region [36].

Among the studies we reviewed, we found that analyses using PE models generally reported larger RFS Program-induced LUC quantities compared to analyses using CGE models, both in absolute terms and relative to the projected quantity of additional biofuel (Table 3). PE models reported a range of 0.14–2.45 million acres of net cropland expansion per billion-gallon per year increase in biofuels (averaging 0.80), while CGE models reported a range of 0.01–0.38 million acres (averaging 0.23) (Fig. 4). This may be because PE models have fewer possibilities overall for economic adjustment given their smaller economic scope [63]. PE models often incorporate a broader range of response behaviors within their focus markets relative to CGE models, however responses from other markets cannot be captured through linkages in labor, capital, materials, and energy input markets across the economy, limiting the overall ability to dissipate the effect of a biofuel policy shock. This also corresponds to findings that PE models generally report larger effects of biofuel policy on crop prices [48]. Those studies in our review using PE models that represent only the agriculture sector, including REAP and BEPAM, indeed reported some of the largest estimates of LUC due to biofuel policies [35,44]. Another reason for the larger estimates of LUC from PE models is that CGE models can have higher implicit supply elasticities relative to PE models, resulting in less production change given a price change [64].

The degree to which a PE or CGE model is preferred for a particular sector depends on how interconnected that sector is to the broader economy in the actual market. Market connectedness is often measured by price relationships, or the existence of cross-price effects. Biofuels are moderately linked to other sectors in the economy, in that changes in biofuels do not likely affect commercial activities like consumer spending or housing stocks, but are also not a small, isolated sector such as aquaculture. Biofuels are a major link between agriculture, energy, and transportation markets, primarily utilizing agricultural sector inputs to blend with petroleum for consumption. Thus, CGE or other models that incorporate all of these linked sectors (i.e., agriculture, energy, transportation) may be preferred in theory, but only insofar as the CGE models include important market detail (e.g., oil price effects on ethanol and octane). The importance of the inclusion of these details depends on the research question being asked. For our study on the effects of the

RFS Program for the entire period these details may be important, whereas for questions about the future effects, inclusion of factors that have long since ended (e.g. VEETC, MTBE phaseout) may be less important.

3.1.7. Economic simulation model components—The reviewed economic simulation modelling studies vary in terms of whether they represent biofuels trade and the energy sector, which have substantial influence on resulting LUC estimates. For example, biofuel trade representation allows production to take place where it is most competitive, and endogenously determines how much domestic biofuel production is needed to meet a given production target. However, trade is also affected by trade policies, and thus the market and the model may diverge if these details are not included. Energy sector representation allows models to endogenously determine baseline biofuel demand that reflect changes in energy markets. Since gasoline and ethanol are direct substitutes in the production of gasoline, up to the ethanol blend wall [65], the ability for models to consider ethanol in energy sector representation is important. Furthermore, detailed transportation sector considerations, such as vehicle technology and consumer preferences, influence demand for transportation energy inputs including ethanol.

Several of the economic simulation models reviewed here provide detailed agricultural sectoral representation, such as differentiation of livestock feed types, land conversion dynamics, and crop intensification options. For example, nearly all models evaluated incorporated distillers dried grains and solubles, a byproduct of ethanol processing that can substitute for a certain proportion of an animal’s feed requirements. Also, models such as BEPAM, FASOM-GHG, and GLOBIOM include pasturing of animals, grazing alternatives, and detailed feed mix options where feedstock proportions can adjust so as not to compete with biofuels.

The studies in our review vary in terms of how land conversion is parameterized, based on land cover definitions included in the model, land substitutability parameters, conversion costs, and land protections. Disagreement among definitions of cropland, pasture, cropland-pasture, forestry, grassland and shrubland influence projections of conversion into crop production, as land transition possibilities are land cover dependent. Additionally, certain models do not allow the possibility of natural (or unmanaged) lands to be included in commercial use, as in the case of GTAP-BIO. CGE frameworks generally include land transitions through an elasticity of transformation function based on relative yields and prices, while PE models typically used constrained optimization with conversion costs and varying yield assumptions across land types. Last, land protections vary by region and land type and exclude certain land types from conversion. The summation of these model features ultimately determines the land available for conversion.

In addition, intensification in agriculture production is included in some form across all simulation models, but different models consider different potential intensification mechanisms such as fertilizer application, irrigation, optimization of crops across regions, and pest management. PE simulation models commonly reflect multi-dimensional production possibilities across a range of inputs and production techniques. Inputs typically include land, labor, water, fuel and fertilizer, and production variants include crop types, regions, fertilizer rates, pesticide application, and irrigation and tillage practices. Each production schedule generates a given level of crop output, greenhouse gas emissions, and other environmental effects tracked by the model. Domestic PE agricultural sector models and the global GLOBIOM model leverage biophysical crop models and statistical analyses to incorporate yield responses from a broader range of such management practices, typically at a sub-national level. The ultimate production decision in the model solution is determined through profit maximization by the producer, weighing the marginal cost of production with the marginal benefit of production. Intensification in the CGE context varies from linking price and yield through an intensification response parameter as in GTAP, to allowing for continuous substitution across inputs often using a constant elasticity of substitution function.

3.2. LUC estimates

3.2.1. Economic simulation model studies—The economic simulation studies we reviewed all reported increases in net cropland due to the policy treatment, though the range in estimates is large (Table 3, Fig. 4). Estimates in absolute terms range from 0.01 to 14.6 million acres of additional cropland relative to a baseline in the absence of the RFS Program (median: 3.95). Adjusting for differences in the magnitude of the modelled policy shock, this corresponds to a range of 0.01–2.45 million acres of net cropland expansion per billion-gallon increase in biofuel volumes (median: 0.41).

Of the four studies that examine the role of CRP lands, all but Chen and Khanna 2018 [33] reported that the majority of estimated cropland expansion occurred on expiring CRP land. Since 2008, when the Food, Conservation, and Energy Act required a reduction in CRP enrollment from 36.8 million acres to no more than 32 million, CRP enrollment has declined [66]. Three studies report effects over more than one time period, but there is mixed evidence of a temporal trend in RFS Program-induced LUC. Taheripour et al., 2020 [26] found substantially less cropland expansion in the five years after 2011 compared with the five years before 2011, while Bento et al., 2015 [32] reported more net cropland expansion in the four years after 2012 compared with the four years before 2012. Khanna et al., 2020 [43] reported equal amounts of LUC in the period prior to and after 2017. Lark et al., 2020, like Taheripour et al., 2020, reported higher levels of cropland expansion in the earlier period (2008–2012) compared with the later period of study (2012–2016). This is consistent with the expectations of higher levels of LUC during the period of increased domestic demand. After roughly 2013, the U.S. gasoline pool was effectively at the blend wall, so unless foreign demand and exports increased, we would expect this decrease in domestic demand and corresponding LUC.

3.2.2. Empirical studies—Despite differences, there is broad agreement among the 14 reviewed empirical studies that the effects of biofuel treatments examined led to an increase in crop and corn extensification (Table 2). However, the econometric studies had so many fundamental differences (three examined proximity to biorefineries, five examined biorefinery capacity, two examined crop price, three examined corn price, and one examined ethanol capacity and prices) that sample sizes were too small to draw meaningful statistics. Thus, we provide a brief narrative of the set of studies by common approach.

Those studies which estimated the effect of ethanol plant proximity on land use agree that LUC is more likely closer to ethanol plants. Brown et al., 2014 [50] reported that a 1% decrease in distance to ethanol refineries in Kansas corresponded to a 5–15% increase in corn acreage over 2007–2009. Stevens 2015 [59] reported a 300,000 acre increase in corn area within 30 miles from refineries in four midwestern states over 2002–2014. Wright et al., 2017 [11] reported an 11 million acre increase in crop acreage within 25 miles of refineries across the country over 2008–2012. If we focus on the same states as in Stevens and annualize the estimated LUC within a 25 or 30 mile buffer, Wright et al. reported an 86,000 acre increase in aggregate crop acreage per year while Stevens reported a 25,000 acre increase in corn acreage specifically.

Those studies which estimated the effect of ethanol refinery capacity reported that LUC increases with increasing local ethanol plant capacity [51,56]. Motamed et al., 2016 [57] reported that a 1% increase in refining capacity will increase crop acreage by 1.5% and total cropland acreage by 1.7% across 12 midwestern states. Li et al., 2019 [34] reported a notably smaller effect, estimating that a 1% increase in a county’s effective ethanol capacity would lead to a 0.03–0.30% increase in corn acreage and a 0.02–0.03% increase in total crop acreage. Li et al. estimated the effect of both refinery capacity and crop prices and argued that estimates of the effect of refinery capacity can be biased if the model does not also include crop price effects, due to omitted variables. They further demonstrated that the effect of price increases on crop acreage was larger than the effect of refineries by a factor of three, further emphasizing the magnitude of this potential bias in studies which focus on refinery characteristics alone.

The empirical studies which focused on the effect of crop prices (Table 2) reported increasing area of planted corn and crop due to increasing prices, though the magnitudes of these estimated effects vary. Of the studies which estimated the effect of a 1% increase in crop price nationally, Barr et al., 2011 [49] reported a 0.01–0.03% increase, and Li et al., 2019 [34] reported a 0.07–0.08% increase in net cropland area. In 8 midwestern states, Langpap & Wu 2011 [55] reported a 0.06–0.14% increase in crop acreage due to a 1% increase in crop prices. Effects of a 1% increase in corn prices are larger: Secchi et al., 2011 [58] estimated a resulting 0.16–0.56% increase in cropland in Iowa, Hendricks et al., 2014 [52] reported a 0.29–0.40% increase in corn acreage in three midwestern states, and Li et al., 2019 [34] estimated a resulting 0.18–0.29% increase in corn acreage nationally.

There is limited evidence from empirical studies that ethanol plants have an impact on CRP enrollment. Krumel et al., 2015 [54] reported that ethanol plant expansion of 139 million gallons will result in a 0.05–0.06% increase in early exit from the CRP. Secchi et al., 2011 [58] reported that a 1% increase in corn price will lead to a 0.7–1.5% decrease in CRP land. On the other hand, Ifft et al., 2019 [53] found that a 100-million-gallon increase in ethanol capacity results in 13% less land leaving the CRP. The authors attributed this unexpected finding to other programmatic changes to the CRP that were concurrent with the expansion in biofuel production, including crop price increase, and other local factors correlated with ethanol plant locations.

3.2.3. National-scale historical evaluations—After assessing the broader literature, we further examined the subset of studies which estimated the historical nation-wide impacts of the RFS Program (rather than prospective studies examining potential future effects of the Program). Retrospective studies have the benefit of at least one set of observations against which to compare to a counterfactual scenario, while prospective studies are required to simulate two unobserved scenarios. There is substantial uncertainty across many parameters needed for prospective modelling exercises, including for example macroeconomic trends, the pace of technological advancements, the role of advanced biofuels, and trends in international agricultural production.

We identified six studies which were national in scope, attempted to isolate the RFS Program as a driver of LUC by controlling for other factors known to influence LUC, and reported net cropland expansion retrospectively beginning in at least 2010 when the RFS2 went into full effect. Three economic simulation studies met these criteria and reported an increase of 1.0 million acres over 2004–2011 and 0.2 over 2011–2016 [26], 1.0 million acres over 2009–2012 and 1.5 over 2012–2015 [32], and 3.2 million acres over 2007–2012 [33]. Three empirical modelling studies also met these criteria, and reported net cropland increase of 2.7 million acres within 50 miles from ethanol refineries – their likely range of influence-over 2007–2012 [11], 2.1 million acres over 2008–2016 due to estimated crop price increases attributable to the RFS Program [47], and 4.8 million acres over 2003–2008 and 2.3 million acres over 2008–2014 due to ethanol refinery capacity while controlling for crop price effects [34]. By narrowing to these six studies, our best estimate of the *historical* effects from the RFS Program was a net increase of 1.1–7.0 million acres of cropland nationally.

4. Discussion

Economic theory suggests that redirecting crop production to biofuels will result in increasing crop prices, and direct and indirect expansion of the area devoted to crop production. Indeed, all of the studies in our review, spanning scales from state to global assessments, reported that biofuel policies increased the area of cropland in the U.S. However, the range of biofuel induced LUC estimates reported in the literature is large, due in part to dramatic differences in empirical and economic simulation models including differences in geographic and temporal scope, scenario and treatment design, land cover outcomes, biofuel types considered, and model attributes [67]. Across computable general equilibrium (CGE) and partial equilibrium (PE) economic simulation model studies we found a range of 0.01–2.45 million acres of net cropland expansion per billion-gallon increase in biofuels. Empirical approaches reporting national-scale estimates fall within this range, reporting 0.38–0.66 million acres per billion-gallon increase. Empirical studies had a much smaller range of estimates and were closer to PE approaches than CGE.

This is one of the first reviews to examine the growing body of empirical estimates of cropland expansion due to U.S. biofuel policy, and to compare those to the degree possible with simulation modelling studies. We find that range in the empirical estimates of nation-wide net cropland expansion per billion-gallon increase in biofuel production is narrower than estimates based on economic simulation models (Fig. 4). However, this may be due to the relatively smaller number of empirical studies reporting national-scale results (three, versus nine PE models and six CGE models). It may also be due to the diversity of parameter inputs required in economic simulation approaches that compound uncertainties. In addition, we find that reported cropland expansion from national-scale empirical estimates fall within the range of estimates based on PE models, but are generally larger than estimates based on CGE models. This may be because PE models better reflect regional land management decision making in more detail, more closely corresponding to the treatment effects investigated by empirical approaches.

The empirical studies included in this review base their estimates on economic (price changes) and/or spatial (proximity to ethanol refineries) treatment effects. On the other hand, economic simulation models incorporate both influences within a framework that permits producers a broader range of responsive behaviors with a welfare maximization objective, including both extensification and intensification. These models vary considerably in which data, parameters, or assumptions affect the responsiveness of LUC to crop prices and/or ethanol capacity. For example, crop price responses are mediated by factors including production intensification and trade. With respect to ethanol capacity expansion, simulation models often treat feedstock, location, capacity, and production as endogenous to macroeconomic conditions and policy in the agricultural and/or energy markets. Further, these models generally make a simplifying assumption regarding the absence of market distortions such as monopolistic competition, tax incentives, imperfect information, and barriers to entry. Thus, even when empirical and economic modelling approaches are based on common input data and have harmonized geographic and temporal scopes, the differences in representation of price and refinery influences and market realities leads to the production of differing estimates of LUC attributable to biofuel policy.

4.1. Recommendations

Based on our review we identified several research gaps that will be critical to address in future efforts to evaluate the effects of the RFS Program on land use change dynamics. These priorities include:

1. Improving methods to isolate RFS Program impacts – A key priority is better isolation of the RFS Program effects from other factors influencing biofuel production and consumption. There have recently been important advancements in this effort, including refinement of model sector detail and economic breadth to support endogenous baseline biofuel production that reflect these influential factors [26]. Empirical approaches that capture a broader range of potential drivers of cropland expansion are also needed. For example, a recent study evaluating the impacts of both refinery capacity and crop prices on LUC demonstrated the value of decomposing the relative influences of different treatment effects [34]. Building on these efforts will be necessary to evaluate the role of individual biofuel policies in isolation.

2. Expanding the types of biofuels considered – We chose to focus our assessment on corn ethanol, in part because of the large role corn ethanol plays in the U.S. market, and because there have been relatively few evaluations (simulation or

empirical) of the role of soy biodiesel and other biofuels as drivers of LUC nationally. Expanding the body of research focusing on soy biodiesel and other biofuels is necessary for comprehensive evaluation of the RFS Program.

3. Extending the time frame of evaluation - Just six economic simulation modelling studies and two national-scale empirical studies evaluate a period starting in 2006 or earlier, when the RFS1 went into full effect. Extending the time frame of evaluations to include investigation of RFS Program impacts prior to 2008 is critical. Leveraging the historical record of satellite imagery available prior to 2006, and increasingly sophisticated approaches to estimate treatment effects based on such imagery [68], will be one approach to filling this gap.

4. Building model intercomparisons - Given that different models have different strengths and applications to a particular regulatory or scientific need, complete harmonization is not expected [7]. However, a model inter-comparison effort, in which a set of models are driven by harmonized input parameters and assumptions to isolate differences due to model structure, may be a valuable step towards improving our understanding of variation among model outputs and narrowing the range in reported estimates of biofuel-induced LUC, as in Ref. [69]. The earth system modelling community has developed benchmarking data and tools to support intercomparison projects, which may be a useful approach for the land change modelling community to adopt [70]. Edwards, Mulligan, and Marelli 2010 [31] highlight several requirements for effective model intercomparison including dedicated funding, baseline alignment, scenario harmonization, and standards for comparable data formats and reporting. Efforts to isolate highly sensitive input parameters and assumptions, as in Plevin 2016 [71] and Plevin et al., 2010 [23], will also help to identify areas of uncertainty and prioritize areas of alignment. A recent intercomparison effort between GTAP and GLOBIOM models of indirect LUC from sustainable aviation biofuel pathways illustrates that harmonization and alignment of data and assumptions substantially narrowed the gap between assessments [72,73].

5. Integrating model approaches - An ideal simulation modelling study would be global in scope, to account for trade dynamics and international market interactions, and would represent all relevant markets including agriculture, forestry, land, transportation, and energy markets. One approach to reconciling these competing goals is through model integration or harmonization efforts which leverage the relative benefits of CGE or alternative global modelling frameworks that capture important economy-wide interactions, with PE models that have detailed representation of the U.S. land sector. This is similar to what the EPA conducted for the original Regulatory Impact Analysis for the RFS2 [36], harmonizing the FASOM-GHG model for domestic impacts and the FAPRI-CARD to analyze global impacts. Such analyses can involve a significant undertaking, particularly if baseline alignment is expanded to include soft or hard multi-model linkages.

6. Spatially downscaling model outputs - Another potential area of improvement is via spatial downscaling of LUC from economic simulation models. This can be accomplished via models that operate at more refined spatial scales (e.g., state level rather than national). Alternatively, this can be accomplished by linking LUC outputs from economic simulation models to approaches that estimate the relative likelihood of that LUC occurring at fine spatial scales. For example, Mehaffey, Smith, and Van Remortel 2012 [74] designed a methodology for disaggregating the state-level estimate of biofuel induced LUC from FAPRI's CARD model to a pixel scale, by masking unavailable lands and assigning LUC likelihood based on soil productivity. Other spatial downscaling tools such as Demeter, which support spatial disaggregation of LUC projections from integrated human-earth system models, assign likelihood of LUC at a fine scale based on historical patterns of conversion [75]. These approaches can help inform the extent to which LUC is likely to have impacted other environmental metrics of interest that are spatially heterogeneous across large model simulation units. This might include, for example, critical habitats, areas with high carbon stocks, or other landscapes of conservation interest.
7. Improving accessibility of spatial outputs - Measuring and monitoring the effect of biofuel policies on environmental features that vary over fine spatial scales, including for example water quality, biomass, and critical habitats, require spatially refined model outputs that are accessible to a wide range of end users. Just five of the studies we examined produced publicly available mapped results [33,34,47,52,55]. Future studies that take advantage of the growing availability of large scale high spatial resolution data, improve the resolution of the spatial distribution of estimated effects, and make those outputs available and accessible, will contribute to the broader evidence base for detailed biofuel policy impact evaluation.

5. Conclusion

The RFS Program volumetric requirements under EISA end in 2022, and future volumes will be determined by the EPA based on a broad analysis. Understanding the role of biofuels in driving changes to the U. S. landscape is therefore an important part of that analysis. We reviewed 29 studies published since 2008 that linked U.S. biofuel policy to domestic LUC, and detailed methodological differences across simulation and empirical modelling approaches. Our review provides a perspective on the comparability challenges among the breadth of approaches applied, includes a comparison across simulation and empirical analyses, and identifies key research gaps. The reported magnitude of net crop acreage increases due to U.S. biofuel policy vary widely. Studies estimating the historical, nationwide impacts of the RFS Program reported 1.1–7.0 million acres of net cropland expansion resulting from the program. Additional refinements to the modelling and empirical approaches reviewed in this study can further improve our understanding of the land use change driven by biofuels and the RFS Program.

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List of abbreviations:

ADAGE	Applied Dynamic Analysis of the Global Economy
AEO	Annual Energy Outlook
AEPE	Agricultural Energy Partial Equilibrium
AEZ	Agro-ecological Zone
BEPAM	Biofuel and Environmental Policy Analysis Model
CGE	Computable General Equilibrium
BG	Billion Gallons
CDL	Cropland Data Layer
CRP	Conservation Research Program
EPA	U.S. Environmental Protection Agency
EISA	Energy Independence and Security Act
FAPRI	Food and Agricultural Policy Research Institute Modeling System
FASOMGHG	Forestry and Agricultural Sector Optimization Model with Greenhouse Gases
GLOBIOM	Global Biosphere Management Model - Global Biosphere Management Model
GTAP	Global Trade Analysis Project
LUC	Land Use Change
MTBE	Methyl Tertiary Butyl Ether
NASS	National Agricultural Statistics Service
PE	Partial Equilibrium
PEEL-Co	Partial Equilibrium Economic Land-Use
REAP	Regional Environment and Agriculture Programming Model
RFS	Renewable Fuel Standard
USDA	U.S. Department of Agriculture

VEETC	Volumetric Ethanol Excise Tax Credit

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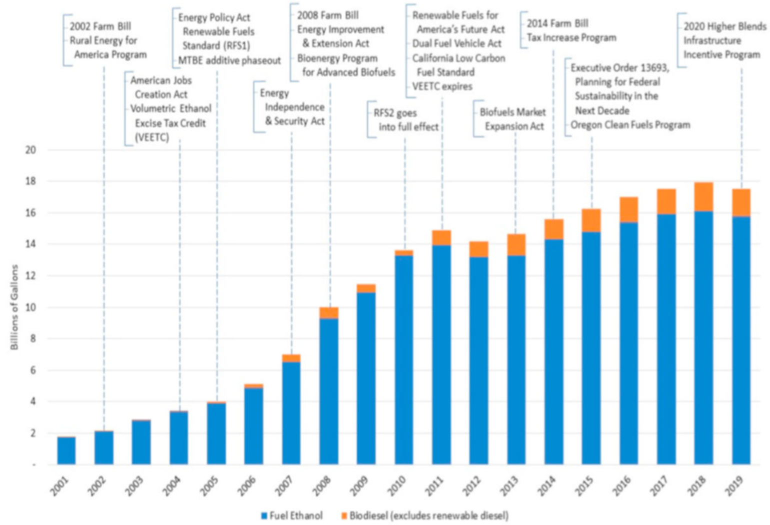

Fig. 1.

U.S. historical biofuel production, and timeline of relevant biofuels policies, 2001–2019.

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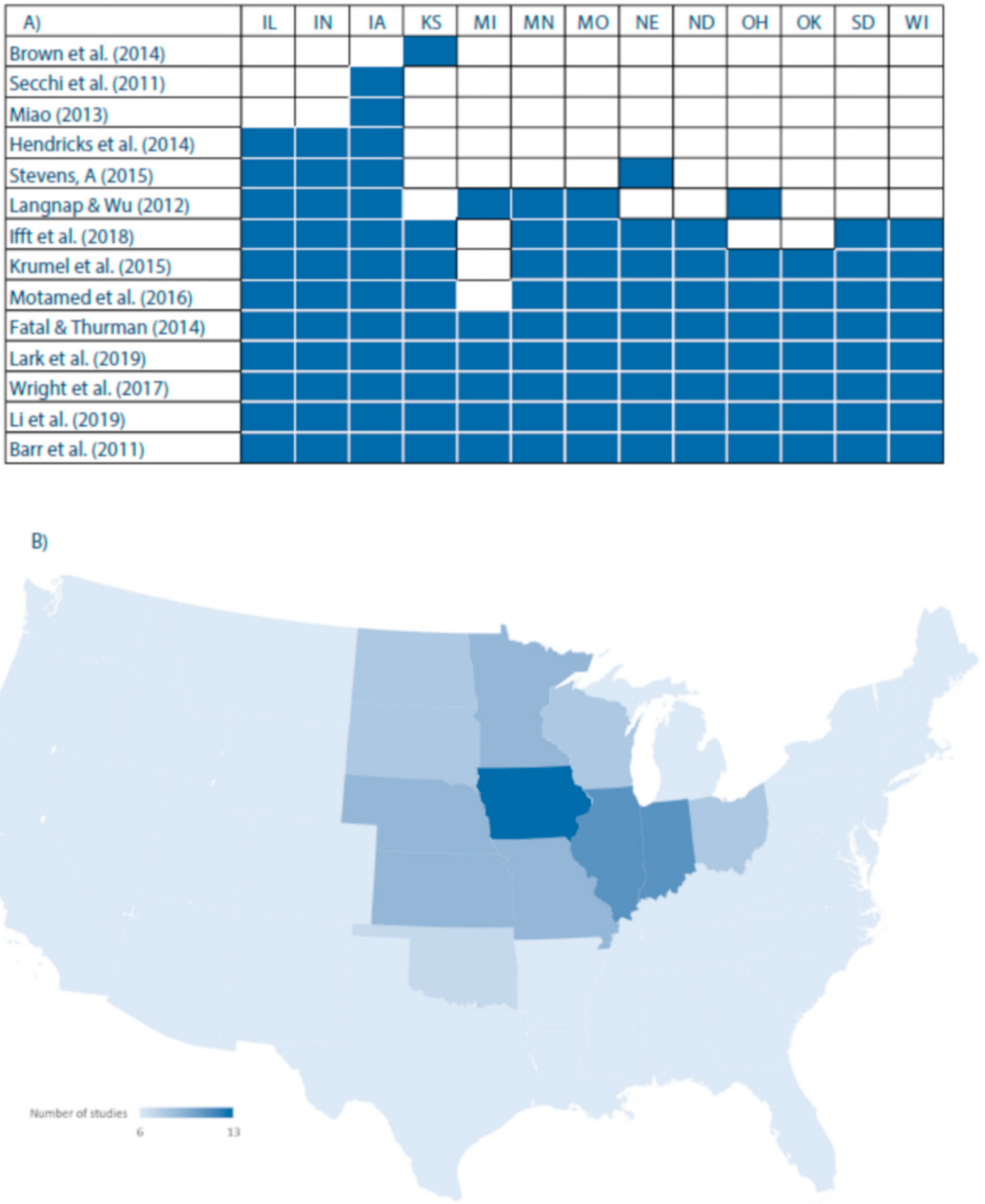

Fig. 2.

The geographic scope of reviewed empirical studies investigating the impacts of biofuel production on LUC. A) The state-level coverage of the empirical studies. B) Map of the number of studies estimating effects of biofuel production on LUC in each state, showing the concentration of investigations in the midwest, with the most studies examining biofuel effects in Iowa, followed by Illinois and Indiana.

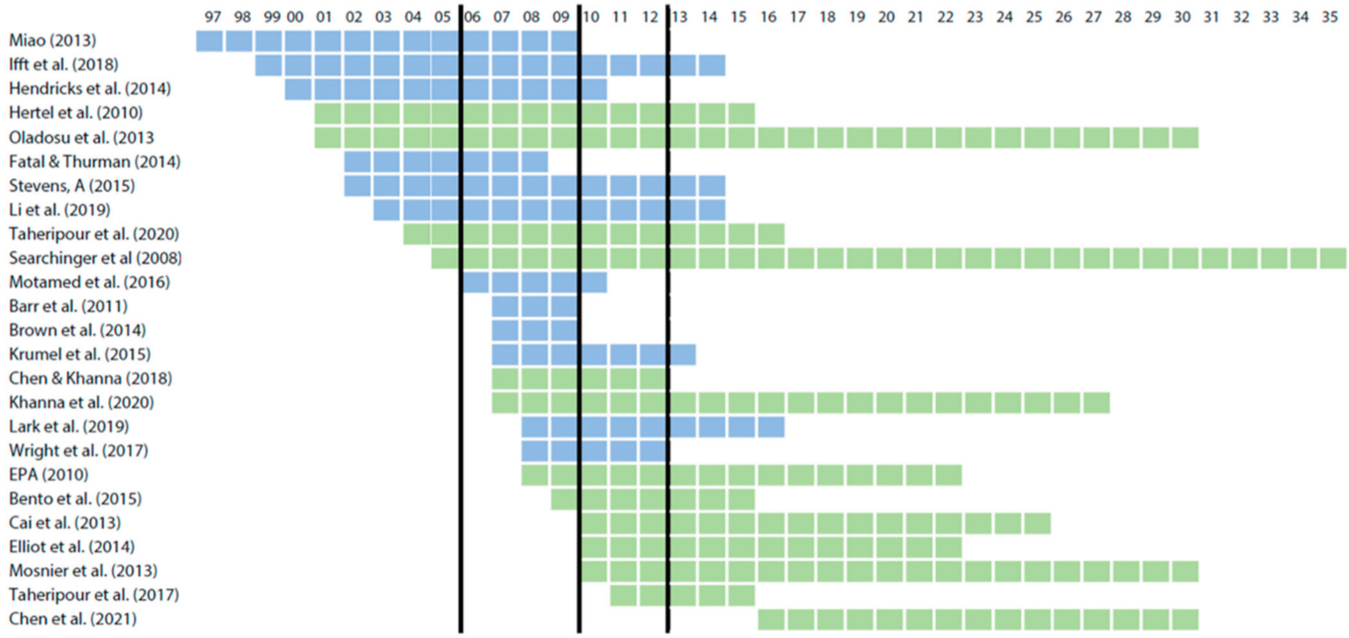

Fig. 3.

Time periods over which each study in our review estimated the effect of biofuel policy on land use change, ordered by first year of analysis. *Blue* = *empirical studies, Green* = *economic simulation model studies. Vertical lines indicate: 2006 enactment of RFS1, 2010 enactment of RFS2, and 2013 the point at which U.S. gasoline consumption approached the maximum ethanol blend in most vehicles (the blend wall).*

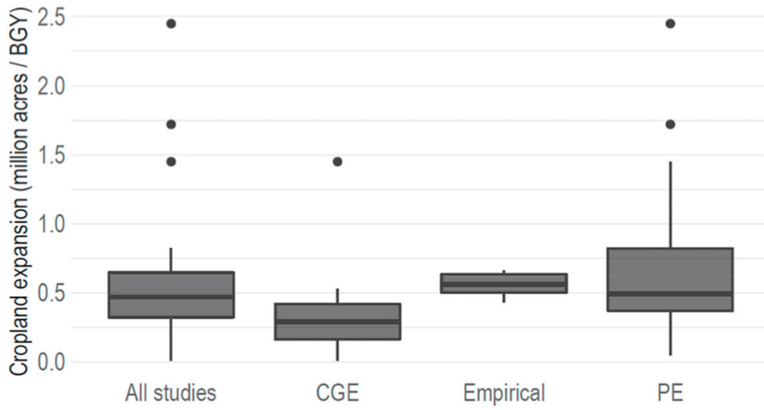

Fig. 4.

Reported net cropland expansion per billion-gallon increase in biofuel production, by study type (Partial Equilibrium (PE) (n = 10), Computable General Equilibrium (CGE) (n = 6), or national empirical modelling approaches (n = 3)). For the purpose of this figure we include the results reported by Taheripour 2020, which use a combined CGE and PE model, in the boxplots for both the CGE and PE studies.

Table 1

Summary of 15 economic simulation model studies assessed, their model type and name, reference and biofuel policy scenarios, the types of biofuels and LUC considered, their spatial extent and resolution, and the study period.

Study	Model Type[a]	Model[b]	Reference scenario	Biofuel policy scenario	Biofuels considered	Land use effect	Spatial extent	Spatial resolution	Study period
Searchinger et al., 2008 [5]	PE	FAPRI	Projected ethanol production in 2016	Ethanol production increases by 14.8 BGY over baseline in 2016	Corn ethanol	Change in cultivated area	Global	Regions (the US is one region)	2005–2035
Malcolm, Aillery, and Weinberg 2009 [35]	PE	REAP	USDA projection of 13.3 BG corn ethanol production in 2015	RFS mandate met in 2015	Corn ethanol	Change in corn, crop, and CRP acreage	Contiguous U.S.	10 US subregions (Aggregated States)	2015
EPA 2010 [36]	PE	FASOM-GHG	2007 AEO projection (11.1 BG of corn ethanol production in 2015)	RFS mandate met up to 2022	Corn ethanol, biodiesel, cellulosic ethanol, and other advanced biofuels	Changes among cropland, cropland pasture, forest pasture, rangeland, private timberland, developed land, and CRP	Contiguous US	63 US subregions (States and sub-states)	2008–2022
Hertel et al., 2010 [37]	CGE	GTAP-BIO	Biofuel production maintained at 2001 levels	13.25 BGY increase in corn ethanol production	Corn ethanol	Changes among forest, pasture, and cropland	Global	AEZs[c] (the US includes 10)	2001–2015
Mosnier et al., 2013 [38]	PE	GLOBIOM	Biofuel production meets RFS2 goals in 2020 (15 BGY corn ethanol, 13 BGY cellulosic ethanol)	Corn ethanol volume reaches 24 BGY and cellulosic 7.5 BGY in 2020	First- and second-generation biofuels	Changes among unmanaged forest, managed forest, cropland, short-rotation tree plantation, managed grasslands, other natural vegetation	Global	50 × 50 km grid cells	2010–2020
Oladosu and Kline 2013 [39]	CGE	GTAP-DEPS	Biofuel production maintained at 2001 levels	Corn ethanol increases to 13.3 BG and biodiesel to 0.5 BG in 2010, and remains at this level through 2030	Corn ethanol, biodiesel, cellulosic ethanol, and other advanced biofuels	Changes among forest, shrub/grassland, agriculture including pasture, and other land use	Global	AEZs (the US includes 10)	2001–2030
Cai et al., 2013 [40]	CGE	ADAGE-Biofuel	Biofuel production maintained at 2010 level until 2025	RFS production mandate is met in 2022	Corn ethanol, Soy biodiesel, Cellulosic ethanol	Changes among cropland, pastureland, managed and natural forest, and natural grassland	Global	Regions (the US is one region)	2010–2022
CARB 2014 [41]	CGE	GTAP-BIO	Biofuel production maintained at 3.41 BGY	Corn ethanol production increases to 15 BGY	Corn ethanol (*the study includes other biofuels, but not simultaneously with corn ethanol)	Changes among forest, pasture, cropland pasture, and cropland	Global	AEZs (the US includes 10)	2004 - no date

Study	Model Type[a]	Model[b]	Reference scenario	Biofuel policy scenario	Biofuels considered	Land use effect	Spatial extent	Spatial resolution	Study period
Elliot et al., 2014 [42]	PE	PEEL-Co	Ethanol production maintained at 2006 level	Corn ethanol production reaches 15 BGY by 2015	Corn and cellulosic ethanol	Changes among cropland and pasture, fallow land, forest, woody wetland, shrubland, and grassland.	Contiguous US	County	2010–2022
Bento, Klotz, and Landry 2015 [32]	PE	Multi-market equilibrium model	VEETC is in place resulting in 12 BGY of ethanol production in 2015	RFS2 replaces or substitutes for the VEETC, resulting in an additional 2.9–3.0 BGY of ethanol production in 2015	Corn ethanol	Corn area increase into non cultivated land, cultivated land, and CRP land	Global	Non-spatial	2009–2015
Taheripour, Zhao, and Tyner 2017 [27]	CGE	GTAP-BIO-ADV11	Biofuel production maintained at 2011 levels	Corn ethanol production expands to 15 BGY	Corn ethanol, soy biodiesel, Cellulosic ethanol	Changes among forest, pasture, cropland pasture, and cropland	Global	AEZs (the US includes 10)	2011–2015
Chen and Khanna 2018 [33]	PE	BEPAM	Corn ethanol production maintained at 2007 levels	Corn ethanol production reaches 13.2 BGY in 2012	Corn ethanol	Conversion of CRP and cropland pasture to cropland	Contiguous US	Crop reporting districts	2007–2012
Taheripour, Baumes, and Tyner 2020 [26]	Combined PE + CGE	GTAP-BIO (CGE) + AEPE (PE)	Simulated historical baseline without the RFS	Simulated historical baseline with the RFS	Corn ethanol, Soy biodiesel, Cellulosic ethanol	Change in cropland in production	Global (CGE) and National (PE)	AEZs (the US includes 10)	2004–2011 and 2011–2016
Khanna, Wang, and Wang 2020 [43]	PE	BEPAM	Ethanol production maintained at 2007 levels	Corn ethanol production increases to observed 2017 level of 15 BGY, and is maintained at this level until 2027	Corn ethanol	Change in the area of corn, soy, other crops, and cropland pasture	Contiguous US	Crop reporting districts	2007–2017 and 2007–2027
Chen et al., 2021 [44]	PE	BEPAM	Biofuel production maintained at 2007 levels	Corn ethanol production increases to 15 BG and biodiesel production increases to 1.6 BG by 2030	Corn ethanol, Soy biodiesel, Cellulosic ethanol	Change in the area of corn, soy, wheat, other crops, and idle cropland	Contiguous US	Crop reporting districts	2016–2030

[a] Partial Equilibrium (PE) and Computable General Equilibrium (CGE).

[b] Food and Agricultural Policy Research Institute Modeling System (FAPRI), Regional Environment and Agriculture Programming Model (REAP), Forestry and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG), Global Trade Analysis Project - Biofuels (GTAP-BIO), Global Biosphere Management Model - Global Biosphere Management Model (GLOBIOM), Global Trade Analysis Project - Dynamic Energy Policy Simulations (GTAP-DEPS), Applied Dynamic Analysis of the Global Economy (ADAGE-Biofuel), Partial Equilibrium Economic Land-Use (PEEL-Co), Global Trade Analysis Project - Biofuels - Including Cellulosic Biofuels (GTAP-BIO-ADV11), Biofuel and Environmental Policy Analysis Model (BEPAM), Agricultural Energy Partial Equilibrium (AEPE).

[c] Agro-ecological zones (AEZs) are regions aggregated by common natural resource characteristics and agricultural productivity.

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Table 2

Summary of 14 empirical studies assessed.

Study	Influence/ Treatment	LUC type	Spatial extent	Spatial resolution	Study period	LUC attributable to the influence/treatment
Barr et al., 2011 [49]	Crop prices	Change in crop acreage	Contiguous US	Non spatial	2007–2009	A 1% increase in the price of crops results in a 0.007–0.029% increase in cropland acreage
Brown et al., 2014 [50]	Ethanol plant proximity	Change in corn acreage	Kansas	5 acre grid cells	2007–2009	A 1% decrease in the distance to a refinery corresponds to a 5–15% increase in corn extensification
Fatal and Thurman 2014 [51]	Ethanol plant proximity and capacity	Change in corn acreage	Contiguous US	County	2002–2008	An additional 1 million gallon of capacity at an ethanol plant results in 5.21 +− 0.68 additional acres of planted corn in a given county.
Hendricks et al., 2014 [52]	Corn prices	Change in corn acreage	Iowa, Illinois and Indiana	Fields (based on the USDA's Common Land Unit boundaries)	2000–2010	A 10% increase in the price of corn results in a 2.9–4.0% increase in corn acreage
Ifft, Rajagopal, and Weldzuis 2019 [53]	Ethanol plant location and capacity	CRP re-enrollment	Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, Wisconsin	County	1999–2014	A 100 million gallon increase in ethanol capacity results in 13% less land leaving the CRP
Krumel, Wallander, and Hellerstein 2015 [54]	Ethanol plant proximity and capacity	CRP re-enrollment	North Dakota, South Dakota, Minnesota, Wisconsin, Nebraska, Kansas, Iowa, Illinois, Indiana, Ohio, Oklahoma, Missouri	County	2007–2013	Average increase in ethanol capacity expansion (of 139 million gallons/two years) corresponds to a 0.05–0.06% increase in early exit from the CRP program.
Langpap and Wu 2011 [55]	Corn prices	Changes in crop acreage	Ohio, Illinois, Indiana, Iowa, Missouri, Michigan, Wisconsin, Minnesota	Fields (based on USDA's Natural Resource Inventories)	NA	A 1% increase in the price of corn results in a 0.06%–0.14% increase in cropland acreage
Lark et al., 2021 [47]	Crop prices	Change in corn and crop acreage	Contiguous US	Fields (based on the USDA's Common Land Unit boundaries	2008–2016	A 30% increase in corn price and a 20% increase in soybean price results in 1.8 million acres of cropland expansion and reduced rates of abandonment by 0.4 million acres, or a net increase in cropped area of 2.1 million acres.
Li, Miao, and Khanna 2019 [34]	Ethanol plant proximity and capacity, and corn and crop prices	Change in corn acreage and crop acreage	Contiguous US	County	2003–2014	A 1 dollar increase in corn received prices will increase corn acreage by 2532 acres (6.3%) and a 1 dollar increase in crop price index will lead to an increase in total crop acreage by 4484 acres (4.8%). When ethanol plant capacity increases by 1 million gallons, corn acreage will increase by 884 acres (2.2%) and crop acreage by 599 acres (0.65%) in counties within 25 miles of a plant.

Study	Influence/ Treatment	LUC type	Spatial extent	Spatial resolution	Study period	LUC attributable to the influence/treatment
Miao 2013 [56]	Ethanol plant location and capacity	Change in corn acreage	Iowa	County	1997–2009	Establishment of a 100-million-gallon ethanol plant increased corn acreage by 8–14%
Motamed, McPhail, and Williams 2016 [57]	Ethanol plant production capacity	Change in corn and crop acreage	Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Wisconsin	10 × 10 km grid cells	2006–2010	A 1% increase in refining capacity increases corn acreage by 1.5% and total cropland acreage by 1.7%.
Secchi et al., 2011 [58]	Corn prices	Change in corn acreage and CRP re-enrollment	Iowa	30 × 30 m grid cells	Non spatial	A 27% increase in corn price leads to a 41% reduction in CRP land and a 15% increase in cropland. A 67% increase in corn price leads to a 65% reduction in CRP land and a 15% increase in cropland. A 96% increase in corn price leads to a 71% reduction in CRP land and a 15% increase in cropland.
Stevens 2015 [59]	Ethanol plant proximity	Change in corn acreage	Illinois, Indiana, Iowa, Nebraska	Fields (based on the USDA's Common Land Unit boundaries)	2002–2014	300,000 acre increase in corn acreage within 30 miles from refineries
Wright et al., 2017 [11]	Ethanol plant proximity	Change in crop acreage	Contiguous US	3.5 × 3.5 mile grid cells	2008–2012	4.2 Million acre increase in cropland within 100 miles from refineries, 2.7 million acre increase within 50 miles, and 1.1 million acre increase within 25 miles

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Table 3

Reported net cropland expansion due to modelled biofuel policies among national studies. Modelled biofuels include corn ethanol in the case of all studies, in addition to soy biodiesel and cellulosic ethanol in the case of Taheripour, Zhao and Tyner (2017), Taheripour, Baumes and Tyner (2020), Oladosu & Kline (2013), Mosnier et al. (2013), Elliot et al. (2014), Chen et al. (2021), Cai et al. (2013), and EPA (2010). We also include in this table the three empirical studies which reported nation-wide impacts of biofuel expansion on net cropland expansion (Lark et al., 2021, Li et al., 2019, and Wright et al., 2017). For these empirical studies we use the observed increase in corn ethanol volumes over the study period as the simulated increase, with the exception of Lark et al., 2021 which attributes a portion of the total observed increase in biofuel volumes to the RFS Program.

Study	Model Name and Type[a]	Time period	Biofuel induced net cropland expansion in the U.S. (million acres)	Proportion of net cropland expansion from CRP land (if reported)	Simulated increase in biofuel volumes from the RFS (BGY)	Net cropland expansion per increase in biofuel volumes from the RFS (million acres/BGY)
Lark et al. 2021 [46]	Empirical	2008–2016	2.1		5.5	0.38
Chen et al. 2021 [43]	BEPAM (PE)	2016–2030	14.6		8.5	1.72
Taheripour, Baumes, and Tyner 2020 [25]	GTAP-BIO (CGE) and AEPE (PE)	2004–2011	1.01		0.7	1.45
		2011–2016	0.16		1.5	0.05
		2004–2016	1.17		2.2	0.53
Khanna, Wang and Wang 2020 [42]	BEPAM (PE)	2007–2017	1.2		8.5	0.14
		2017–2027	1.2		0	
Li, Miao, and Khanna 2019 [33]	Empirical	2003–2012	6.9		10.4	0.66
		2003–2014	7		11.5	0.61
		2008–2012	2.1		4.2	0.50
		2008–2014	2.3		5.3	0.43
Chen & Khanna 2018 [32]	BEPAM (PE)	2007–2012	3.15	31%	6.7	0.47
Taheripour, Zhao, and Tyner 2017 [26]	GTAP-BIO (CGE)	2011–2015	0.01		1.1	0.01
Wright et al. 2017 [10]	Empirical	2008–2012	2.7		4.2	0.64
Bento, Klotz, and Landry 2015 [31]	Multi-market equilibrium model (PE)	2009–2012	0.99	75%	3	0.33
		2012–2015	1.48	84%	3	0.49
CARB 2014 [40]	GTAP-BIO (CGE)	2004–2017	4.45		11.6	0.38
Elliot et al. 2014 [41]	PEEL-Co (PE)	2010–2022	7.2		10.1	0.71
Mosnier et al. 2013 [37]	GLOBIOM (PE)	2010–2020	7.4		9	0.82

Study	Model Name and Type[a]	Time period	Biofuel induced net cropland expansion in the U.S. (million acres)	Proportion of net cropland expansion from CRP land (if reported)	Simulated increase in biofuel volumes from the RFS (BGY)	Net cropland expansion per increase in biofuel volumes from the RFS (million acres/BGY)
Oladosu & Kline 2013 [38]	GTAP-DEPS (CGE)	2001–2030	3.2		11.6	0.28
Cai et al. 2013 [39]	ADAGE-Biofuel (CGE)	2010–2022	3.7		18.6	0.2
EPA 2010 [35]	FASOM (PE)	2008–2022	8.1	65%	17.1	0.47
Hertel et al. 2010 [36]	GTAP-BIO (CGE)	2001–2015	3.95		13.3	0.3
Malcolm, Aillery, and Weinberg 2009 [34]	REAP (PE)	2015	4.9	63%	2	2.45
Searchinger et al 2008 [5]	FAPRI (PE)	2005–2035	5.44		14.8	0.37

[a] Partial Equilibrium (PE) and Computable General Equilibrium (CGE).