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Agricultural expansion induced by biofuels: Comparing predictions of market-equilibrium models to historical trends

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Abstract

Predicting global land use change (LUC) due to biofuel expansion and predicting greenhouse gas emissions attributable to LUC are both complex. This paper has the simpler objective of describing what the weight of historical experience in maize production during the past five decades in the US suggests about how much gross agricultural acreage may need to expand to accommodate higher crop demand and how this compares with predictions in the literature on LUC due to biofuels. We disaggregate historical change in crop production in the US into intensive and extensive margin effects and use the latter to predict a range for LUC due to US maize ethanol mandates. Analysis of historical data suggests that while for brief periods (2 or 3 years) acreage expansion could occur at the high rates predicted by several studies, in the long-run net expansion is likely to be smaller than such predictions.

1 Introduction

Driven by public policies, biofuel production, in particular maize ethanol in the US, has expanded several fold during the past mhade (FAO, 2008, Khanna et al., 2008, De Gorter and Just, 2009). These policies were motivated by the expectation that biofuels can simultaneously both improve fuel security and mitigate greenhouse gas (GHG) emissions. While the impact on fuel security (by reducing the share of imports and/or by diversifying the types and sources of fuel supply) is not a subject of much debate, its impact on the environment is controversial. A majority of the early literature (prior to 2008) on the environmental footprint of biofuels suggested they can contribute to reducing GHG emissions (Farrell et al., 2006, Sheehan et al., 2000, de Carvalho, 1998). Subsequent literature however paints a complex picture. It recognizes that in globalized world, regional or national policies can have large impacts in international markets complicating the calculations especially for a global pollutant such as GHG. Using well-established simulation models of economic and trade policies such as FAPRI/CARD and GTAP, this literature hypothesizes that the allocation of for cropland for maize ethanol will raise world price of agricultural commodities and thereby induce agricultural expansion, a phenomenon referred to as indirect land use change (iLUC), which leads to GHG emissions (from clearing of above ground biomass and from soil) previously unaccounted for in environmental lifecycle assessment of biofuels. It is also hypothesized that when these are accounted for, biofuels, specifically maize ethanol and biodiesel from vegetable oils are more GHG intensive than current gasoline or diesel (Searchinger et al., 2008, O'Hare et al., 2009, Hertel et al., 2010). Although this literature emphasizes GHG emissions, iLUC has implications for a broader range of environmental issues such as biodiversity, soil fertility, air and water pollution etc. (OECD, 2008) As a consquence, major biofuel regulations such as US Renewable Fuel Standard(RFS) (EPA, 2009), California Low Carbon Fuel Standard (LCFS) (ARB, 2009), European Union's Renewable Energy Directiveand UK Renewable Transport Fuel Obligationrequire that policy targets be achieved using biofuels whose land use change related GHG emissions do not outweigh the GHG benefits calculated based on the footprint of direct supply-chain and end-use. In particular, the RFS and LCFS require that every batch of biofuel supplied be identified with an estimate of GHG emissions due to iLUC.

Quantifying global land use change due to the biofuels is a complex task. Predicting GHG emissions related to LUC which requires predicting changes in land management for different categories of land in different parts of the world is another challenge. These are beyond the scope of this paper and so it is not our objective to contribute a new improved estimate of iLUC or its related GHG emissions. Instead, it has a simpler objective of analyzing what historical data on US agriculture, specifically maize production since 1961, suggests about the first part of the problem, namely, how much agricultural acreage may need to expand to accomodate increased crop demand for biofuel and compare this with the current literature on iLUC. Our analysis proceeds in three steps. In the first step we disaggregate the change in agricultural production into intensive margin (change in productivity per acre) and extensive margin (change in acreage) effects. It is worth clarifying here, that we do not intend to identify a causal relationship between acreage and output, but identifying a correlation. In the next step, we develop a simple one-crop, one-region economic model of crop supply and crop demand, which we use to compute the net change in supply due a given ethanol mandate. We show using mathematical proof why the net change supply derived using a one-crop, one-region model is an upper-bound on the net change in supply one will derive using a larger multi-commodity, multi-region model such as the large partial and general equilibrium models of international trade that are employed by the existing literature. Finally, we combine the estimate of the average extensive margin effect and the economic model to predict LUC for US maize. We however do not derive any conclusions whatsoever about the implications of estimates for the lifecycle GHG intensity of maize ethanol or any particular kind of biofuel or any specific biofuel policy. To reiterate, we only aim to estimate iLUC using an alternative approach that is not common in the current iLUC literature. We conclude by comparing the relative advantage and disadvantages of our approach and identifying directions for further research.

2 Literature

While there exists a large literature on biofuels, we focus on the literature that derives quantitative estimates of land use change to biofuels. Within this literature, the assessment of iLUC impacts generally proceeds in two steps. The first step involves the calculation of the land requirement to meet demand for food, feed, fiber and biofuel at any given instant in time (when there exists a market for environmental services, say in the form of price on carbon or price on biodiversity, then the demand for land in such markets can be taken into account in this framework). The current approach is to use regional or national-level economic models of international trade in goods and services to simulate the impact of policy such as biofuel mandate on variables such a prices and consumption of finished goods, intermediate goods and primary inputs etc. Gross LUC within each region is computed as the difference in land consumption between the biofuel policy scenario and a counter-factual scenario. The second step then employs biophysical models of land use to compute the change in GHG emissions from change in land use patterns within each region. The changes in each region is aggregated to compute global iLUC and associated GHG emissions. The study by Searchinger et al. (2008) was amongst the first to use this approach to quantify iLUC. Using the FAPRI/CARD system of partial equilibrium (PE) models of international trade in agriculture, they predict that 15 billion gallons of maize ethanol, which is the US Renewable Fuel Standard target for 2015, will increase global land use by 10.8 million hectares (mha) and the associated average GHG emissions would be 108 gCO_2/MJ per unit of ethanol. This increases the lifecycle emissions per MJ of maize ethanol by 140% (assuming a direct lifecycle value 77 gCO_2/MJ as reported in Farrell et al. (2006)) and implies that lifecycle GHG emission intensity of per MJ of ethanol is almost twice that of gasoline from conventional crude oil. Focussing only on the biophysical aspects of land use change, Fargione et al. (2008) predict that converting rainforests, peatlands, savannas, or grasslands to produce food cropbased biofuels creates a biofuel carbon debt by releasing 17 to 420 times more CO_2 than the annual greenhouse gas (GHG) reductions that these biofuels would provide by displacing fossil fuels. Different from Searchinger et al. who analyze the long-run equilibrium from a large cumulative increase in ethanol, Fabiosa et al. (Fabiosa et al., 2009) analyze the short-run equilibrium from smaller 10% increase in ethanol demand and report a 50% smaller iLUC for each percent increase in ethanol demand. They point out that their land allocation effects may be understated because of large stock adjustments occurring in the short term. Using the modified FAPRI/CARD system of models, and making several changes to Searchinger et al.'s calculations, namely, assumption relating to crop yield projections and oil price, assuming no deforestation within the US, and emplying an alternative model to GREET for direct lifecycle emissions called BESS (which is supposed reflect recent advances in maize and ethanol production technology and hence a lower lifecycle GHG intensity for maize ethanol), Dumortier et al. (Dumortier et al., 2009) compute a iLUC GHG intensity of 21.33 gCO_2/MJ.

Whereas the above studies adopt a partial equilibrium approach, Hertel et al. (2010) use the GTAP computable general equilibrium (CGE) model to compute iLUC. Using more recent data and co-product credits to land usethey calculate that the accumulated global agricultural expansion due to a 13.23 billion gallon increase in maize ethanol would be 4.2 mha and the associated GHG emissions would be 30 gCO_2/MJ per unit of ethanol. This implies an increase in the lifecycle emissions per MJ of maize ethanol of almost 40%. A more recent study by Tyner et al. (Tyner et al., 2010) predicts that a 13.23 billion gallon increase in maize ethanol would only induce a 1.5 million hectare expansion in global agricultural acreage and the associated GHG emissions would not be large enough to render maize ethanol more GHG intensive than conventional gasoline, i.e., even accounting for iLUC emissions maize ethanol is beneficial. This implies an increase in the lifecycle emissions per MJ of maize ethanol by 15%.

The significance of the estimate of 15% is that it implies maize ethanol provides GHG benefits when compared to conventional gasoline even after accounting for iLUC. Taken together with the fact the both the yield of biomass per hectare and the yield of biofuel per unit of biomass are increasing with time and that the oil supply is undergoing a transition towards more GHG intensive unconventional sources (such as oilsands etc.), this suggests that maize ethanol can contribute to mitigating climate change. However, if iLUC raises average GHG intensity by 40% (as imputed from Hertel et al. (2010)) then maize ethanol is likely to be as GHG intensive as gasoline from oilsand, not to mention conventional gasoline. It is worth mentioning that all these studies predict lower iLUC emissions for cane ethanol and cellulosic ethanol which are not yet commercial. In summary, uncertainty about the magnitude of iLUC and the associated GHG emissions, present a major challenge to implementing biofuel regulations that require accounting of indirect emissions.

3 Method and model

3.1 Disaggregating historical change in crop output into intensive and extensive margin effects

To understand the historical relationship between production and acreage, we disaggregate the annual change in output into three parts namely, a change attributable solely to change in productivity per acre holding acreage fixed, a change attributable to change in acreage while holding productivity per acre fixed and a change attributable to both change in acreage and change in productivity. Mathematically, this can be described as follows. Let q denote the annual production, A denote the annual harvested acreage and y the average output per acre. This derives the identity $q = yA$. Given a productivity change, dy, and a change in acreage, dA between two points in time, then the corresponding change in output dq can be expressed as,

$$\begin{aligned} dq &= (q + dq) - q = (y + dy)(A + dA) - yA \\ &= Ady + (y + dy)dA \end{aligned} \tag{1}$$

Then $\rho = \frac{(y+dy)dA}{dq}$ represents the share of the change in output attributable to change in acreage i.e., the extensive margin. $1 - \rho$, then represents the change in output due solely to change in productivity, i.e., the intensive margin. A value of $\rho < 0.5$ implies the major fraction of change in output accrued from change in productivity while $\rho > 0.5$ implies that acreage change contributed the major fraction of change in output. While we can expect that typically $\rho \in (0, 1)$, under certain conditions we may find either that $\rho < 0$ or $\rho > 1$. When acreage increases ($dA > 0$) and yield decreases ($dy < 0$) , say due to adverse weather such that production declines ($dq < 0$) during a given periods, then $\rho < 0$. Alternatively, when acreage decreases ($dA < 0$) and yield increases ($dy > 0$) such that production increases ($dq > 0$), then again $\rho < 0$. In this case output increases while acreage shrinks. When acreage decreases ($dA < 0$) and yield increases ($dy > 0$) and production decreases ($dq < 0$) such that $|dq| < |(y + dy)dA|$, then $\rho > 1$.

Using county level data recorded by the National Agricultural Statistics Survey of the USDA, we calculate ρ for each county in nine major maize growing states (IL, IN, IO, KA, MO, NE, OH, SD, WI) in the US. These states account for approximately 70% of US maize production. We calculate ρ for different time spans such as one, five, ten, fifteen years etc. between the years 1961 and 2009. We then compute a weighted average extensive margin for the 9 state aggregate. where the weight is the ratio of change in output in a given county to the total change in output across all counties. Mathematically this can be described as follows. Let subscript i denote a county within state j and subscript t denote time. The weighted-average aggregate extensive margin between time $t-k$ and t is computed as follows,

$$\rho_t^k = \frac{\sum_{j=1}^{N}\sum_{i=1}^{n_j} \rho_{ijt}^k \Delta q_{ijt}^k}{\Delta q_t^k} \; \forall t \in (1..T) \tag{2}$$

where, N is the number of states, n_j is the number of counties in state j, $\Delta q_{ijt}^k = q_{ij,t} - q_{ij,t-k}$ is the change in output in county i in state j between time $t-k$ and t, and $\Delta q_t^k = \sum_{j=1}^{N}\sum_{i=1}^{n_j} \Delta q_{ijt}^k$ is the aggregate change in output across all counties in all states. When $k=1$, we derive the annual average extensive margin. When $k=5$ we derive the quinquennial average extensive margin and so on.

Figure 1 plots the extensive margin for the annual change in production (ρ_t^1), against annual change in acreage (Δq_t^1), for each year since 1961. It shows that the extensive margin is unstable ranging between -4.372 and 13.00 (not shown in figure) with a simple mean of 0.646. The running mean over a five year period exhibits relatively less instability (as expected) varying between -0.223 and 1.56 with a mean of 0.625. However, a simple mean may be misleading if there is a correlation between extensive margin and the change in the output. When we weight ρ_t^1 by Δq_t^1, the mean decreases to 0.512. The relationship between cumulative quantity change and cumulative extensive margin for different time spans relative to 2009 is shown in figure 2. In other words it shows the extensive margin for the cumulative change for different time spans such as (2008 to 2009), (2007 to 2009), (2006 to 2009) and so on with the last observation being for the span 1980 to 2009. The 5 year cumulative margin excluded, the remaining values range between 0.153 and 0.548. Table 1 lists the mean extensive margin both on an annual basis and cumulative basis for various time spans between 1961 and 2009. The extensive margin on a cumulative basis is generally smaller (the exception being the ρ_{2009}^5) in magnitude than the mean of the annual variation during any given time period (note the difference in the scale of the y-axis between figure 1 and figure 2). This is consistent with the findings in the empirical literature that productivity growth is the major driver of change in the long run(Federico, 2005, Miranowski and Cochran, 1993, Mundlak, 2005, Sunding and Zilberman, 2001). Furthermore, since technology adoption is a gradual process, the relative share of extensive margin in a given change in output will tend to be higher in the short-run than in the long-run. We will use the range of values reported here to predict the range within which indirect land use change may occur in the future as a result of expansion of maize biofuel in the US.

We then compute a weighted average of the cumulative extensive margin, ρ^k, over all pairs of years with a given time span k i.e., $\{t_i, t_i + k\}\forall i \in [1..(T-k)]$. This is computed as

$$\rho^k = \frac{\sum_{t=1}^{T-k} \rho_t^k \Delta q_t^k}{\sum_{t=1}^{T-k} \Delta q_t^k} \tag{3}$$

Given an estimate of ρ^k, we can predict a range for the mean predicted change in acreage from time $t-k$ to t for a given increase in production, dq^k and a projected increase in productivity, $\widehat{dy_t^k}$ as follows.

$$\widehat{dA_t^k} = \rho^k \frac{dq^k}{y_{t-k} + \widehat{dy_t^k}} \tag{4}$$

Figure 3 plots the ρ^k versus k. The simple mean $\bar{\rho} = \frac{\sum_{k=k_0}^{K} \rho^k}{K-k_0} = 0.377$. For $k > 5$, $\bar{\rho} = 0.372$.

The appendix contains a similar plot for soybean in the US.

3.2 Model to compute the impact of biofuel mandate on crop demand and supply

The previous section described an empirical approach to estimate the extensive margin effect which can be used to predict LUC for a given increase in crop demand. In this section we develop a model to compute this increase in crop demand given an increase in demand for biofuel. For this we extend the model of Rajagopal et al. (Rajagopal et al., 2007). To simplify the mathematical exposition, we illustrate this assuming there is only one crop which is used for both food and fuel. In doing so, we are being conservative in that the change in crop supply (and therefore land use) we derive from the one crop model is an upper-bound on the change in supply of the biofuel crop derived when assuming more than one crop which are substitutes and compete for land. This is presented as a formal proposition along with proof in the appendix (see proposition 1 in supporting material). Let us assume that a given crop has two uses, namely, food (subscript f) and biofuel (subscript b). Let p and q denote price and quantity respectively. Let S and D_f crop supply and crop demand for food as a function of price. Let ϵ_s and ϵ_d denote the elasticity of crop supply and crop demand for food consumption respectively. Let Q_b denote the quantity of crop required for producing a given quantity of biofuel, B and Q_0 denote total consumption. Let ϕ denote the co-product credit. The effective crop utilization for biofuel is $Q_b^{eff} = (1-\phi)Q_b$. The market-clearing condition implies that total supply equals total demand

$$S = D_f + Q_b^{eff} = Q_0 \tag{5}$$

To analyze the effect of a increase in the level of the biofuel mandate, let us differentiate the market clearing equation.

$$dS = dD_f + dQ_b^{eff} \tag{6}$$

Using the definition of elasticities of supply and demand, for small increases in crop use for biofuel relative to total crop supply and demand, we have,

$$\epsilon_s \frac{dp}{p} Q_0 = \epsilon_d \frac{dp}{p} D_f + dQ_b^{eff} \tag{7}$$

Rearranging we get,

$$\frac{dp}{p} = \frac{dQ_b^{eff}}{\epsilon_s Q_0 - \epsilon_d D_f} = \frac{(1-\phi) dQ_b}{\epsilon_s Q_0 - \epsilon_d D_f} \tag{8}$$

The net change in crop production is

$$dS = \epsilon_s \frac{dp}{p} Q_0 = (1-\phi) \left[\frac{\epsilon_s}{\epsilon_s - \epsilon_d D_f / Q_0} \right] dQ_b \tag{9}$$

Since $\epsilon_s \geq 0, \epsilon_d \leq 0, 0 \leq \phi \leq 1$ and $D_f/Q_0 \leq 1$, we have, $dS \leq dQ_b$ i.e., increase in crop production cannot exceed increase in crop use for biofuel. We next relate the above expression with empirical model of section 3.1 to develop a relationship between a biofuel mandate and increase in acreage of the crop used for biofuel. Let B denote the initial quantity of biofuel and let η denote the yield of biofuel per unit of crop. Then the quantity of crop required for biofuel, $Q_b = \frac{B}{\eta}$. The change in crop requirement for a change dB in the mandate is $dQ_b = \dfrac{dB}{\eta}$ (assuming η fixed). Using equations (4), (9), and substituting $dS = dq$, we can write,

$$\begin{aligned} \widehat{dA_t^k} &= \rho^k \frac{dq^k}{y_{t-k} + \widehat{dy_t^k}} \\ \widehat{dA_t^k} &= \rho^k \frac{1-\phi}{y + d\widehat{y}} \left[\frac{1}{1 - (\epsilon_d/\epsilon_s)(D_f/S)} \right] dQ_b \end{aligned} \tag{10}$$

We can see that larger the biofuel mandate, larger is acreage expansion ceteris paribus. Similarly, higher the rate of growth in productivity, smaller the acreage expansion ceteris paribus. Similarly smaller the ratio of elasticity of crop demand to elasticity of crop supply, smaller is acreage expansion ceteris paribus.

3.3 Computing global land use change due to change in acreage of biofuel crop

Using an approach similar to that in section 3.2 we can show that if the global average productivity of agricultural land does not decline, then the increase in global agricultural acreage due to a biofuel demand shock cannot exceed the change in acreage of the crop used to produce biofuel (This is stated as proposition 2 with mathematical proof in supporting material). This implies that change in acreage of the biofuel crop is an upper bound on global land use change if global average productivity does not decline when agriculture expands into new lands. Existing estimates in the literature indeed support the hypothesis that net global agricultural expansion is a fraction, $\delta < 1$, of the expansion in biofuel crop acreage. Searchinger et al. (2008) predict an iLUC of 10.8 mha for a 12 million hectare increase in maize acreage ($\delta = 0.9$). Hertel et al. (2010) predict global iLUC of 4.2 mha for a 6 million hectare increase in maize acreage ($\delta = 0.7$). However, in contrast to predicting expansion of biofuel crop acreage due to biofuel expansion which is relatively simple, predicting global agricultural expansion due to increase in biofuel crop acreage is far more complex. Numerical computation or statistical estimation of the latter is beyond the scope of this paper. Therefore, once we compute the expansion of maize acreage using the models described in section 3.1 and 3.2, we simply employ Hertel et al.'s estimate for $\delta(= 0.7)$ to compute global LUC.

4 Numerical exercise

We use the values for the extensive margin (ρ) reported in table 1 to derive a range for expansion of maize acreage in the US in response to US ethanol mandates. Ethanol production in the US was averaged about 1.3 billion gallons during the 1990s reaching 1.46 billion in 1999. Since we would like to compute the effect of increasing maize ethanol production by 15 billion gallons, which is both the target set by the Energy Security and Independence Act (EISA) 2007 and is also the quantity assumed by Searchinger et al. in their 2008 Science paper for computing land use change, we extrapolated ethanol production to reach 16.3 billion gallons by 2017 for a net increase of 14.8 billion gallons since 1999. We use actual data on ethanol production and maize acreage, production and yield between 1999 and 2009. For future ethanol production we use targets under EISA 2007 for the years 2010 through 2015. For the years 2016 and 2017, we assume the same annual increase in ethanol production as for year 2015 stipulated by the EISA 2007. For future productivity of maize per unit of land we use USDA's projections for the years beyond 2009. We also analyze the sensitivity to the ratio of elasticity of crop supply and crop demand (ϵ_s/ϵ_d) whose range is chosen as (-3,-0.5). This is representative of elasticities of supply and demand reported in the literature. For instance Roberts and Schlenker (2010) estimate that elasticity of global supply of food calories is approximately twice the elasticity of global demand elasticities for food calories. While the elasticities themselves tend to be higher in the long run compared to short-run, the ratio is less variable and hence likely to lie within the range -3 to -0.5. We report results for simulation using three different time steps, namely, an annual time step ($\Delta t = 1$), five year time step ($\Delta t = 5$) and nine year time step ($\Delta t = 9$). Since we only model acreage expansion for US maize, in order to derive global iLUC we simply multiply the former by the ratio global iLUC to US maize acreage expansion imputed from Hertel et al. They compute maize acreage expansion as 6 mha and global iLUC as 4.2 mha which implies a ratio of 0.7.

Table 2 shows the sensitivity of US maize acreage expansion to ρ and to ϵ_s/ϵ_d for three different time steps, namely, 1 year, 5 years and 9 years. Our estimates are within the same order of magnitude as that reported in the literature. Figure 4 plots the results for the 9 year time step. Based on the average cumulative extensive margin, $\rho^9 = 0.372$ (the mean over all time spans (k) > 5, see figure 3), and $\epsilon_s/\epsilon_d = -2$, we predict maize acreage expansion in US attributable to 14.83 billion gallon increase of maize ethanol to be 4.41 mha. Using $\rho^9_{2009} = 0.339$, the acreage expansion is 4.02 mha. In comparison, Hertel et al. (2010) predict 6 mha increase for 13.23 billion gallons. Using the multiplier of 0.7, and linearly scaling from 14.83 to 13.23 billion gallons we predict global iLUC to be 2.75 mha and 2.51 mha based on the average 9 year and last 9 year margins respectively.

Finally we calculate sensitivity of iLUC to future yield shocks. For this we assume the yield shock to be a multiplicative uniformly distributed random variable between 0.95 and 1.05. In other words, the shock causes the yield to lie between 95% and 105% of projected yield in a given year. The mean, minimum and maximum iLUC for 10000 trials for cumulative nine year extensive margins, $\rho_t^9 = 0.372$ and $\epsilon_s/\epsilon_d = -2$ were 2.76 mha, 2.69 mha and 2.82 mha respectively. For the nine year period ending in 2009, $\rho_{2009}^9 = 0.339$ the mean, min and max are predicted to be 2.51, 2.45 and 2.57 mha respectively.

5 Discussion

Policy makers are faced with the a need for a reasonable *ex ante* estimate of LUC and LUC related emissions for implementing biofuel mandates and biofuel blending standards such as the RFS and LCFS respectively. The assumption about the role of intensive margin (increase in productivity) and extensive margin (increase in acreage) in meeting crop demand due to biofuel is key to deriving good prediction of iLUC due to biofuels. Beyond biofuels, a good understanding of these two phenomena is crucial to understanding the sustainability of food production. Towards this end, and different from the current approaches for estimating iLUC, we disaggregate the historical trend in relationship between production and acreage into intensive and extensive margin effect and use the latter to predict a range for LUC due to maize ethanol.

Although data suggests that the extensive margin is unstable, it varies with the time span (long-run is generally smaller than short-run i.e, $\rho_t^{k1} < \rho_t^{k2}$ for $k1 > k2$) and it varies over time for a given time span ($\rho_{t1}^{k} \neq \rho_{t2}^{k}$), it also suggests the average cumulative extensive margin lies within a reasonably narrow range $(0.32, 0.38)$ with a mean around 0.37 for a broad span of 6 to 30 years (see figure 3). Using the mean estimate of 0.37 our mean estimate for global agricultural acreage expansion for 14.83 billion gallon increase in maize ethanol is 3.08 mha. This is 34.4% lower than Hertel et al. (after adjusting for the fact that Hertel et al. calculate iLUC for only 13.23 billion gallon increase) and 71.4% lower than Searchinger et al. (2008). If the extensive margin is 0.4 our global iLUC estimate increases to 3.32 mha and if the margin is 0.2 it decreases to 1.66 (multiply table 2 by 0.7). While our predictions are in the same order of magnitude as previous estimates we predict smaller net expansion in the long-run than most studies. The percentage reduction in GHG emissions is likely to be higher than percentage reduction in LUC as a lower estimate of LUC implies less deforestation. Our range of estimates are however almost than twice that of Tyner et al. (2010). It is worth pointing that all estimates including ours refer to gross acreage as opposed to net acreage. With some of the agricultural lands under double-cropping, i.e., multiple harvests of either the same crop (e.g. rice in south asia) or different crops (e.g. wheat and sunflower) the gross harvested acreage is larger than the net harvested acreage. For instance if a fraction α of the gross harvested area (A_g) is double cropped, then the net harvested area (A_n) is $\frac{A_g}{1+\alpha}$. We return to this in the concluding paragraph. Ours is a conservative estimate also for the reason that being a one crop model, we do not incorporate cross price elasticities between crops, which (as we show in the appendix) will lower our estimates further.

Previous estimates on iLUC were derived using more detailed models that have a strong theoretical basis (as in the case of CGE) and/or also capture the interlinkages between multiple economic sectors and regions (as with CGE, PE and mathematical programming models) that determine iLUC. These models also have a long track record in economic and policy analysis. The objective of our paper is therefore not to derive a better estimate but to estimate iLUC using an alternative approach and to compare the predictions from large numerical models against historical evidence. To this end, we derived a direct correlation between output and the extensive margin based on historical data over about five decades (1961 to 2009) from 915 counties across 9 major maize growing states in the US. A strength of our model its transparency to the assumptions that derive the predictions, which in our case are two parameters, namely, the share of the extensive margin in total change in output and the ratio of elasticity of maize supply and maize demand. Our work highlights the need for more empirical research on the contribution of intensive and extensive margins in increasing global agricultural output and on the elasticities of supply and demand for calories. The fact that our estimates are of the same order of magnitude as those from more detailed models serves to improve the confidence in the range of estimates reported in the literature. The method we describe can be applied to generate predictions about iLUC due to sugarcane and more broadly to develop hypotheses about the land intensity of future food supply.

In relying on correlations in historical data for prediction the future, the critical assumption is that the future is structurally similar to the past. However, for a variety of reasons the future may turn out different than the past. For instance, if future agriculture expansion occurs on marginal land with poorer soils and less favorable agro-climatic conditions with lower productivity, productivity growth rate may decline or even become negative. That said, higher agricultural commodity prices which is the driving force for agricultural expansion has traditionally been shown to accelerate adoption of yield enhancing technologies in existing farmland counteracting the reduction in yield, if any due to expansion into marginal land. Hertel et al. (2010) assume these two counter-acting forces offset each other. These are hypotheses for future empirical research.

In addition to biofuel-specific studies of land use change which is the focus of this paper, there is a rich tradition of applied research on economics and management of land. One strand of this literature applies statistical techniques to analyze economic problems, to test economic theory, and to estimate key parameters such as elasticities which partial and general equilibrium models rely on for prediction. Some of the relevant key findings of this literature are the following. High rate of technical innovation has led to a tripling of world-output between 1950 and 2009 while agricultural acreage expanded by less than 30% (Federico, 2005, Mundlak, 2005, Sunding and Zilberman, 2001). Historical analyses suggest that extensification occurs first in order to capture land base and establish ownership rights and intensification begins in earnest only subsequently and that government policies affect both. Extensification was supported homesteading policies and development of the railroad and transportation while intensification was supported by the establishment of the land grant systems and dedicated government support for research(Miranowski and Cochran, 1993). Thus while acreage may expand in the short-run, technology adoption and innovation led to lower price and induced contraction of land in the longer-run. Our correlations are consistent with such findings. Incorporating the dynamics of land use is an area for future research.

A comparison of iLUC due to biofuels with the actual expansion underway driven by global economic and population growth highlights the much bigger policy challenge of reducing GHG emissions while achieving economic growth. FAO data shows that global agricultural acreage has expanded by about 93 mha from 1999 to 2009. This implies that the increase in acreage attributable to maize ethanol would represent only 1.3% of global acreage expansion between 1999 and 2009. Figure 5 shows that the increase in maize acreage explains less than $1/4^{th}$ the total global acreage expansion during this period. Discounting co-product credit for maize, the increase in maize use for ethanol accounts for 40% of the increase in maize output withinin US and for only for 18% of the global increase in maize output. While we focussed on LUC due to maize ethanol, there exist alternative biofuels, the most important being cane ethanol produced in Brazil. Different from the approach of the LUC literature on maize ethanol, Hausman (2009) econometrically estimates land response to change in commodity prices in Brazil over the past three decades. Using county-level data from 1973 to 2005, the author finds that land use change in Brazil is more a product of reaction of soybean production to market prices than the reaction of sugarcane production. Indeed soybean acreage may have responded to US ethanol mandates, but data also suggests that the steepest increase in soy production was between 1990 and 2000 before the expansion of maize ethanol in US. This also suggests that while agricultural acreage may expand somewhat in the long-run as biofuels displace a larger share of crude oil globally, economic and population growth are the major drivers of land use.

Nevertheless, agricultural expansion due to biofuels is important in and of itself for although biofuels induce only a small fraction of the total global agricultural expansion, it also represents a small fraction of the current global oil use.. The target of 15 billion gallons of ethanol represents (on energy equivalent basis) approximately 7% of current consumption of gasoline in US and less than 2% of gasoline use world-wide. Given that several countries around globe aim to increase biofuel use, a global target of 20% replacement of gasoline by ethanol, may entail land-use change on a significantly larger scale. To this end, the pertinent policy question is not the land use impact of the US RFS mandates taken in isolation but the impact of world-wide adoption of biofuels on a significant scale. The approach we outline can be extended to derive order of magnitude estimates of global biofuel expansion. In this context, the need for a global agreement towards conservation of ecologically important areas that may be affected by expansion of agriculture regardless of whether it is driven by food, pasture, fuel or timber cannot be over-emphasized. Past studies show that government policies can have a drastic impact on land use. In the past they have both encouraged deforestation (say, establishment of railroad which was crucial for agricultural expansion in Brazil(Fearnside, 2005)) and also been successful in inducing conservation (say, through payments of ecosystem services in Costa Rica (Pagiola, 2008) and Mexico(Alix-Garcia et al., 2008))

Another important but under-emphasized aspect is the accounting of land that is under multiple cropping, i.e., land with more than one harvest per year. Availability of irrigation together with the favorable climatic conditions such as in the tropics enables multiple harvests within a year. Combining sub-national irrigation statistics with geospatial information on location and extent of irrigation schemes in the different regions of world, Siebert et al. (2005) calculate that about 274 mha of agricultural area (19% of global agricultural acreage of 1440 mha (http://faostat.fao.org) is equipped for irrigation worldwide with more than 41% of this area located in the tropical regions not including South America. Puma and Cook (2010) report that gross irrigation, the amount of water that actually has to be extracted from external sources such as lakes, rivers, and groundwater, has steadily increased over the course of the 20th century. While climatic conditions and seasonal availability of irrigation water, in the case of irrigation from seasonal rivers, may imply that land equipped for irrigation still yields only one harvest per year, it nevertheless suggests that net expansion of agriculture into new lands will be a fraction of the gross iLUC predicted by our model and also the existing literature on iLUC. Indeed irrigation and irrigation infrastructure have their own environmental impacts. Statistics on multi-cropping are either not easily found in the literature or are not comprehensive with data available only for specific multi-crop systems in specific regions of the world. Developing a global inventory of double cropped agricultural systems is an important area for future research.

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References

J. Alix-Garcia, A. De Janvry, and E. Sadoulet. The role of deforestation risk and calibrated compensation in designing payments for environmental services. *Environment and Development*

Economics, 13(03):375–394, 2008. ISSN 1355-770X.

ARB. Proposed Regulation to Implement the Low Carbon Fuel Standard, Volume I Staff Report: Initial Statement of Reasons. California Environmental Protection Agency and Air Resources Board, 2009.

I.M. de Carvalho. Greenhouse gas emissions and energy balances in bio-ethanol production and utilization in Brazil (1996). *Biomass and Bioenergy*, 14(1):77–81, 1998.

H. De Gorter and D.R. Just. The welfare economics of a biofuel tax credit and the interaction effects with price contingent farm subsidies. *American Journal of Agricultural Economics*, 91 (2):477–488, 2009.

J. Dumortier, D. J. Hayes, M. Carriquiry, F. Dong, A. Elobeid, J.F. Fabiosa, and S. Tokgoz. Sensitivity of carbon emission estimates from indirect land-use change. *Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa, USA*, July(Working Paper 09-WP 493), 2009.

EPA. Regulation of fuels and fuel additives: Changes to renewable fuel standard program. Notice of proposed rulemaking 40 CFR Part 80; EPA-HQ-OAR-2005-0161; FRL-XXXX-X; RIN 2060-A081, US Environmental Protection Agency, 2009.

J.F. Fabiosa, J.C. Beghin, F. Dong, A. Elobeid, S. Tokgoz, and T.H. Yu. Land allocation effects of the global ethanol surge: Predictions from the international fapri model predictions from the international fapri model. *Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa, USA*, March(Working Paper 09-WP 488), 2009.

FAO. The State of Food and Agriculture - Biofuels: Prospects, risks and opportunities. *Food and Agricultural Organization*, 2008.

A.E. Farrell, R.J. Plevin, B.T. Turner, A.D. Jones, M. O'Hare, and D.M. Kammen. Ethanol can contribute to energy and environmental goals. *Science*, 311(5760):506–508, 2006.

P.M. Fearnside. Deforestation in brazilian amazonia: history, rates, and consequences. *Conservation Biology*, 19(3):680–688, 2005. ISSN 1523-1739.

G. Federico. *Feeding the world: an economic history of agriculture, 1800-2000.* Princeton Univ Pr, 2005. ISBN 069112051X.

C Hausman. Biofuels and Land Use Change: Sugarcane and Soybean Acreage Response in Brazil. *SSRN eLibrary*, 2009.

T.W. Hertel, A.A. Golub, A.D. Jones, M. O'Hare, R.J. Plevin, and D.M. Kammen. Effects of US Maize Ethanol on Global Land Use and Greenhouse Gas Emissions: Estimating Market-mediated Responses. *BioScience*, 60(3):223–231, 2010.

M. Khanna, A.W. Ando, and F. Taheripour. Welfare effects and unintended consequences of ethanol subsidies. *Applied Economic Perspectives and Policy*, 30(3):411, 2008.

J. Miranowski and M. Cochran. Economics of Land in Agriculture. *Agricultural and environmental resource economics*, page 392, 1993.

Y. Mundlak. Economic growth: Lessons from two centuries of american agriculture. *Journal of Economic Literature*, 43(4):989–1024, 2005. ISSN 0022-0515.

OECD. Biofuel support policies biofuel support policies: An economic assessment. *Organisation for Economic Co-operation and Development*, ISBN 978-92-64-04922-2, 2008.

M. O'Hare, RJ Plevin, JI Martin, AD Jones, A. Kendall, and E. Hopson. Proper accounting for time increases crop-based biofuels' greenhouse gas deficit versus petroleum. *Environmental Research Letters*, 4:024001, 2009.

S. Pagiola. Payments for environmental services in Costa Rica. *Ecological Economics*, 65(4): 712–724, 2008. ISSN 0921-8009.

MJ Puma and BI Cook. Effects of irrigation on global climate during the 20th century. *Journal of Geophysical Research*, 115(D16):D16120, 2010. ISSN 0148-0227.

D. Rajagopal, SE Sexton, D. Roland-Holst, and D. Zilberman. Challenge of biofuel: filling the tank without emptying the stomach. *Environmental Research Letters*, 2(9), 2007.

M.J. Roberts and W. Schlenker. The U.S. biofuel mandate and the world food prices: An econometric analysis of the demand and supply of calories. *Presented at the National Bureau of Economic Research Agricultural Economics Conference*, 2010.

T. Searchinger, R. Heimlich, RA Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.H. Yu. Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319(5867):1238, 2008.

J. Sheehan, V. Camobreco, J. Duffield, H. Shapouri, M. Graboski, and KS Tyson. An overview of biodiesel and petroleum diesel life cycles. Technical report, NREL/TP-580-24772, National Renewable Energy Lab., Golden, Colorado, USA, 2000.

S. Siebert, P. Doll, J. Hoogeveen, J.M. Faures, K. Frenken, and S. Feick. Development and validation of the global map of irrigation areas. *Hydrology and Earth System Sciences Discussions*, 2:1299–1327, 2005.

D. Sunding and D. Zilberman. The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of agricultural economics*, 1:207–261, 2001. ISSN 1574-0072.

W.E. Tyner, F Taheripour, Q Zhuang, D Birur, and Baldos U. Land use changes and consequent co2 emissions due to us corn ethanol production: A comprehensive analysis. Technical report, Department of Agricultural Economics, Purdue University, 2010.

Time period	Mean annual extensive margin ρ_t^1	Cumulative extensive margin relative to 2009 ρ_{2009}^{k} *
2004 to 2009	0.6306	1.0664
1999 to 2009	0.6937	0.3676
1994 to 2009	0.7982	0.2911
1989 to 2009	0.6322	0.3537
1984 to 2009	0.6266	0.2413
1979 to 2009	0.5473	0.2289
1974 to 2009	0.5259	0.2791
1969 to 2009	0.6712	0.4796
1964 to 2009	0.6687	0.4352
1961 to 2009	0.6463	0.4381

* Cumulative change with respect to a fixed end year, namely, 2009 but varying time spans i.e, k = 5, 10, 15..

Table 1: Extensive margin based on annual and cumulative aggregate change for 9 major maize growing states in the US between 1961 and 2009

	ϵ_s/ϵ_d *				ϵ_s/ϵ_d				ϵ_s/ϵ_d		
ρ_t^1 **	-1	-2	-3	ρ_t^5 ***	-1	-2	-3	ρ_t^9 ****	-1	-2	-3
0.4	3.94	5.07	5.61	0.3	2.87	3.71	4.12	0.2	1.82	2.37	2.64
0.5	4.93	6.33	7.01	0.4	3.83	4.95	5.5	0.3	2.73	3.56	3.96
0.6	5.91	7.60	8.41	0.5	4.78	6.19	6.87	0.4	3.64	4.75	5.28
0.7	6.90	8.87	9.81	0.6	5.74	7.43	8.24	0.5	4.55	5.93	6.61

* ratio of elasticity of maize supply to maize demand
** mean annual extensive margin
*** mean cumulative extensive margin for 5 year intervals
**** mean cumulative extensive margin for 9 year intervals

Table 2: Corn acreage expansion in mha in US for 14.83 billion gallon increase from 1999 to 2017 under different scenarios of elasticities and extensive margins

Figure 1: Extensive margin for annual change (ρ_t^1) for nine state aggregate ($\rho_{1972}^1 = 11$ is not shown). The figure shows that the extensive margin is unstable ranging between -4.372 and 13.00 (not shown in figure) with a simple mean of 0.646. The running mean over a five year period exhibits relatively less instability (as expected) varying between -0.223 and 1.56 with a mean of 0.625.

Figure 2: Extensive margin for cumulative change with respect to 2009 for nine state aggregate (numbers next to arrows indicate the time elapsed since the year 1961). In other words it shows the extensive margin for the cumulative change for different time spans such as (2008 to 2009), (2007 to 2009), (2006 to 2009) and so on with the last observation being for the span 1980 to 2009. The 5 year cumulative margin excluded, the remaining values range between 0.153 and 0.548.

Figure 3: Weighted average cumulative extensive margin for all pairs of years for a given span, k, (> 5) for US maize (see equation (3)). The simple mean $\bar{\rho} = \frac{\sum_{k=k_0}^{K} \rho^k}{K-k_0} = 0.377$. For $k > 5$, $\bar{\rho} = 0.372$.

Figure 4: Corn acreage expansion in mha in US for 14.83 billion gallon increase from 1999 to 2017 under different scenarios of elasticities and extensive margins

Figure 5: Share of cumulative change in global agricultural acreage (= 93 mha) between 2000 and 2009 attributable to specific crops. It shows that the increase in maize acreage explains less than $1/4^{th}$ the total global acreage expansion during this period.