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Research paper

Biofuel impact on food prices index and land use change

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ABSTRACT

Food price and land use data over an extended time period have been examined to identify possible correlations between biofuel production and food price or land use changes. We compared the food price index before and after the biofuel boom in the 2000s to evaluate biofuel's impact on the inflation rate. We found that the U.S. food price inflation rate since 1973 could be divided into three distinct regions. The inflation rate was lowest at 2.6% during 1991–2016, which encompasses the biofuel boom. Among many factors, continuously rising food production per capita was identified as the likely cause of low food price inflation during this period. The US exports of corn have not declined since the 1990s and soybean exports are rising at a steady rate. Among several variables tested as a cause of food price index increase, crude oil price had the highest correlation. We also manually verified the automated land use classification of satellite image covering 664 km^2 in three selected areas in the US. We found that 10.90% of non-agricultural land was misclassified as agriculture, whereas only 2.23% of agricultural land was misclassified as non-agricultural. The automated classification showed an 8.53% increase in agricultural land from 2011 to 2015, while the manual classification showed only 0.31% (± 1.92%) increase. This result was within the margin of error alluding to no significant land use change. We concluded that automated satellite image land use classification should be verified more rigorously to be used for land use change analysis.

1. Introduction

While some scientific papers have shown biofuel as renewable and environmentally friendly [1–6], others [7–10] have concluded the opposite and suggested that biofuel is bad for the environment, reduces the US export of corn and soybean, makes food prices go up, and converts more non-agricultural land to agricultural land. These contradictory results have created public confusion. The rapid growth in biofuel (mainly corn ethanol and biodiesel in the US) was largely the result of mandated supply of transportation fuel containing specified quantities of renewable fuels [11]. Considering recent biofuel growth and its importance on the future of the liquid fuel supply, the environment, and food prices, it is important to have a clear understanding of biofuel's impacts to help build robust energy and environmental policies.

The first comprehensive life-cycle inventory for biodiesel produced in the United States from soybean oil was completed by Sheehan et al., in 1998 [12]. The study found that for every unit of fossil fuel used during the life cycle of biodiesel production, 3.2 units of energy are obtained from the biodiesel. The study also found that the use of biodiesel reduces net emissions of Greenhouse Gas (GHG) by 78.45%. Biofuel Life Cycle Analysis (LCA) that included indirect land use change was first published by Searchinger et al., in 2008 [7]. They argued that "to produce biofuels, farmers can directly plow up more forest or grassland, which releases to the atmosphere much of the carbon previously stored in plants and soils through decomposition or fire. The loss of mature forests and grasslands also foregoes ongoing carbon sequestration as plants grow each year, and this foregone sequestration is the equivalent of additional emissions. Alternatively, farmers can divert existing crops or croplands into biofuels, which causes similar indirect emissions. The diversion triggers higher crop prices and farmers around the world respond by clearing more forest and grassland to replace crops for feed and food". Using a worldwide agricultural model, the paper forecasted that with 56 billion liters (15 billion gallons) of corn ethanol in 2016, the following things would happen:

1. As fuel demand for corn increases, soybean and wheat lands switch to corn, prices increase by 40%, 20%, and 17% for corn, soybeans, and wheat, respectively.
2. U.S. agricultural exports decline sharply (corn by 62%, wheat by 31%, soybeans by 28%, pork by 18%, and chicken by 12%).
3. When other countries replace U.S. exports, farmers must generally

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Abbreviation

ABC	Annual Basis Carbon
AG	Agricultural land
CDL	CropScape Cropland Data Layer
COP	Crude Oil Price
CPI	Consumer Price Index
DDG	Distillers' Dried Grains
EISA	Energy Independent and Security Act
EPA	United States Environmental Protection Agency
FAO	Food and Agricultural Organization of the United Nations
FPI	Food Price Index
GHG	Greenhouse Gas
GLP	grassland/pasture land
ILUC	Indirect Land Use Change
GLS	Grass/Shrubland
LCA	Life Cycle Analysis
LUC	Land Use Change
MRLC	Multi-Resolution Land Characteristics Consortium
NLCD	National Land Cover Database
RFS	Renewable Fuel Standard
USDA	U.S. Department of Agriculture
USDOE	U.S. Department of Energy
USGS	U.S. Geological Survey

cultivate more land per ton of crop because of lower yields.
4. The US will bring 10.8 million acres of additional land into agriculture.

In general, the expansion of agricultural production due to the increase in biofuel demand is considered to cause indirect land use change (ILUC). However, quantification of land use change due to biofuel is difficult to observe or measure directly and hence it is often simulated using a combination of economic and environmental models [6]. Several models have been developed to estimate the ILUC impact. The EPA uses FASOM [13] to simulate the impacts of policies on land use and GHG emissions, FAPRI [14] for international trade for grain, oilseed, and livestock, and GTAP [15] is used for global trade analysis. Although none of these models were originally intended for the purpose of modeling ILUC from biofuels, numerous improvements and revisions are being made to these models to make them more suitable for this purpose. These improvements are supposed to provide greater spatial resolution, better representation of crop and livestock intensification, and inclusion of coproducts and their displacement effects. Given these improvements, it is reasonable to expect that overall modeling will become more reliable, although some experts argue this is unattainable and never will be realized [16].

A problem with a complex model is that they require a large list of input parameters that define the equations of the model. Unfortunately, the literature on many of the necessary parameters is weak or even nonexistent [17]. Gao et al. [18] argue that the estimation of biofuel's impact on deforestation is complex and it is not possible to obtain a reliable quantitative estimate of the global impact of biofuel development on deforestation. Deforestation is occurring due to many causal factors, some of which are independent while others are interdependent. These factors, which are mostly local but are sometimes regional or national, fall into six broad areas: 1) economic (legal and illegal mining and other activities unrelated to commodity prices), 2) biophysical (fire, pests), 3) cultural (communal decision making), 4) technical (slash and burn to boost fertility), 5) demographic (rapid growth of populations and the rural poor), and 6) political (programs to help the landless poor) [19]. The current Land Use Change (LUC) models account mainly for economic factors and attempt to capture economically driven responses such as price-yield elasticity, double cropping, and agricultural expansion to marginal land.

Many countries have rules in place to limit biofuel production from food crops. For instance, in the US, the Energy Independence and Security Act of 2007 (EISA) limits the types of feedstocks that can be used to make renewable fuel as well as the land used to produce them. Renewable biomass includes planted crops and crop residues harvested from "existing agricultural land" which includes cleared or cultivated and actively managed fallow and nonforested land [20]. The EPA developed an aggregate land use approach to verify the eligibility of renewable biomass. Using the USDA's Farm Service Agency (FSA) crop acreage data, the EPA assesses land use change from year to year. The first step of this approach involved determining the total amount of "existing agricultural land" in the United States at the enactment date of the EISA, which was 162.7 million ha (402 million acres). Secondly, at the end of each calendar year, the EPA conducts a posterior assessment of total agricultural land to determine if the national agricultural land acreage increased above the 2007 baseline. An investigation is triggered if the EPA finds that the total amount of qualified land used for feedstock production is equal to or greater than 160.7 million ha (397 million acres) – i.e., within 5 million acres of the EPA's established 402 million acre baseline, Using this approach, the EPA has determined that the national aggregate baseline of 402 million acres has not been exceeded since the Renewable Fuel Standard (RFS2) was implemented in 2010 [21].

Failing to incorporate significant factors adds uncertainty in model predictions. Because of the uncertainties and model assumptions, the range of published ILUC values is enormous: from about 200% below, up to 1700% above the carbon footprint values of fossil fuels [22]. Thornley and Gilbert [23] have calculated the GHG savings from Argentinian soybean biodiesel with two sets of assumed options. They found that one set of assumption provided 65.9% savings in carbon where the other set of assumptions showed −66.5% carbon savings. They concluded that balancing risks and rewards is an essential part of biofuel development and uncertainty complicates risk balancing. Their conclusion further supports the argument that model predictions with uncertain parameters should be measured against real-world data and indicators.

There are significant uncertainties in economic models. From empirical evidence, research study [17] finds that crop yield price elasticity is closer to zero and not close to the values used in recent versions of the GTAP, one of the frequently applied economic models to estimate LUC. Accurately estimating the extent of yield change in response to commodity price, or whether the yield from newly converted land would be the same as older cultivated land is difficult if not impossible. Therefore, it is critical to examine model assumptions and validate underlying model predictions with empirical evidence.

Generally, an LCA, as outlined by ISO 14040 [24] and ISO 44044 [25], is used to compare the GHG emissions from a biofuel to the petroleum fuel it replaces. However, alternate methods such as Annual Basis Carbon (ABC) [26] have been used for biofuel carbon accounting. The authors differentiate the ABC method from LCA by using a single system boundary enclosing both the biofuel and fossil fuel supply chains and focusing on the source of carbon than the final product as in LCA. The ABC method argues that inclusion of ILUC requires projecting commodity market behavior and its results become not only highly uncertain but also scientifically untestable, erasing any hope that disputes might be eventually resolved through better data [9]. ABC framework treats ILUC as a problem to be mitigated rather than attempting to incorporate its effects as adjustments to the level of GHG reduction assigned to biofuels [26]. Using the ABC method DeCicco et al. [9,27] have concluded that ethanol and policies encouraging biofuel production are likely to increase greenhouse gas emissions.

In order to estimate the agricultural land use change in the US, a paper from Lark et al. [8] utilized land use data derived from machine-classified satellite imagery. These studies commonly utilize the NASS CropScape Cropland Data Layer (CDL) [28] and the Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Database (NLCD) data [29]. However, neither the NLCD nor the CDL is designed for land use change analysis. The MRLC website [30] states that the NLCD is "Land cover information for local, state, and federal managers and officials to assist them with issues such as assessing ecosystem status and health, modeling nutrient and pesticide runoff, understanding spatial patterns of biodiversity, land use planning, deriving landscape pattern metrics, and developing land management policies." The NASS [31] acknowledges that the spatially-distributed CDL is not official data; official data is available from the yearly NASS reports and is aggregated to the county level. Use of data not appropriate for the purpose could lead to an inaccurate conclusion.

While potential price increases due to the increasing demand for corn and oil are easy to imagine, the implications of biofuel on the feed market may not be obvious. It should be noted that the primary coproduct of U.S. ethanol production is distillers' dried grains (DDG). About a third of corn volume used to make ethanol ends up as DDG [32]. DDG output began to increase along with increased ethanol production. In recent years, mills have started to produce corn oil, another coproduct, before the DDG is processed. Adding these coproducts to the ethanol production process has increased the supply of biodiesel and animal feed without adding more resources, including land, to corn production.

Like DDG's relationship to ethanol, the production of soybean meal increases as more soybean oil is used to make biodiesel. Soybeans contain only about 20% oil; the remaining 80% is meal primarily used for animal feed [33]. Processed soybeans are the world's largest source of animal protein feed, and the United States is the world's leading soybean producer [34]. The amount of soybean oil used to produce biodiesel increased about three folds from 2009 to 2015 to help meet the Renewable Fuel Standard (RFS) mandate. The increased use of soybean oil for biodiesel also resulted in the three-fold production increase of soybean meal [35,36].

Even though biofuel mandates may cause global cropland expansion, deforestation, and grassland conversion, a causal correlation between biofuel deployment, commodity prices, and land use change has not been definitively established, which is a key objective of this work. The purpose of this study was to investigate (using real-world data) the accuracy of economic models and satellite imagery in predicting the impact of biofuel on food price and land use change. It would have been ideal comparing the land use change and food price increase using real-world data with and without biofuel. However, with and without analysis is not possible as there is no data for what the price would have been without biofuel after the biofuel boom and vice versa. As an alternative, this paper relies on comparing before and after the biofuel era data to quantify the impact of biofuel.

2. Materials and method

Publicly available data from the USDA, World Bank, and FAO were used in this study. All data sources are referenced and can be downloaded from the respective sources. The data analysis and plotting were done using Microsoft Excel and Matlab®'s Statistical and Machine Learning Toolbox (www.mathworks.com). In order to estimate the average increase in food prices over the years, the cumulative consumer food price index (CPI) was plotted since 1973 using the USDA data [37]. The CPI measures the average change over time in the prices paid by urban consumers for a representative market basket of consumer goods and services. Statistical analyses were used to determine if there were significant correlations between biofuel production and whether the relationship was causal and if food prices were disproportionately increasing because of biofuel by comparing the food price increase rate before and after the biofuel boom. Since the variables used in correlation analysis of biofuel production and prices had very different units and scale, the data were normalized for a visual comparison of relative change. The actual values from 1991 to 2016 were transformed to relative values, a unitless number between 0 and 1, using the following equation:

$$Relative\ value = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value}$$

A regression analysis was performed on a global scale between Global Food Price Index (FPI) [38] and other candidate variables, such as world population [39], per capita production of cereal and oil crops [40], ethanol and biodiesel production [41], inflation rate [39], and Brent Crude oil price [42]. FPI and CPI for food are similar concepts, but the list of food included in FPI and CPI may not be the same.

Automatically classified satellite imagery was used by Lark et al. [8] to estimate the amount of agricultural land use change. To evaluate the accuracy of automated land classification of satellite data, we performed a raster analysis of NASS CropScape Cropland Data Layer (CDL) [28] and National Land Cover Database (NLCD) data [29] on selected areas for the years 2011 and 2015. The CDL is a raster, geo-referenced, crop-specific land cover data layer created annually for the continental United States using moderate resolution satellite imagery. The classification process used to create the CDL prior to 2006 was based on a maximum likelihood classifier approach using an in-house software package. Starting in 2006, NASS began utilizing a new satellite sensor, more extensive training/validation data, and new commercial off-the-shelf software called See5 which uses a decision tree learning algorithm coupled with a Bayesian type probabilistic model for pixel classification. They also began using the USGS NLCD to help identify non-agricultural land cover [43].

The NLCD is a Landsat-based, 30-m resolution land cover database for the US. NLCD provides spatial reference and descriptive data for characteristics of the land surface such as thematic class (for example, urban, agriculture, and forest) but does not further specify the crop type like in CDL. These databases are in the public domain and free to download and use. Years 2011–2015 were the most current land classification data available at the time of this analysis and overlapped with the years used in Lark et al.

In this research we chose three counties centered around Moscow, ID (latitude and longitude of NW corner 46.769, −117.04 to SE corner 46.696, −116.872), Lemoore, CA (NW corner 36.331, −119.881 to SE corner 36.245, −119.713), and Le Roy, NY (NW corner 43.024, −78.08 to SE corner 42.946, −77.912). These locations were chosen for their differing climates and proportion of land types. The areas encompass a variety of land coverage to assess classification error for each category. One of the objectives of this study was to quantify automated land classification error under several different categories, so relatively uniform areas such as a corn belt in the Midwest were not chosen as they had less diverse land use. The chosen areas, although unlikely to be influenced by biofuel production, provided enough diversity to quantify the land classification error. Each area was measured to be 221,324 km^2. A total of seven automatically classified images were downloaded for the above locations: CDL data layers from 2015 for all three areas, CDL data layers from 2011 for ID and NY, and NLCD data layers from 2011 for ID and NY. The raster maps were imported into ArcMap V10.4 (ESRI, Redlands, CA) for analysis. To estimate the automated land classification accuracy, the classified map was overlaid on the satellite image available from ESRI for the same year. The classification for each cell was manually verified and corrected for error. For manual verification of the land use classification, we overlaid the data onto a satellite image of the area for the same year and season for reference. For pixels that had multiple potential categories-i.e. a cell that borders a field and forest - we picked the classification that predominantly filled the cell. If this was indiscernible, the category that filled the mid-point of the cell was used for the classification as this is the method used by classification software. The corrected classification was compared to the original classification to determine the error.

3. Results and discussion

3.1. Biofuel and food price index

The plot of cumulative CPI over time helped to visualize the average rate of inflation as the slope of the linear line (Fig. 1). The plot shows that while the price of food is increasing, the inflation rate remained stable through the biofuel boom. Visually inspecting the trend, we found that the period from 1973 to 2016 could be divided into three distinct regions. From the period of 1973–1981, food prices were increasing at a steady rate of 8.3% per year with a coefficient of determination (R^2) of 0.987, and standard error of 2.7%. From 1981 to 1991 this had dropped to a rate of 3.8% increase per year with an R^2 of 0.984 and standard error of 1.7%. Finally, trend lines show that from the period of 1991–2016 there was a rate of 2.6% increase per year with an R^2 of 0.997 and a standard error of 1.1%. This period encompasses the biofuel boom yet does not demonstrate an associated increase in food price inflation throughout. A regression analysis showed no significant difference in inflation rate between 1991 and 2000 (pre-biofuel boom era), and 2000–2016 (post biofuel boom era) from the average 2.6% inflation rate for the entire range.

While food price inflation rates in the United States have been stable, the U.S. has been ramping up biofuel production. The US ethanol production from 1980 to 2000 grew linearly at a rate of 256.7 ML (67.9 million gallons) per year. From 2000 to 2010, the height of the biofuel boom, ethanol production grew exponentially, increasing from 6.0 GL (1.6 billion gallons) produced in 2000 to 50.3 GL (13.3 billion gallons) produced in 2010. The growth rate slowed down from there, with production increasing to 58.2 GL (15.4 billion gallons) in 2016 [44]. The US Energy Independent and Security Act (EISA) of 2007 effectively limits the RFS mandate on corn starch-based ethanol volume to 15 billion gallons per year [45,46]. Even though RFS require only 15 billion gallons/year, the US production of corn ethanol has been exceeding that volume each year since 2016 [47]. Similarly, biodiesel production from 2001 through 2008 followed an exponential growth trend. The growth in biodiesel production went from 34 ML (9 million gallons) of biodiesel in 2001 to 2.56 GL (678 million gallons) in 2008. From there production fluctuated, reaching 5.92 GL (1,567 million gallons) in 2016 [48].

A rapid increase in global demand for grains and oilseeds triggered the 1971–74 run-up in prices. A series of events, including the Soviet Union's unexpected purchase of a large amount of grain in the global market in the early 1970s is partially responsible for higher inflation during that period [49]. The lower inflation rate in recent years may partially be due to higher per capita food production. Using the USDA data for crop production [50] and population [39], the per capita corn and soybean production in the US was calculated. Corn production grew from 750 kg (29.5 bushels) in 1991 to 1,192 kg (46.9 bushels) per capita in 2016. Similarly, soybean production grew from 215 to 362 kg (7.9–13.3 bushels) per capita, an annual 2.3% and 2.8% increase for corn and soybean respectively. In contrast, the per capita production of corn and soybean from 1973 to 1991 grew by only 0.6% and 0.4% respectively. It's worth noting that during 1991–2016, the inflation rate was relatively high in 2007–2008 and again in 2011–2012 (Fig. 1). Many factors contribute to higher short-term commodity price increases. Trostle et al. [51] attributed the 2008 price increase to a crude oil price increase, the US dollar value depreciation, biofuels, weather, the declining global stock-to-use ratio and economic and population growth. The paper also attributed the commodity price increase of 2011 to weather, economic growth and declining stock-to-use ratio. Short term food price increases have been blamed on biofuel based on simplistic analyses. Simplistic analyses may not reveal the main drivers of food insecurity and ignore opportunities for bioenergy to contribute to solutions [52].

The US export data [50] for corn from 1991 to 2016 showed no significant change ($R^2 = 4.95 \times 10^{-5}$, with $p > F = 0.97$) over time (Fig. 2). For the same period, the soybean export grew at the rate of 1.2 ± 0.2 Million MT/year ($R^2 = 0.86$, with $p > F = 1.06 \times 10^{-11}$). The results indicate that there may be an anomalous year like 2013, stemming from the 2012 drought year, where corn and soybean exports were low. In general, there was no change in corn exports during the biofuel era, and there was a steady increase in soybean exports before and after the biofuel boom. On average, corn made up 54.3% (± 0.02%) of total grain exports whereas soybean made up 97.0% (± 0.003%) of total oilseed exports.

While biofuel demand may have some part in increasing crop prices, there are many other attributing factors, including market speculation, stockpiling policies, trade restrictions, macroeconomic shocks to money

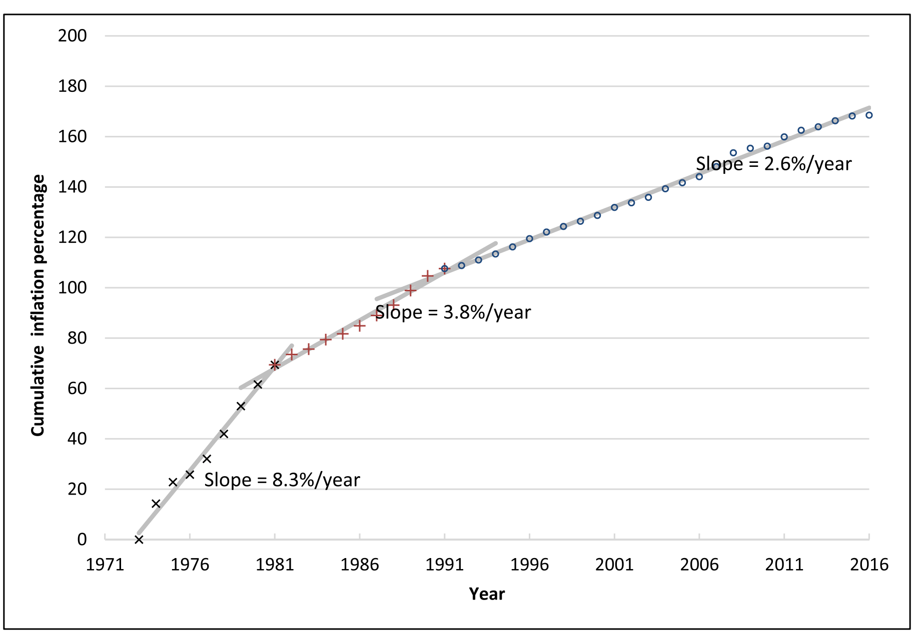

Fig. 1. The United States cumulative CPI for food with 1973 as a baseline. The slope of the line is the average inflation rate. The timeframe was visually divided into three distinct inflation periods. The period from 1991 to 2016 had the lowest average inflation rate compared to other periods. Data Source: [37].

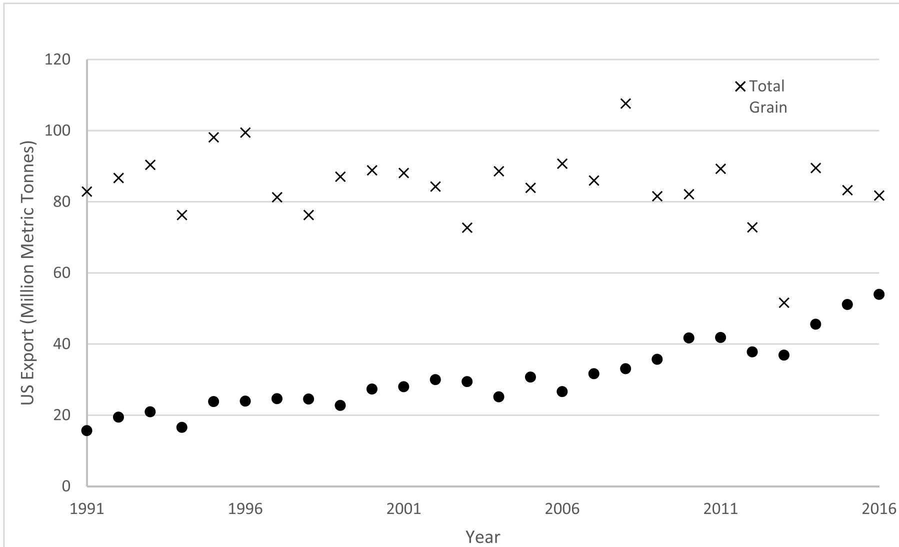

Fig. 2. The United States export of corn (corn makes up about 54.3% of total grain exports) and soybean (soybean makes up 97% of total oilseed exports). Data Source: USDA [50].

supplies, exchange rates, and economic growth. Time series annual average corn and soybean prices [53] were correlated with potential variables that could impact their prices. The variables considered were US population [39], total corn production [50], total soybean production [50], West Texas Intermediate crude oil price [42], urban CPI other than food and energy [54], ethanol production [44], and biodiesel production [55]. Among the selected variables, both corn and soybean price had the strongest correlation with crude oil price. Corn price had a weaker correlation with CPI other than food and energy (r = 0.66), population (r = 0.65) and corn production (r = 0.55), and a stronger correlation with crude oil price (r = 0.82) and with ethanol production (r = 0.79). Similarly, soybean price had a weaker correlation with CPI other than food and energy (r = 0.75), population (r = 0.74) and soybean production (r = 0.68), and a stronger correlation with crude oil price (r = 0.86) and with biodiesel production (r = 0.83).

The plot of relative corn and soybean price with strongly correlated variables showed that crude oil price has a significant impact on crop price (Fig. 3). The plot also shows the relative growth of ethanol as linear until about 2000, and then exponential until 2010. Our results agree with observations made by Tadesse et al. [56] that crude oil prices, in particular, can have dramatic effects on food price volatility, with a 1% increase in oil price volatility correlating to a 0.42–0.45% in food price volatility. Economic factors can have a severe effect as well; for example, the export boom of the 1970s caused food prices to skyrocket, with corn prices almost tripling [57]. Since population, prices, production, and inflation rates were correlated, it was not possible to estimate the absolute effect of biofuel on corn and soybean price.

On a global scale, food production is increasing at a higher rate than the population. Using FAO data [40], we found that per capita cereal production has increased from 352 kg in 1991 to 383 kg in 2016; per capita oil crop has increased from 14.5 kg of oil to 28.4 kg of oil equivalent. Correlation analysis of FPI with other selected variables discussed previously showed that the FPI had the highest correlation (r = 0.92) with crude oil price. The relation was even stronger in the biofuel era (since the year 2000) with a correlation of 0.94. Compared to this, FPI had a correlation of 0.87 and 0.77 with world ethanol and biodiesel production respectively. A linear model predicting FPI using crude oil price and the population was found to be:

$$FPI = 39.5 * N + 1.1 * COP - 184.3$$

Where COP is the crude oil price (Brent Crude Oil Price, \$/barrel) and N is the global population in billions. The linear model had R^2

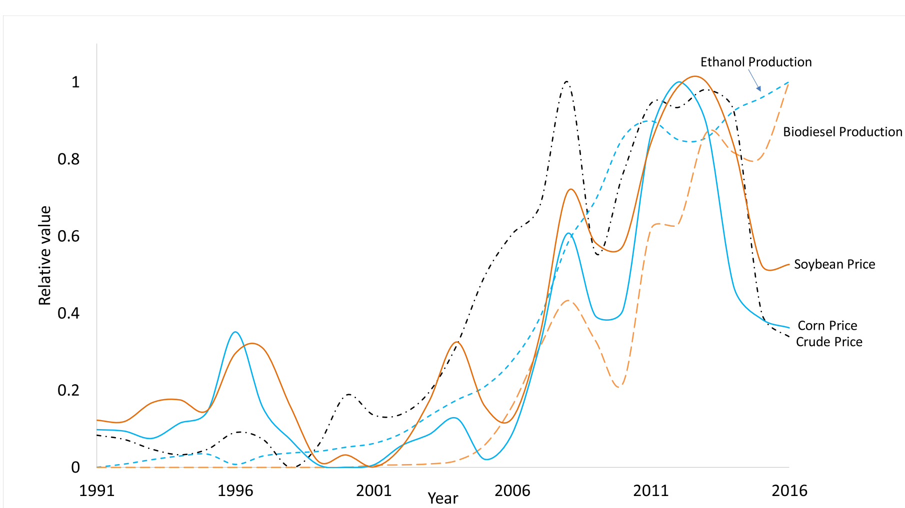

Fig. 3. U.S. corn and soybean prices compared to crude oil price, ethanol, and biodiesel production (normalized). Both corn and soybean have the highest correlation with crude oil price. Data sources: [42,44,53,55].

value of 0.96. The predicted FPI with this regression model and actual FPI is shown in Fig. 4.

The correlation does not always mean causation, so we also tested using Granger Causality [58] to determine if FPI had causal relation with population and the COP at a 95% confidence interval and time lag up to three years. The null hypothesis was that there was no causal relation between N and COP on FPI. The Granger causality test between COP and FPI resulted in F value of 1.21 and critical value (c_v) from the F distribution of 0.0041. Since F > c_v we rejected the null hypothesis of no causality and concluded that FPI has a causal relation with COP. Similarly, a Granger causality test between N and FPI had F = 1.71 with the same c_v of 0.0041, indicating that N and FPI also had a causal relationship.

It is worth noting that even though FPI has a causal relation with oil price and population, it was not possible to single out these two variables as the only cause of increasing FPI due to a significant positive correlation between population, food production, ethanol production, crude price, inflation rate, and other economic factors. We chose oil price for its highest correlation with FPI, and the population was another logical choice to explain the increase in FPI. From this analysis, we concluded that the per capita food production is increasing over time and the biofuel provided a market for the excess grain and oil. Although the price of food is most strongly correlated with crude oil price, other candidate variables that could raise food price such as biofuel volume were also significantly correlated with both food price and oil price. Hence, it was not possible to point out a single factor causing food price increase.

3.2. Land use change analysis using satellite data

The downloaded map had labelled categories for each crop grown in that area [59] which we consolidated as agricultural land (AG) except for the grassland/pasture (GLP) category. Although the original raster legend classified GLP as part of agriculture [60], after overlaying CDL on satellite images for manual verification, we found that only a small fraction of land classified as GLP was agricultural. In Idaho, for instance, we found only 10.57% of GLP belonged to AG. The rest belonged to other categories, mostly virgin grassland (grassland never used for agriculture), wild meadows, shrubland, and some developed land. To account for GLP classification error, we included two separate analyses: 1) GLP as a separate category, and 2) reclassifying GLP as one of the manually verified land use categories. GLP areas that were virgin grassland, wild meadows and shrubland were included with Shrubland, and this category was relabeled as Grass/Shrubland (GLS). Although non-agriculture land categories included Developed, Shrubland, Wetland, Forest, Barren, Open Water (Water), and Perennial Ice/Snow, there was no perennial ice/snow in the areas considered in this study.

The snapshot in Fig. 5 shows an example of errors found during this analysis. In this image, we see large swaths of residential and open developed land being identified as cropland.

Overall findings from this analysis are summarized in Table 1, and the amount of land incorrectly classified is 27.86% (± 2.52%). Most of this error was from misclassification of other lands as agriculture (10.90%). If all GLP land were considered AG land as according to the CDL legend [59], the total incorrectly classified land as AG would have been 18.77% (sum of AG and GLP). A disproportionate amount of error classifying other lands as cropland may be due to a random pixel being classified as AG land. This kind of error happens if there is a higher fraction of AG land in training data sets used to develop the classification algorithm than the area under study.

There were also AG lands incorrectly classified as other categories. Fig. 6 shows the breakdown of the specific errors in the agriculture misclassifications. GLP is not included in this analysis. The classification error was divided into two categories, the agricultural land classified as some other land and some other land classified as agricultural. It was observed that, compared to 10.90% of land incorrectly classified as agricultural, only 2.23% of agricultural land was incorrectly classified as a different category. This corresponds to 8.66% of net land incorrectly classified as agriculture.

The highest misclassification as agriculture came from grass/shrubland (4.58%). Classifying grassland as cropland is one of the weaknesses in the remote sensing analysis. Lark et al., 2017 identified the grassland to cropland misclassification error as one of the weaknesses of utilizing the CDL and cautions that, due to the spectral similarity of grassland and cropland during remote sensing classification, it is difficult to discern among various grassland vegetation types accurately [61]. However, it was surprising to see the second-highest classification error (4.23%) from the developed category to agriculture. Further analysis showed that California and New York had a particularly high rate of misclassification of developed land as agriculture land.

We suspect that this high rate of classification error is stemming from unrepresentative a-priory probability assigned to land categories. The training dataset is obtained from the USDA Farm Service Agency's Common Land Unit (CLU) program. The CLU is not in the public domain and therefore could not be verified for it's a priori probability of agriculture to non-agriculture fraction. If the training dataset had more agricultural pixels, say 90%, then a boundary pixel would be classified as agriculture 90% of the time. If the training rules are applied to an area that has only 80% agriculture, 10% more boundary pixels will be classified as agriculture. The CDL classifies only agricultural land, and non-agricultural land classification was adopted from NLCD.

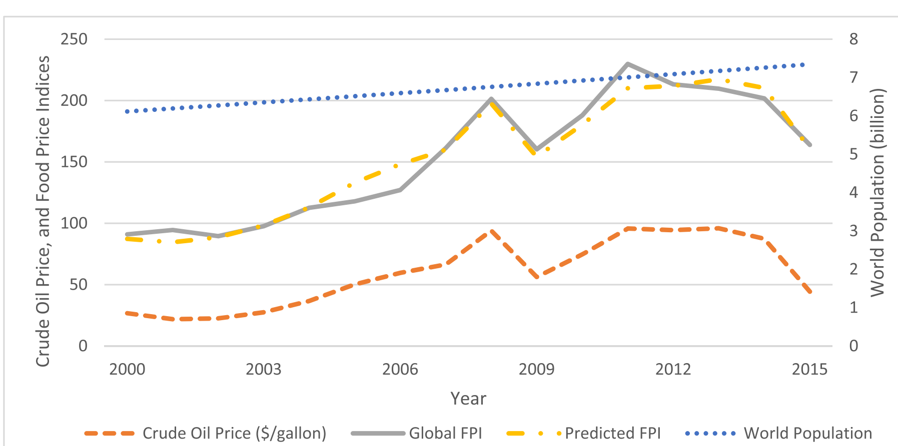

Fig. 4. The world FPI in relation to crude oil price and global pollution from 2000 to 2015. A linear model predicted FPI followed closely with actual FPI. Data Sources: [38,39,42].

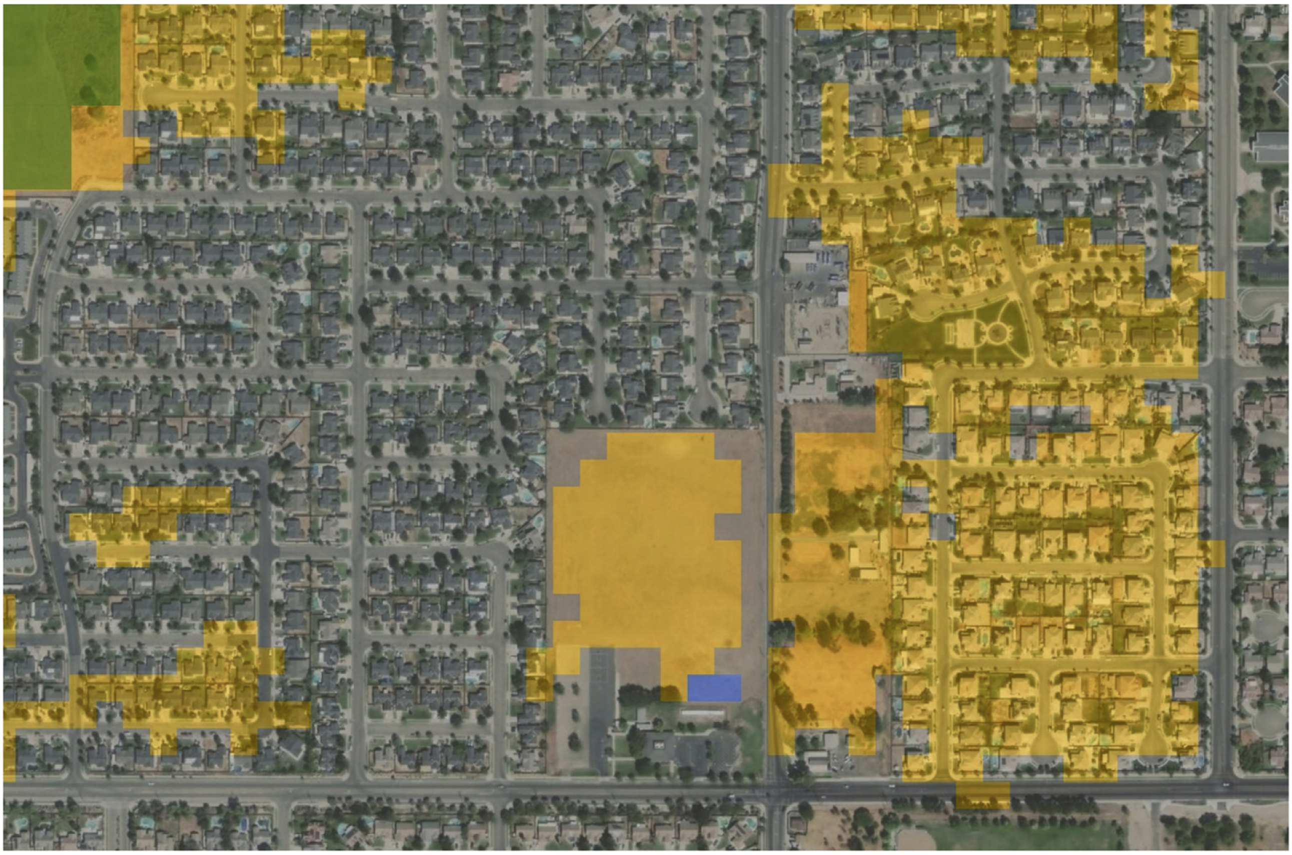

Fig. 5. California raw CropScape data 2015 showing erroneous classification in the city of Lemoore as cropland (yellow), open water (blue) and grass/shrub (green) pixels. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Percentage of total land incorrectly classified in CDL and NLCD data for the selected region in the year 2011 and 2015.

Data Source[a]	Percent of total land incorrectly classified as								
	Developed	GLS	AG	GLP	Wetland	Forest	Barren	Water	Total
CDL ID 2015	2.13	5.38	7.45	2.79	0.00	0.07	0.00	1.38	19.19
CDL CA 2015	2.49	0.01	19.19	0.16	0.65	0.08	0.12	0.00	22.71
CDL NY 2015	2.43	1.39	6.15	9.87	0.08	7.98	0.43	3.15	31.48
CDL ID 2011	2.45	3.36	3.08	21.75	0.00	0.02	0.00	1.83	32.50
CDL NY 2011	2.32	2.98	8.81	4.80	0.07	3.93	0.50	14.02	37.41
NLCD ID 2011	1.85	2.05	15.94	N/A	0.00	0.11	0.00	1.91	21.87
NLCD NY 2011	2.48	1.67	15.66	N/A	0.03	8.37	0.00	1.68	29.90
Average Error	2.31	2.41	10.90	7.87	0.12	2.94	0.15	3.43	27.86
Standard Error	0.09	0.65	2.27	3.23	0.09	1.45	0.08	1.80	2.52

[+] NLCD data does not have GLP category.
[a] ID, CA, and NY represent 221, 324 km^2 areas of Idaho, California, and New York states. CDL uses NLCD data for all non-agriculture category classification.

We also analyzed the effects of these errors on land use change calculation. This was estimated by performing error analyses of CDL data between 2011 and 2015 to determine land use change in ID and NY. Two change analysis raster layers were created, one for original data from the satellite and one for our manually verified data (Table 2). The average of NY and ID's original data showed that the GLP had decreased by 15.82 km^2, wetland by 0.45 km^2 and barren land by 0.15 km^2. From these, 8.53 km^2 was converted into AG, and 5.50 km^2 was converted to GLS. The manually verified image analysis showed that AG land had increased by only 0.31 km^2 with a 95% confidence interval of ± 2.7 km^2. This corresponds to 0.05 ± 0.41% of the land area change to agriculture. Since the confidence interval included zero, the null hypothesis that “there is no significant land use change” could not be rejected and we concluded that the land use change was not statistically significant.

4. Land use change model limitation

4.1. Model assumptions and predictions analysis

The economic models have predicted that biofuel induced demand for corn will make other crops switch to corn and will increase the food price. The results from Fig. 1 shows that the inflation rate of commodity price for food in the US remained the same at about 2.6% increase per year before and after the biofuel era. It was true that price of corn and soybean has increased temporarily from 2006 to 2008 and again in 2010–2012, however, the corn and soybean price followed more closely with crude oil price than biofuel production (Fig. 3). A global analysis also confirmed that the food price index had a significantly higher correlation with crude oil price and population than the biofuel (Fig. 4).

The empirical data did not support the model prediction that

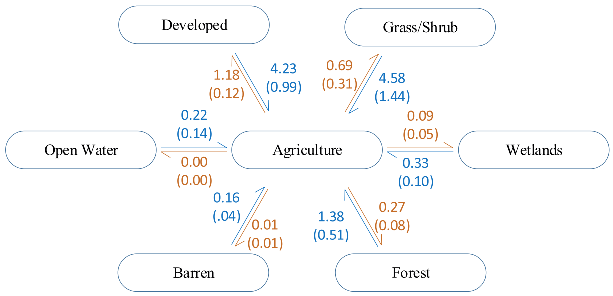

Fig. 6. Breakdown land classification error as a percent of total land. Arrows point to the direction of error. For instance, 4.23% of the land that should have been classified as the developed land was incorrectly classified as agriculture whereas only 1.18% of land that should have been classified as agriculture was classified as developed. The number in parentheses shows the standard error of estimation.

increases in biofuel will reduce the export of corn and soybean. Except for a bad crop year in 2012–2013, exports of corn have been relatively steady, contrary to the predicted 62% reduction. Differing to a predicted 31% reduction of soybean exports, the export of soybeans has seen a steady growth of 1.19 million MT/year since 1991. This trend did not change after the biofuel era (Fig. 2). Exports of soybeans, vegetable oil, and protein meal have been increasing as wealthier populations shift from staples to more diversified products [62].

As models have predicted, the corn acreage did increase but only until 2012. NASS survey data [63] shows that corn acreage increased from 32.1 million ha (79.5 million acres) in 2000 to a high of 39.4 million ha (97.3 million acres) in 2012 and then decreased to 35.6 million ha (88 million acres) in 2015. Soybeans rose from 30.0 million ha (74.2 million acres) in 2000 to 33.4 million ha (82.6 million acres) in 2015. Increase in corn and soybean acreage mostly came from reductions in wheat, barley, and sorghum [32].

The FAO data [64] shows that US agricultural land is decreasing at an average of 5.9 thousand sq. km and world agricultural land is decreasing at an average of 56.5 thousand sq. km each year between 2000 and 2015 (Fig. 7). The shrinking agricultural land while biofuel production is ramping up contradicts the economic models' predictions that the world will need more land to replace lost agricultural production.

The reason that the world needs less area to grow food may partially be explained by improving land productivity. Despite declining agricultural land, World Bank data shows that global crop production index and the food production index have been increasing at an average of 2.8% per year since 2000. Crop production index shows agricultural production for each year relative to the base period. It includes all crops except fodder crops. Food production index covers food crops that are considered edible and that contain nutrients. Coffee and tea are excluded because, although edible, they have no nutritive value. According to World Bank data [65] for cereal, a major food crop around the world, the yield is increasing at the rate of 59 kg/ha (52 lbs/acre) per year. World population growth rate, on the other hand, has been declining and the 2017 rate is at 1.16% [66].

We also investigated the cause of discrepancies in GHG emissions from biofuel results between the ABC method [27] and the LCA method. ABC method is different from LCA and has its own sets of assumptions. Some of the assumptions worth noting of the ABC method compared to an LCA analysis are listed below.

1. The ABC method does not credit the carbon uptake by plants used to produce biofuel. The ABC method only credits the carbon uptake by the plants over last year due to yield increase. If crop yield stays the same for a year, the carbon absorbed by plants made into biofuel does not get any credit. Additionally, if the yield decreases for any reason such as draught, the reduced carbon uptake due to yield loss is counted against biofuel. In contrary, standard LCA credits the carbon uptake by the crop used to produce biofuel, regardless of its yield.
2. No credit is given to biofuel for replacing petroleum fuel. If one gallon of biofuel is produced, whatever biogenic CO_2 is produced throughout its lifecycle is accounted against biofuel without crediting the reduced CO_2 emissions from displaced petroleum fuel.
3. For ethanol, both CO_2 emitted during fermentation and during combustion is added to calculate total emissions, whereas for gasoline, only CO_2 emitted during combustion is considered and nothing emitted during drilling, pumping, transportation, and refining is considered.

The LCA compares biofuel emissions to equivalent petroleum fuel emissions. This is assuming that one unit of energy in biofuel can replace one unit of energy from petroleum fuel. By not giving biofuel credit for emissions from replaced petroleum fuel, the analysis is accounting for emissions from one unit of petroleum plus one unit of biofuel. The assumptions made in the ABC method were the main reason for the different results from LCA.

4.2. Use of satellite image for land use change analysis

Lark et al. [8] using automatically classified NLCD land coverage map found that a significant amount of previously untouched grassland was converted to cropland from 2008 to 2012. In contrary, agricultural census data from 1950 to 2012 showed that land dedicated to agriculture has declined by approximately 100 million ha (246 million acres) [67]. Even after the biofuel boom, a linear regression line fitted to FAO data [40] from 2000 to 2016 shows that cropland in the US is declining at 1.6 million ha/year (4 million acres/year) ($R^2 = 0.92$), and agricultural land is declining at 0.6 million ha/year (1.5 million acres/year) ($R^2 = 0.78$). FAO defines cropland as "Land used for cultivation of crops. The total of areas under arable land and permanent crops" and agricultural land as "Land used for cultivation of crops and animal husbandry. The total of areas under cropland and permanent meadows and pastures." A higher rate of decline in cropland compared to agricultural land indicates the fact that permanent meadows and pastures may not be converting to cropland.

The use of satellite data is prone to error in classifying certain land

Table 2
Land Use Change Analysis between 2011 and 2015. Negative numbers represent decreases in land area, and positive numbers are increases in the land area.

Data source	Land Use Change from 2011 to 2015 in km^2							
	Developed	GLS	AG	GLP	Wetland	Forest	Barren	Water
ID Original	1.03	16.26	24.77	−41.98	0.13	−0.19	−0.01	0.00
ID Corrected	−0.28	−0.77	0.61	0.00	−0.04	0.40	0.01	0.07
NY Original	−0.02	−5.27	−7.71	10.35	−1.02	4.01	−0.28	−0.05
NY Corrected	0.01	−0.16	0.00	0.00	−0.01	0.15	0.00	0.00
Average Original	0.51	5.50	8.53	−15.82	−0.45	1.91	−0.15	−0.03
Average Corrected	−0.14	−0.47	0.31	0.00	−0.03	0.28	0.01	0.04

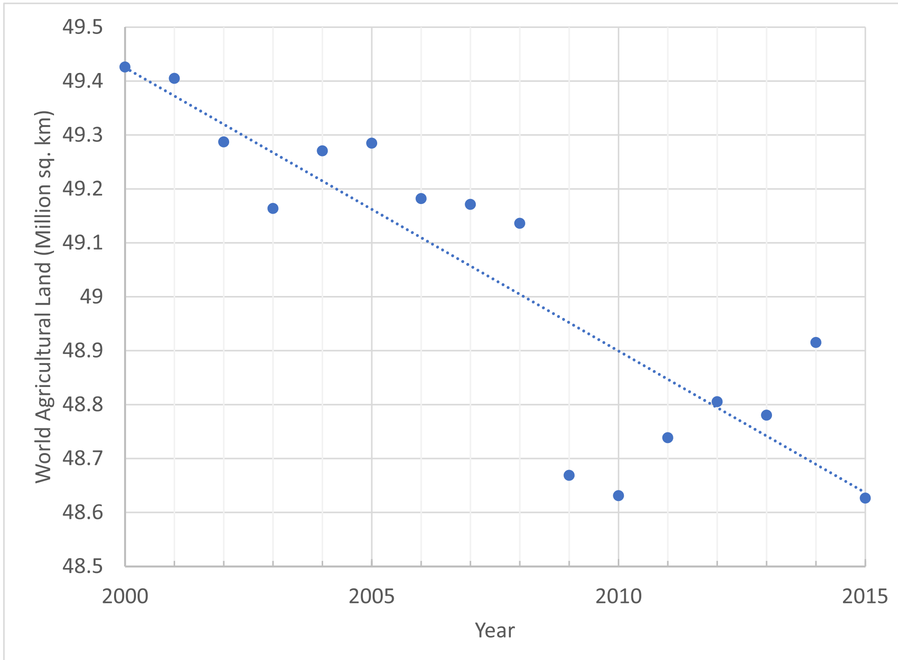

Fig. 7. FAO data [64] shows that the world agricultural land area is shrinking at an average rate of 56.5 thousand sq. km per year since 2000.

uses, such as distinguishing between cropland used to grow hay, and pasture land used for grazing [68]. As shown in Table 1, we found a total of 27.9% error in automated satellite image land classification. A report by Wickham [69] also found that the NLCD land classification was less than 40% accurate in determining agricultural gain and loss. This is a common problem with satellite imaging [70]. Acknowledging these inaccuracies, the NASS notes that “Pixel and acreage counts are not official estimates” [28]. Although an automated satellite image classification provides a convenient way to quantify land use change, the results could be misleading if not carefully verified. The documented problems suggest that automated land classification needs a rigorous verification before it is used to quantify the land use change.

5. Conclusion

Impacts of biofuel on food price and land use change are difficult to observe or measure directly and hence they are often simulated using economic models. However, economic models may fail to incorporate significant non-economic factors, and that model parameter values may not be representative making the model predictions inaccurate. This paper compares the model outcome predicting the impact of biofuel to the real-world data.

Economic models predict that biofuel will increase the food price. A comparison of the average increase in commodity price index (CPI) showed no evidence of a higher rate of CPI for food before and after the biofuel boom of 2000. The food price inflation rate from 1991 to 2000 (before significant biofuel production era), and from 2000 to 2016 (after the biofuel fuel boom) were not significantly different from the 2.6% rate of average inflation for the entire range. Among several factors contributing to a relatively lower inflation rate compared to recent history, increasing per capita food production and the higher feed production as a co-product of biofuel were pointed out as significant factors. Although corn and soybean prices were rising temporarily during the biofuel era, the price dropped sharply after 2012–2013 despite increasing biofuel production. This indicates that biofuel may not be the real cause of corn and soybean price increase.

Another contradiction in model prediction is that, despite the increasing amount of biofuel production, the US corn and soybean export has not declined. While US exports of corn and grain, in general, had not changed significantly since 1991, oilseed exports had been increasing at an average rate of 1.2 million MT/year. This phenomenon was attributed to growing per capita grain and oil crop production. Corn and soybean production per capita grew at an annual 2.3% and 2.8% respectively between 1991 and 2016.

Globally, it was found that the food price index (FPI) had the highest correlation with crude oil price and 96% of the variability could be explained from the crude oil price and world population. The correlation between the FPI with crude oil price was causal at a 95% confidence interval. Looking at these discrepancies between model predictions and observed data, we concluded that the assumptions in economic models predicting the impact of biofuel on food prices and indirect land use change needs to be revised, and carefully assessed to see if the model captures the complex real-world dynamics adequately by validating the results against real-world data. Additionally, the causality of correlations must be justified and tested to ensure that predictions remain valid for the foreseeable future.

This paper also evaluated the accuracy of machine classified satellite images land coverage map. Although these resources were not built for land use change research, they are being used for that purpose. We analyzed three selected areas in the US with a total of 664 km^2 from a diverse geographic location, and manually verified the CropScape CDL automated satellite image land use classification and NLCD image data. We found an average of 27.86% of total land cover classification error. The misclassification errors were not random, 10.9% of the non-agriculture land was classified as agriculture whereas only 2.23% of agricultural land was classified as something else, so a net 8.66% of the non-agriculture land was classified as agriculture land. This observed phenomenon was attributed to higher a priori probability of agricultural land compared to other categories to classify a border pixel.

Automated CDL image classification from 2011 to 2015 shows an average increase in agriculture land of 8.53 km^2, which is 1.28% of the land area considered. When the manually verified land classifications were compared, the agricultural increase was only 0.31 km^2 with a 95% confidence interval of $\pm$ 2.7 km^2. This corresponds to 0.05 $\pm$ 0.41% of the land area. Since a 95% confidence interval of the change in the agricultural area included zero, it was concluded that land area change to agriculture was not statistically significant. Based on our findings, it was concluded that satellite analysis is not an accurate method of determining land use change. In summation, our findings indicate that there has been no significant change in US food prices due to biofuels and biofuels have not caused any significant agricultural land use change. We conclude that machine classified satellite images do not have needed accuracy yet to be used for land use change analysis.

Declarations of interest

None.

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