February 18, 2021

Attention: Docket ID No. EPA–HQ–OAR–2020–0322

U.S. Environmental Protection Agency
1200 Pennsylvania Avenue, NW
Washington, DC 20460

Re: Comments on *Notice of Receipt of Petitions for a Waiver of the 2019 and 2020 Renewable Fuel Standards* (86 Fed. Reg. 5182; January 19, 2021)

Dear Docket Clerk:

The Renewable Fuels Association (RFA) appreciates the opportunity to submit these comments in response to the U.S. Environmental Protection Agency's (EPA) *Notice of Receipt of Petitions for a Waiver of the 2019 and 2020 Renewable Fuel Standards* (86 Fed. Reg. 5182; January 19, 2021). The waiver requests submitted to the EPA included three separate letters from state governors and a letter from an attorney representing a group of small refineries, the members of which were not publicly disclosed.

RFA is the leading trade association for America's ethanol industry. Its mission is to drive expanded demand for American-made renewable fuels and bioproducts worldwide. Founded in 1981, RFA serves as the premier forum for industry leaders and supporters to discuss ethanol policy, regulation, and technical issues. RFA's 300-plus members are working to help America become cleaner, safer, more energy secure, and economically vibrant.

Section 211(o)(7)(A) of the Clean Air Act (CAA) states that the EPA Administrator may waive "the national quantity of renewable fuel required" under the Renewable Fuel Standard (RFS) "(i) based on a determination by the Administrator, after public notice and opportunity for comment, that implementation of the requirement would severely harm the economy or environment of a State, a region, or the United States; or (ii) based on a determination by the Administrator, after public notice and opportunity for comment, that there is an inadequate domestic supply." The waiver requests fail to demonstrate harm as required by the statute and as interpreted by the EPA in its prior denials of waiver petitions in 2008[1] and 2012,[2] in that:

- *The harm experienced by refineries in 2020 was caused by the COVID-19 pandemic, not the RFS.* The governors sought the waivers principally as a way to provide relief from the pandemic's impact on transportation fuel

[1] 73 FR 47168
[2] 77 FR 70752

consumption, and this was also a primary justification in the small refiners' letter. However, the EPA has previously stated that for a waiver to be approved, it must be determined the RFS *caused* severe economic harm; contribution to such harm would not be sufficient, if it occurred. Additionally, since the annual RFS obligations are expressed as percentages, the actual 2020 volume requirements automatically readjusted in response to the downturn in transportation fuel consumption. It is also important to recognize that *all* segments of the energy sector, including the ethanol industry, experienced economic hardship as a result of COVID-19.

- *A waiver would have no impact on renewable fuel volumes or transportation fuel prices during the compliance years for which it was requested, since they are in the past.* The governors' letters asked for a waiver for 2020, and the letter from the small refiners' attorney requested a waiver for 2019 as well. The EPA previously rejected petitions on the basis that severe economic harm would not occur if a waiver would not "repair" the alleged harm, or if the waiver would have only negligible effects on renewable fuel volumes or transportation fuel prices.

- *A substantial inventory of renewable identification numbers (RINs) was carried over into 2019 and 2020 that would be available to small refineries and other obligated parties to use for compliance.* Additionally, prices of the category of RINs associated with ethanol (so-called D6 RINs) were at historical lows in 2019 and were below average in 2020.

- *Academic research and the EPA's own statements establish that refiners pass along the cost of RINs via the price they charge for fuels in the wholesale market.* As a result, there could be no economic harm to refineries from the increase in RIN prices that occurred in late 2020.

- *The refineries are asking the EPA to use a waiver to circumvent a court ruling, and their request that a general waiver be tailored specifically to small refineries is inconsistent with the statutory requirement that a waiver be nationwide in scope.* Their request is a thinly veiled attempt to circumvent a January 2020 decision by the U.S. Court of Appeals for the Tenth Circuit, which ruled that under the previous administration the EPA had improperly granted small refinery exemptions from the RFS. Additionally, their request is plainly inconsistent with CAA section 211(o)(7)(A), which as noted above states that any waiver is to be implemented "by reducing the *national* quantity of renewable fuel required." (Emphasis added).

- *EPA requires petitioners seeking a general waiver to demonstrate that the RFS caused severe harm to the economy of a State, region, or the United States.* Even if the petitioners were able to establish that the RFS itself was the cause of severe harm, the statute requires that they must show the harm was experienced by a State, region, or the United States – not by individual refiners or a group of refiners.

- *The petitioners did not provide any economic analysis substantiating the need for a waiver, as explicitly required by the EPA's 2008 guidance on future requests for waivers.*

Further substantiation of each of these points is provided below. Additionally, a letter that the EPA received from the National Wildlife Federation (NWF) is addressed, even though the organization does not qualify as a party that can submit a waiver petition.

Any harm experienced by refineries was caused by the COVID-19 pandemic, not the RFS. RFS obligations automatically adjust downward if there is a decline in fuel consumption such as was experienced in 2020.

Letters requesting a waiver from the 2020 renewable volume obligations (RVOs) were submitted to the EPA by Governor Edwards of Louisiana[3] on April 7, by the governors of four oil states on April 15,[4] by and Governor Wolf of Pennsylvania on May 11.[5] Most of the content of the letters was identical, with all three stating that a waiver was necessary because "the macroeconomic impacts of COVID-19 have resulted in suppressed international demand for refined products, like motor fuels and diesel." The letter sent on behalf of small refineries requested a waiver from their individual RVOs for 2019 and 2020.[6]

The pandemic did take a toll on transportation fuel consumption in 2020. The February 2021 *Short-Term Energy Outlook* by the U.S. Energy Information Administration (EIA) estimated that motor gasoline consumption declined to 8.04 million barrels per day (mmbd) in 2020 from 9.31 mmbd in 2019. It was also a very difficult year for ethanol producers, as U.S. ethanol consumption fell to 0.82 mmbd in 2020 from 0.95 mmbd in 2019. Both gasoline and ethanol consumption decreased by 13%.

The cause of the difficulties experienced by refiners in 2020 is apparent from the governors' requests. Following introductory paragraphs, the letters dated April 7 and 15 stated, "Let us be clear: on Friday, March 13, 2020, President Trump declared a national emergency related to control of the novel coronavirus known as COVID-19." Governor Wolf makes similarly notes that "our industry continues to be impacted by the novel coronavirus known as COVID-19." The small refiners' letter began by listing a triad of causes for their difficulties: "[t]he Tenth Circuit's recent ruling in *Renewable Fuels Association v. EPA*, effectively eliminating small refinery hardship relief, coupled with the COVID-19 pandemic and the precipitous drop in crude oil prices due to the Russia-Saudi Arabia disagreement."

The EPA characterized the letters in its Notice of Receipt of Petitions by observing, "They argue that reduced gasoline and diesel demand *due to the coronavirus pandemic*

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[3] Letter from Louisiana Governor John Bel Edwards to EPA Administrator Andrew Wheeler (April 7, 2020).
[4] Letter from Texas Governor Greg Abbott, Utah Governor Gary Herbert, Oklahoma Governor Kevin Stitt, and Wyoming Governor Mark Gordon to EPA Administrator Andrew Wheeler (April 15, 2020)
[5] Letter from Pennsylvania Governor Tom Wolf to EPA Administrator Andrew Wheeler (May 11, 2020)
[6] Letter from LeAnn Johnson Koch to EPA Administrator Andrew Wheeler (March 30, 2020)

has harmed refiners, and that the 2020 RFS volume requirements are and will continue to inflict further harm on these parties."[7]

Given that the pandemic was the cause of the refineries' difficulties, implementation of the RFS cannot have led to severe economic harm. The EPA has been consistent that a determination of such harm can only be made if the RFS is the cause; even if the petitioners demonstrated the RFS was a *contributor* to economic harm (which they have not done), that would not be sufficient justification for a waiver. In its 2012 Notice of Decision Regarding Requests for a Waiver of the Renewable Fuel Standard, EPA wrote, "The statute authorizes a waiver where 'implementation of the requirement would severely harm the economy.' In the 2008 waiver determination, EPA concluded the straightforward meaning of this provision is that implementation of the RFS program itself must be the cause of the severe harm. We found that the language provided by Congress does not support the interpretation that EPA would be authorized to grant a waiver if it found that implementation of the program would significantly *contribute* to severe harm."[8]

Moreover, the mechanism by which the annual RFS requirements are implemented makes a waiver unnecessary. In his letter, Governor Edwards proposed a specific remedy for the impact of the pandemic: "Such a waiver should lower the total RVO by an amount commensurate with the current projected shortfall in national gasoline and diesel consumption." This is already the case, since the annual RVOs under the RFS are expressed as *percentages* that specify what share of an obligated party's gasoline and diesel production must be comprised by renewable fuels. Because of this, the absolute volume of renewable fuel required to be used decreased proportionally with transportation fuel consumption in 2020. For example, assuming combined gasoline and diesel consumption decreased by 12% (compared to projected volume from EIA's October 2019 *Short Term Energy Outlook* that was used by EPA to calculate the 2020 standards), the actual renewable fuel volume requirements also would have been reduced by 12%. In this way, the annual RVOs already have a built-in mechanism for accommodating fluctuations in gasoline and diesel consumption—even large ones.

A waiver would have no impact on renewable fuel volumes or transportation fuel prices during the compliance years for which it was requested, since they are in the past.

As noted above, the governors requested a waiver for compliance year 2020, while the letter sent on behalf of small refineries also included 2019. Both years are in the past, so even if the EPA were to grant a waiver, biofuel usage and transportation fuel prices in those years would not change. Given this, for practical purposes severe economic harm cannot be demonstrated, since EPA in 2008 and 2012 rejected petitions after analysis showed that waivers would have negligible effects on these metrics. In its 2008 Notice of Decision Regarding the State of Texas Request for a Waiver of a Portion of the Renewable Fuel Standard, the Agency concluded, "EPA believes that waiving the RFS mandate would not significantly affect the use of ethanol during the time period at issue,

[7] 86 FR 5183 (emphasis added)
[8] 77 FR 70773 (EPA's emphasis)

and the most likely result is that implementation would have no effect. Therefore it is unlikely that implementation of the mandate would cause harm to the economy."[9]

Additionally, in the same decision, the Agency noted that granting a waiver under such circumstances would be contrary to the goals of the RFS, stating, "EPA believes that generally requiring a high degree of confidence that implementation of the RFS would severely harm an economy would appropriately implement Congress' intent for yearly growth in the use of renewable fuels, evidenced by the 2005 and 2007 mandates for such growth."[10]

A substantial inventory of RINs was carried over into 2019 and 2020 that would be available to small refineries and other obligated parties to use for compliance.

In its final rulemaking for the 2020 RVO, the EPA estimated that there were 3.48 billion 2018-vintage RINs carried over into 2019 and available for compliance with that year's standards.[11] This was equivalent to 17.4% of the 2019 total renewable fuel standard, close to the 20% carryover limit (the estimates implied that the number of D6 RINs was 18.7% of the implied conventional biofuel requirement). The EPA assumed that the same number of 2019 carryover RINs would be available to meet the 2020 standards, and as a result the RIN bank represented a nearly identical percentage of the 2019 total renewable fuel standard (the same is the case for D6 RINs).

The latest data available from the EPA indicate that the carryover RIN bank is likely somewhat lower but still large. As of Jan. 10, 2021, there were 2.53 billion 2019 RINs and 17.17 billion 2020 RINs available.[12] (The 2019 compliance deadline for small refiners was extended, and the EPA has proposed further extending it along with the 2020 compliance deadline for all obligated parties.)

As discussed above, since the annual RVOs are expressed as percentages, the actual volumes of renewable fuels required in 2020 fell proportionally with gasoline and diesel consumption. However, the number of carryover RINs from prior years was unaffected. Therefore, the carryover RIN bank would have covered an even larger share of the effective 2020 requirements. If there were 2.53 billion 2019 RINs carried over into 2020, they would have represented 12.6% of the original 2020 volume obligations. If it is assumed that fuel usage fell 12% in 2020, carryover RINs would have met 14.3% of the actual requirement. That is, contrary to the arguments in the waiver requests, the pandemic made it somewhat easier to meet the 2020 RVOs in aggregate.

Additionally, D6 RIN prices were at historical lows in 2019 and remained subdued for most of 2020, as a result of the expansion in the number of small refinery exemptions

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9 73 FR 47183

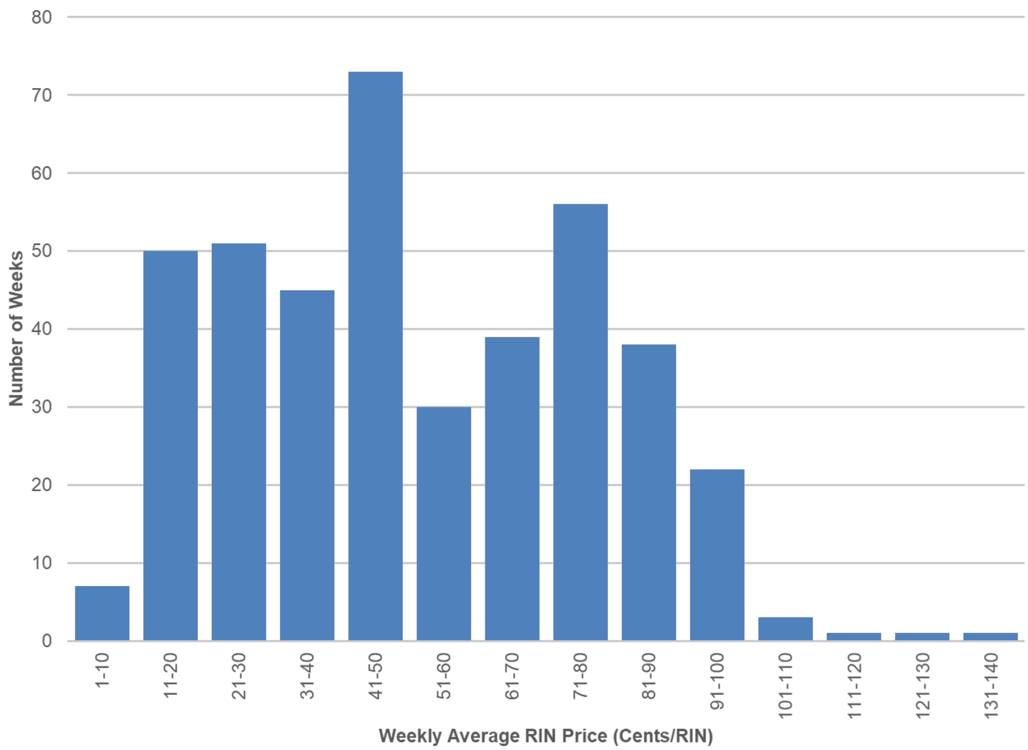
10 73 FR 47172

11 Nick Parsons, "Carryover RIN Bank Calculations for 2020 Final Rule," U.S. EPA Office of Transportation and Air Quality (December 3, 2019), available at www.regulations.gov docket number EPA-HQ-OAR-2019-0136-2052.

12 EPA, Public Data for the Renewable Fuel Standard, available at https://www.epa.gov/fuels-registration-reporting-and-compliance-help/available-rins. There are also 27 million 2018 RINs available for compliance with the 2019 standards.

granted over the last few years. The average price of a D6 RIN was 18 cents in 2019 and 43 cents in 2020, both of which are low compared to prices experienced since 2013 (Exhibit 1). This provided an inexpensive means of RFS compliance for any refiners that did not obtain a sufficient number of RINs through biofuel blending.

Exhibit 1: Distribution of Weekly Average D6 RIN Prices, 2013-2020



Source: RFA analysis of OPIS data
Note: The distribution shows the number of weeks from 2013 to 2020 that the RIN price was within a certain range.

Academic research and the EPA's own statements establish that refiners pass along the cost of RINs via the price they charge for fuels in the wholesale market.

It is widely accepted, including by many refiners and EPA itself, that obligated parties are able to pass through their RIN costs to buyers of refined product at the wholesale level. This, along with the large available RIN bank, would have kept refiners from experiencing economic harm in connection with complying with the RFS in 2019 and 2020.

The EPA in 2015 stated, "Merchant refiners . . . should not therefore be disadvantaged by higher RIN prices, as they are recovering these costs in the sale price of their products."[13] In its 2017 Denial of Petitions for Rulemaking to Change the RFS Point of Obligation, the EPA elaborated further: "When RIN prices rise, the market price of the petroleum blendstocks produced by refineries also rise to cover the increased RIN

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[13] Dallas Burkholder, "A Preliminary Assessment of RIN Market Dynamics, RIN Prices, and Their Effects," U.S. EPA Office of Transportation and Air Quality (May 14, 2015), available at www.regulations.gov docket number EPA-HQ-OAR-2015-0111-00062.

costs, in much the same way as they would rise in response to higher crude oil prices. The effective price of renewable fuels . . . however, *decreases* as RIN prices increase. When renewable fuels are blended into petroleum fuels these two price impacts generally offset one another for fuel blends such as E10."[14] Later in 2017, in its Renewable Fuel Standard Program Standards for 2018 and Biomass-Based Diesel Volume for 2019: Response to Comments, the Agency flatly stated, "EPA has invested significant resources evaluating the impact of high RIN prices on refiners. After reviewing the available data, EPA has concluded that refiners are generally able to recover the cost of RINs in the prices they receive for their refined products, and therefore high RIN prices do not cause significant harm to refiners."[15]

The small refineries' request that a general waiver be provided only to them is inconsistent with the statutory requirement that any waiver be nationwide in scope, and their request is actually an attempt to circumvent a court ruling.

As discussed above, the letter for the group of small refineries fails to demonstrate severe economic harm because it acknowledges that the difficulties experienced by the industry were caused by "the COVID-19 pandemic and the precipitous drop in crude oil prices due to the Russia-Saudi Arabia disagreement" and were not specific to the implementation of the RFS. Additionally, waivers were requested for the 2019 and 2020 compliance years, which are now in the past; given that such waivers would not change biofuel volumes or transportation fuel prices in those years, severe economic harm cannot be shown according to EPA's past general waiver decisions.

Additionally, the specific actions requested by the attorney for the small refineries are contrary to a plain reading of the statute. The letter indicated that the group was "requesting that the [EPA] use its waiver authority to provide relief to small refineries for the 2019 and 2020 compliance years by waiving small refineries' RFS renewable volume obligations." However, CAA section 211(o)(7)(A) clearly states, "The Administrator, in consultation with the Secretary of Agriculture and the Secretary of Energy, may waive the requirements . . . by reducing the *national* quantity of renewable fuel required." (Emphasis added). The following, CAA section 211(o)(7)(C) then continues, "A waiver granted under subparagraph (A) shall terminate after 1 year, but may be renewed by the Administrator after consultation with the Secretary of Agriculture and the Secretary of Energy." It is evident that granting a waiver to a subset of obligated parties would not be national, and a waiver covering 2019 and 2020 would not be for one year.

This is amplified by the EPA's statements in its 2008 and 2012 decisions not to grant general waivers. In its 2008 decision, the Agency explained, "EPA believes that it would be unreasonable to base a waiver determination solely on consideration of impacts of the RFS program to one sector of an economy, without also considering the impacts of the RFS program on other sectors of the economy or on other kinds of impact."[16] It

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[14] U.S. EPA, "Denial of Petitions for Rulemaking to Change the RFS Point of Obligation," (November 22, 2017), available at www.regulations.gov docket number EPA-HQ-OAR-2016-0544. (EPA's emphasis)

[15] U.S. EPA, "Renewable Fuel Standard Program Standards for 2018 and Biomass-Based Diesel Volume for 2019: Response to Comments," (December 12, 2017), available at www.regulations.gov docket number EPA-HQ-OAR-2017-0091-4990

[16] 73 FR 47172

subsequently addressed the refining industry in particular, noting that the "decision will affect not only refiners, importers and other regulated parties in Texas but also refiners, importers, and other regulated parties throughout the nation who must comply with the renewable fuel standards and other requirements in order to produce gasoline and renewable fuel for use in the United States. A waiver would affect the national volume of renewable fuel that is required, and would therefore affect parties all across the nation who produce gasoline or renewable fuel."[17]

Regarding the timeframe for the waiver, in its 2012 decision the Agency noted, "EPA clearly has authority to grant a waiver for a period of one year only, and any renewal would need to be the subject of a separate, if related, action."[18]

This request utterly fails to meet the criteria for a waiver. That's because it is actually a thinly veiled attempt to get the EPA to use its *general* waiver authority to circumvent both the Tenth Circuit decision and the Agency's established process for considering petitions for individual small refinery exemptions.

The petitioners did not provide any analysis substantiating the need for a waiver, as called for in the EPA's 2008 guidance on future requests for waivers.

In its 2008 waiver decision, the EPA established guidance on future requests for waivers. The Agency advised, "EPA expects that applicants would provide a comprehensive and robust analytical basis for any claim that the RFS itself is causing harm, and the nature and degree of that harm."[19] The governors' letters were two pages in length and did not include any analysis. The letter from the attorney for the group of small refineries was lengthier and included an aptly titled "Argument" section, but that focused on legal issues and did not contain what could be described as an analysis. The Agency's 2008 guidance indicated that petitions that lacked such substantiation could be denied without an opportunity for comment.

There has been no severe environmental harm from the RFS. To the contrary, academic research shows the RFS has reduced greenhouse gas emissions and improved air quality.

The EPA noted in its Notice of Receipt of Petitions that it had "received a letter from the National Wildlife Federation suggesting that relief could be granted on the basis of severe environmental harm." This organization does not qualify to submit a petition to the EPA for a waiver on the basis of severe environmental harm, since CAA section 211(o)(7)(A) establishes that the Administrator "may waive the requirements . . . in whole or in part on petition by one or more States, by any person subject to the requirements of this subsection, or by the Administrator on his own motion." The NWF does not fall under one of those categories.

[17] 73 FR 47184
[18] 77 FR 70758
[19] 73 FR 47183

In its 2012 waver decision, the EPA received comments that raised the issue of potential environmental impacts of the RFS. Since no individuals or organizations meeting the CAA criteria to file a petition had raised this as an issue, the Agency determined, "With respect to the environmental impacts of increased renewable fuel use, the waiver requests are not based on a claim of severe harm to the environment." In its letter last May supporting the governors' waiver requests, NWF openly acknowledges, "These waiver requests are based upon a demonstration of 'severe economic harm.'"[20]

Given that the NWF letter cannot be considered a waiver petition under the criteria established in the CAA and that none of the petitions that were received by the EPA requested a waiver on the basis of severe environmental harm, the EPA should not consider such a claim in making its decision about the 2019 and 2020 waiver requests.

Still, since the EPA mentioned the NWF in its notice, we will take this opportunity to set the record straight on the environmental benefits of ethanol and the flaws in the NWF's allegations.

The first allegation in the letter is a well-worn one for the NWF: that the RFS has caused land use change. Notably, the letter acknowledges that EPA's Second Triennial Report to Congress "declined to draw a direct connection between observed land use change and the RFS."[21] It then refers to "subsequent research," which is actually a continuation of work that Tyler Lark, Holly Gibbs and Christopher Wright have been conducting since 2013 and which was considered and cited in the EPA's report. A common thread across this research is the erroneous usage of satellite-based imagery, and specifically the use of a U.S. Department of Agriculture (USDA) database for a purpose for which it was not suited.

These fundamental flaws were examined in a paper by the Laboratory for Applied Spatial Analysis at Southern Illinois University Edwardsville (SIUE-LASA).[22] It noted that the research by Lark et al. has relied heavily on use of the USDA's Cropland Data Layer (CDL), which assigns land type categories using satellite imagery. The research suggests there has been conversion of grassland and other "native" lands to cropland since the RFS was established. However, the CDL has shortcomings that render it poorly suited for this type of analysis, notably the inability to differentiate between grassland types (native prairie, Conservation Reserve Program, grass hay, grass pasture and fallow/idle grasslands), a problem USDA itself has recognized. Additionally, the research is prone to reflecting "false change," in which a higher share of actual cropland is recognized in the newer, more-accurate CDL versions than in older, less-accurate versions, thus giving the appearance that cropland expanded. The authors from SIUE-LASA summarized their findings by saying, "There are major concerns regarding both the

[20] Letter from National Wildlife Federation President and CEO Collin O'Mara to EPA Administrator Andrew Wheeler (May 29, 2020).

[21] U.S. EPA. Biofuels and the Environment: Second Triennial Report to Congress (Final Report, 2018). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-18/195, 2018.

[22] Pritsolas J. and R. Pearson. 2019. "Critical Review of Supporting Literature on Land Use Change in the EPA's Second Triennial Report to Congress." Available at: https://ethanolrfa.org/wp-content/uploads/2019/07/SIUE-Review-of-Land-Use-Change-Literature-07-2019.pdf

data and the methods that were used by the researchers, which call their findings into question."

The NWF's allegation that "the federal corn ethanol mandate is contributing to climate change" is completely contrary to the scientific consensus, as clearly demonstrated in two studies released in early 2021. A paper by scientists from Harvard University, Tufts University and Environmental Health & Engineering Inc. shows that using corn-based ethanol in place of gasoline reduces GHG by almost half.[23] The "central best estimate" of corn ethanol's carbon intensity is 46% lower than the average carbon intensity of gasoline, according to the study's authors, with some corn ethanol in the market today achieving a 61% reduction. A second study by Life Cycle Associates found that the RFS reduced carbon dioxide-equivalent GHG emissions by nearly one *billion* metric tons between 2008 and 2020.[24] Additionally, the reduction in GHG emissions associated with corn-based ethanol has long been reflected in Argonne National Laboratory's Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) model and is recognized by the California Air Resources Board.

Finally, the NWF made a brief and highly generalized comment that ethanol worsens air quality. This is contrary to real-world emissions trends. Since the RFS was adopted in 2005, ethanol consumption has grown more than threefold, while EPA data from air monitors show that carbon monoxide concentrations are down 31%, nitrogen dioxide is down 22%, ozone is down 13%, fine particulate matter is down 37% and sulfur dioxide is down 81%. The levels of all these pollutants have now fallen below the national standard.

Conclusion

A waiver of the RFS is not justified, for the reasons discussed in detail above. The requests that have been submitted by the governors and the group of small refineries fail to meet the statutory criteria as interpreted in the EPA's prior waiver decisions. Therefore, we ask that the Agency expeditiously reject all of the requests.

Thank you for the opportunity to submit these comments. RFA appreciates your consideration.

Sincerely,

Geoff Cooper
President & CEO

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[23] Scully M. et al. 2021. "Carbon intensity of corn ethanol in the United States: state of the science." *Environ. Res. Lett.* in press https://doi.org/10.1088/1748-9326/abde08

[24] Unnasch. S. and Parida D. 2021. "GHG Reductions from the RFS2 – A 2020 Update." Life Cycle Associates. Available at: https://ethanolrfa.org/wp-content/uploads/2021/02/LCA_-_RFS2-GHG-Update_2020.pdf

Attachments:

Joshua Pritsolas and Randall Pearson (July 2019). "Critical Review of Supporting Literature on Land Use Change in the EPA's Second Triennial Report to Congress."

Stefan Unnasch and Debasish Parida, Life Cycle Associates (February 2021). "GHG Reductions from the RFS2 – A 2020 Update."

Attachment 1:

Critical Review of Supporting Literature on Land Use Change in the EPA's Second Triennial Report to Congress

Joshua Pritsolas and Randall Pearson

Laboratory for Applied Spatial Analysis

Southern Illinois University Edwardsville

July 2019

SOUTHERN ILLINOIS UNIVERSITY EDWARDSVILLE

Critical Review of Supporting Literature on Land Use Change in the EPA's Second Triennial Report to Congress

Joshua Pritsolas and Randall Pearson
Laboratory for Applied Spatial Analysis

Prepared for: Renewable Fuels Association

Executive Summary

This report evaluated the methods and data utilized in the land cover/land use change (LCLUC) research by Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017). These studies received a fair amount of consideration in the Environmental Protection Agency's (EPA) *Second Triennial Report to Congress* (2018). However, there are major concerns regarding both the data and the methods that were used by the researchers, which call their findings into question.

<u>Major Concerns with Data Inputs</u>:

- A critical issue for the reviewed studies is their reliance on the satellite-based Cropland Data Layer (CDL) published by the U.S. Department of Agriculture (USDA) as the primary data. The CDL has several shortcomings, including the inability to differentiate between grassland types (e.g., native prairie, Conservation Reserve Program, grass hay, grass pasture and fallow/idle grasslands). As the USDA's National Agricultural Statistics Service (NASS) (2018b) acknowledges, "Unfortunately, the pasture and grass-related land cover categories have traditionally had very low classification accuracy in the CDL." In fact, NASS (2018b) recommends that researchers use the National Land Cover Dataset (NLCD) for all non-agricultural land cover studies.
- The CDL has improved over time (due to changes in satellite temporal, spatial, and spectral resolutions). However, changes in the accuracy of the CDL make comparisons of land cover and land use across an extended period problematic. As a result, some of the LCLUC estimated in the studies by Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) might represent false change, in which a higher share of actual cropland is recognized in the newer CDL versions than in older versions, thus giving the appearance that cropland expanded.
- Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) identified increases in croplands over the conterminous United States. However, data from the USDA's NASS (2018a) indicate that croplands decreased from 2008 to 2012, and by 2017 cropland acres were below 2007 levels.
- For this report, an in-depth examination of the 2008 and 2012 CDLs was performed for Iowa, since Lark et al. (2015) identified the state as having a substantial amount of land conversion and since their data set was subsequently used by Wright et al. (2017). Additionally, the state is the top producer of ethanol, with approximately 27 percent of capacity as of the end of 2018.
- Assessment of the USDA NASS (2018a) acreage estimates by crop showed that from 2008-2012 in Iowa there was a net increase of only 38,000 acres of cropland as opposed to 263,468 acres as reported by Lark et al. (2015) and 295,100 acres as reported by Wright et al. (2017).
- Analysis of the CDL at the agricultural district level in Iowa showed that critically different types of misclassification were present in two of Iowa's distinctly different districts (north central and south central).

- Misclassification in south central Iowa, where marginally productive cropland is located, showed improvements over time in the CDL by 2012. However, the implications of a comparative analysis using a less-accurate 2008 CDL as the base year and comparing it with more-accurate 2012 CDL results in false change. The more-accurate 2012 CDL accounted for nearly 100 percent of the acreage of corn and soybeans, whereas the less-accurate 2008 CDL accounted for just over 80 percent of acreage (i.e., misclassification was more extensive). As a result, a significant share of what was concluded to be land use change likely was a reflection of better accounting for crop acreage in the CDL over time.
- It is of major importance to consider how studies like Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) were impacted by false change due to misclassification.

<u>Major Concerns with Assessed Methods</u>:

- All studies insinuated that cropland expansion was in some amount attributable to the Renewable Fuel Standard (RFS) program; however, this assumption was not quantified and even the EPA (2018) warned about the issues with attributing causation.
- The major concerns with Wright and Wimberly (2013) were: (1) the lack of an accuracy assessment for their aggregated classification of land types into a corn/soybean category and a grassland category and (2) the use of only two isolated years (a start and end point) to measure LCLUC. The lack of an accuracy assessment is most problematic because without the accuracy assessment it does not give the end-user a high level of confidence in the classification to measure change.
- The main issues with the Lark et al. (2015) study were: (1) the aggregation process that tried to mitigate the CDL's inability to differentiate between grassland types (e.g., native prairie, Conservation Reserve Program, grass hay, grass pasture, fallow/idle grasslands, etc.); (2) the lack of evidence that supported the claim that aggregation mitigated between-class error; and (3) the lack of an accuracy assessment for the LCLUC data set created in this study.
- Lark et al. (2015) reported the omission of 9.4 million acres of unidentifiable long-term land cover (termed "flip-flop"). This omitted land cover of 9.4 million acres was greater than their reported total of 7.34 million acres of gross conversion from non-croplands to croplands.
- Wright et al. (2017) conducted an accuracy assessment of the Lark et al. (2015) adjusted CDL, but the methods used were ambiguous and the results of this accuracy assessment were not elaborated.
- Wright et al. (2017) introduced a uniform bias correction factor across the entire conterminous U.S., which was problematic because non-uniform spatial and temporal errors exist in each of the annual CDLs.
- Wright et al. (2017) reported that the original Lark et al. (2015) data set needed to be corrected due to 12 percent of the identified change being on non-arable lands.

Overall, considerations of the reviewed studies (Wright and Wimberly 2013; Lark et al. 2015; Wright et al. 2017) revealed that fundamental concerns were present throughout the research. The data utilized in these studies contained many inherent issues, and the methods that were implemented to address these issues were presented with many assumptions and lacked evidence to support the claims. Although these studies brought novel ideas to the forefront in addressing the challenges and complexities of understanding national LCLUC, there was still considerable uncertainty surrounding the results. There remain many shortcomings that bring the validity of these studies' findings regarding LCLUC into question and until these shortcomings are addressed, policy makers would be best suited to remain skeptical.

Introduction

The EPA is in process of proposing a reset of the volume requirements associated with the RFS program. A key component to the assessment and decision process of the upcoming reset has been the *Second Triennial Report to Congress* published by the EPA (2018). In this thorough report, one of the EPA's focuses was on environmental and conservation impacts of the current RFS program. Throughout this report, the EPA cited a multitude of different research conducted, but gave a fair amount of consideration to a few studies that focused on cropland expansion throughout the United States after the expansion and extension of the RFS2 under the Energy Independence and Security Act of 2007.

The major findings from these studies suggested that large-scale planting of corn grain and soybeans has increased and changed certain land uses, which resulted in negative environmental and resource conservation impacts. Furthermore, these studies also insinuated that increases in biofuel demands and production over the study time-periods were directly or indirectly attributable to the RFS program.

Given the market and economic impacts that could arise from the upcoming reset to the RFS program, the Renewable Fuels Association (RFA) was interested in a review of specific studies that have been presented in the *Second Triennial Report to Congress* (EPA 2018). As an independent consultant, the Laboratory for Applied Spatial Analysis at Southern Illinois University Edwardsville was contracted by RFA to assess several of these studies. The primary review that will be presented in the following sections of this report will be concerned with studies conducted by Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017). These were the primary studies cited by the EPA (2018) that discussed land use change in the United States. This review will be focused on determining the validity of the data sources (including imagery products) and methods utilized in these studies. During this review, other literature and data sources will be referenced to verify the integrity of these studies.

A basic overview of this report's layout will consist of four sections. First, a highlight of the methods and findings of Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017). Next, a critical assessment of the pros and cons of the methods that were used in these studies. Third, a review of the input data source used in these studies and also an analysis of the CDL compared to the USDA NASS cropland totals. Lastly, a collective overview of the challenges presented in this review and potential recommendations will be discussed.

Literature Review

This section will briefly discuss the data assessed, methods used, and results presented by Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017). This section is intended only as an overview of these studies. It must be noted that none of the three studies reviewed in this report used a base year of 2007 for their analysis. This is important because for crops to qualify as feedstock for biofuels used toward the RFS2, they must come from land cleared or cultivated prior to the enactment of the Energy Independence and Security Act of 2007. The implications of these studies using a base year different than 2007 could misrepresent the results, since a comparative analysis of the impacts of RFS2 would want a base year that started before the policy was implemented.

It is also important to consider that U.S. corn acreage fell by just over 7.5 million acres from 2007 to 2008 (NASS 2018a); therefore, any comparative analysis that used a relatively low point as the base year, such as 2008 for comparative analysis would overstate the possible change in land use/cover. This is of most importance regarding the Lark et al. (2015) and Wright et al. (2017) studies since these studies used a base year of 2008. With this said, it is understood that the CDL did not have full nationwide coverage prior to 2008, but the CDL did have 21 soybean and corn states available in 2007—of which were states that showed much of the cropland expansion in both Lark et al. (2015) and Wright et al. (2017).

The first study reviewed was conducted by Wright and Wimberly (2013). In this study, the authors investigated LCLUC in the Western Corn Belt (WCB) of the United States from 2006-2011. The authors utilized the annual CDL collected by the USDA NASS. These data were all used at 56-meter resolution (unknown if and how the data at 30 meters were resampled), with certain sub-categories being aggregated into two classes: (1) a generalized grassland category (e.g., native grassland, grass pasture, grass hay, fallow/idle cropland, and pasture/hay) and (2) a corn/soybean category. The main portion of this study conducted a bitemporal comparison between 2006 and 2011 for the entire WCB that resulted in a binary output of change or no change. However, certain states (Iowa and North Dakota) were compared from 2001-2011 because these data were available at the time of the study. Once these data were collapsed into the two classes, a five-pixel by five-pixel majority filter was applied to reduce small areas that could have been misclassified. After spatial filtering, the resulting image was aggregated to 560-meter resolution as percent change from grassland to corn/soybean. This newly aggregated data was then smoothed with a quartic kernel function at a bandwidth of 10 kilometers. These methods resulted in annual conversion rates from 2006-2011 in the WCB of approximately 1 to 5.4 percent and a total of approximately 1.3 million acres of grassland converted to corn/soybean.

The second study investigated was researched by Lark et al. (2015). In this study, a similar approach to Wright and Wimberly (2013) was undertaken, but a larger data set was utilized, and more robust methods were implemented to deal with potential pitfalls from the Wright and Wimberly (2013) study. The data set used in this research was the 56-meter CDL of the conterminous United States and investigated LCLUC from 2008-2012 (all 30-meter data was resampled using nearest neighbor method). Different methods were utilized by Lark et al. (2015) to address limitations of a bitemporal approach. In this sense, the authors looked at a trajectory-based approach that attempted to account for errors and variability in the data across time and space. Furthermore, their analysis also utilized ancillary data from the Multi-Resolution Land Characteristics Consortium's (MRLC) NLCD and the United States Geological Survey's Land Cover Trends Dataset to identify long-term trends of LCLUC. Lark et al. (2015) aggregated the entire 2008-2012 CDL data set by year into two classes: crop and non-crop. Once aggregated, these data were stacked into 5-year combinations of crop or non-crop to create "trajectories" (also considering how the NLCD 2001 and 2006 was classified in the beginning of this temporal order). The authors then applied a spatial filter (3-by-3 majority) to reduce misclassification errors and a temporal filter that looked at the patterns of each pixel to classify them as change or no change (to/from crop or non-crop). It must be noted that the authors removed pixels that displayed a "flip-flop" pattern due to no identifiable long-term consistent pattern. Lastly, the authors also utilized a minimal mapping unit (MMU) of approximately 15 acres (20 pixels), which also omitted small area change. Overall, the trajectory-based approach resulted in an adjusted CDL data set that, when analyzed, revealed that gross conversion of non-crop to crop was at 7.34 million acres and gross conversion of crop to non-crop at 4.36 million acres (2.98 million net cropland expansion). Furthermore, the authors identified that 77 percent (5.7 million acres) of the gross conversion occurred on grasslands. Lastly, and of interest, was the amount of reported "flip-flop" or intermittent cropland, totaling 9.4 million acres.

The final study reviewed was conducted by Wright et al. (2017), which investigated cropland expansion in relation to ethanol refineries in the United States from 2008-2012. The authors of this study used the Lark et al. (2015) data set but considered two different aspects that the previous study did not address. First, Wright et al. (2017) added an accuracy assessment and bias correction factor to the Lark et al. (2015) data set. Next, Wright et al. (2017) investigated the rates of cropland conversion based on incremental distances (25, 50, 75, and 100 miles) from ethanol refineries. Important to the methods used, Wright et al. (2017) acquired high-resolution (1 to 2-meter) aerial imagery from the National Agricultural Imagery Project (NAIP) to test the accuracy of the Lark et al. (2015) data set. In this accuracy assessment, the authors used a stratified random sample (n = 150) from all strata as ground-truth testing points with NAIP references. Results from the accuracy assessment revealed that producer and user accuracies (which will be explained in the following section) where high for identifying crop (88.6 and 98 percent, respectively) and non-crop (99.6 and 98 percent, respectively), with slightly less producer and user accuracies reported for cropland conversion (72.7 and 70.4 percent, respectively) and abandonment (97.5 and 43.2 percent, respectively). These accuracy assessments of the Lark et al. (2015) data set showed high bias (125 percent) in overestimation of abandoned croplands, with less biases in estimating crops (-10 percent), non-crops (2 percent), and converted cropland (3 percent). Wright et al. (2017) introduced a bias correction factor to only the abandoned cropland class of the Lark et al. (2015) data set. This correction factor was uniformly applied across the entire conterminous United States data set to correct for the reported overestimation of identifying abandoned croplands but did not correct for the other slightly less biases in the other classifications. With respect to the results from their analysis, the authors found that approximately 4.2 million acres of non-cropland were converted to cropland within a 100-mile radius of ethanol refineries (another 2 million acres outside of this range). Of these 4.2 million acres of converted non-cropland, approximately 3.6 million acres were converted from grasslands within a 100-mile radius of ethanol refineries (another 1.5 million acres were outside the 100-mile radius). Wright et al. (2017) did not report a nationwide total area of crop to non-crop reversion. The authors only showed a bar chart with crop to non-crop acreages at 25, 50, 75, and 100-mile distances of refineries and indicated that total reversion was "substantially reduced" after the bias correction (Wright et al. 2017, 4). However, the authors did report the total abandonment of crop to grasslands at 600,000 acres within 100 miles of ethanol refineries and an additional 590,000 acres outside of the 100-mile radius (total reversion to grasslands of approximately 1.2 million acres).

Assessment of Applicable Methods

Wright and Wimberly 2013

To begin this section a short discussion of the methods outlined in Wright and Wimberly (2013) will be discussed. Wright and Wimberly (2013) acknowledged that two major issues were present in their research. First, by using a short time-period and bitemporal comparison (2006 and 2011) to suggest long-term patterns of land conversion may have been misleading. In other words, the authors recognized that short-term land use with rotational variability may be more reflected in their study instead of long-term LCLUC. Furthermore, this limitation in their research was identified by other researchers (Lark et al. 2015; Lark et al. 2017; Wright et al. 2017) and has also been discussed as a potential overestimation in conversions to cropland (Lark et al. 2015; Dunn et al. 2017; EPA 2018). The total gross conversion of grasslands presented by Wright and Wimberly (2013) of 1.97 million acres from 2006-2011 in the WCB (N. Dakota, S. Dakota, Nebraska, Minnesota, and Iowa) was a slightly higher estimation when compared with Wright et al. (2017), who reported gross conversions of the same area that totaled approximately 1.81 million acres over a shorter (and different) time-period from 2008-2012.

Lastly, Wright and Wimberly (2013) discussed the limitations of the CDL to differentiate between grassland types (e.g., native prairie, Conservation Reserve Program, grass hay, grass pasture, fallow/idle grasslands, etc.). In doing so, the researchers aggregated these categories to one large class to attempt mitigation of classification errors in the sub-categories. Although, this assumption may potentially decrease the classification error between grassland types, the authors presented no accuracy assessment to support this assumption. Furthermore, it is unknown at what level errors could have still been occurring between the aggregated general grassland class and the aggregated corn/soybeans class. This point becomes more important when considering the CDL has varying accuracy levels for different land uses and the accuracies for these land uses across different states and different temporal coverages can have a wide range of overall errors (Dunn et al. 2017; NASS 2018b).

Although this study and the methods used were innovative and well received according to the EPA (2018), other researchers have indicated that this study has potential errors that were not systematically dealt with properly (Lark et al. 2015; Dunn et al. 2017; Lark et al. 2017). Due to these limitations, other research followed by attempting to deal with these shortcomings.

Lark et al. 2015

Assessment of methods used by Lark et al. (2015) attempted to account for the peer-reviewed limitations found in the Wright and Wimberly (2013) research. Although Lark et al. (2015) introduced a trajectory-based approach that incorporated intermittent years, along with ancillary data to better understand long-term change, a critical assessment of Lark et al. (2015) brings several questions to the forefront. To begin with, as discussed in the evaluation of Wright and Wimberly (2013), Lark et al. (2015) also utilized an aggregation process; however, these authors aggregated all CDL classes to either crop or non-crop. This "super class" aggregation process introduced by Lark et al. (2015) could be problematic in locations where croplands other than those used to produce biofuel feedstocks were contributing to cropland expansion totals. Furthermore, Lark et al. (2015) also did not provide an accuracy assessment that this aggregation process mitigated misclassification errors, they only provided a brief description that was an assumption in the supplemental documentation. As other researchers have pointed out, even a small error in differentiating between aggregated crop and non-crop classes in a large-scale study could present biased results (Sandler and Rashford 2018) or the margin of error could be greater than the reported conversions (Dunn et al. 2017). Furthermore, it is likely that the errors were not evenly distributed across the geography of the United States and a good portion of these errors could likely occur in conversion areas (Dunn et al. 2017) or along transition zones between different land uses (since transition zones can confound classification models). Lacking provisions of an assessment of how commission and omission errors were handled by the aggregation process, on a temporal and spatial basis, decreases the robustness of this type of study.

Second, Lark et al. (2015) used a trajectory-based approach that resulted in a binary output of change or no change data layer that was stacked over the 5-year study period, and also incorporated NLCD products from 2001 and 2006 (Figure 1).

Fig. 1: Example of binary change from 2008-2012 (Lark et al. 2015).

The authors focused on classes that showed patterns of change or no change, and attempted to place noise patterns into their appropriate change or no change class. The authors also discussed that other outcomes of "flip-flop" were removed but did not specify how many different combinations occurred or locations of where these other possible combinations resulted (since there are 2^5 = 32 possible outcomes). However, Lark et al. (2015) did separate out the "flip-flop" or intermittent cropland rotations, which resulted in approximately 9.4 million acres of assessed land use. The authors briefly mentioned this interesting portion of assessment but did not provide any further evaluation of where this intermittent cropland was distributed, nor did they discuss the potential likelihood of errors in misclassification impacting these areas.

Next, the minimal mapping unit (MMU) method that Lark et al. (2015) utilized was acknowledged by the authors as a potential limitation that would not properly capture small (< 15 acres or approximately 20 pixels) LCLUC. Lark et al. (2015) suggested that the MMU technique would: (1) reduce small areas of false change due to less accuracy in earlier years of the CDL and (2) improve comparisons of whole field conversion (> 15 acres) with NASS surveyed statistics. Lark et al. (2015) did not report how much total acreage the MMU technique omitted from the study or the spatial distribution of the omitted acreage. Concerning the potential loss of small changes, which a majority could result from small areas of farm fields being reverted to non-crop (short-term or long-term), this process potentially omitted real change from the analysis. In total, these possible reversions (that were omitted) across regions or, in this case, the United States could be quite substantial. Furthermore, Lark et al. (2015) discussed the use of MMU to increase comparability with NASS statistics, which becomes even more confounding. Lark et al. (2015) cited NASS figures that showed a net increase of 2.6 million acres of cultivated cropland from 2008-2012, which was similar to their net increase of 2.98 million acres. However, NASS (2018a) statistics for total cropland from 2008-2012 actually showed a decrease in cropland of approximately 1.1 million acres (Figure 2).

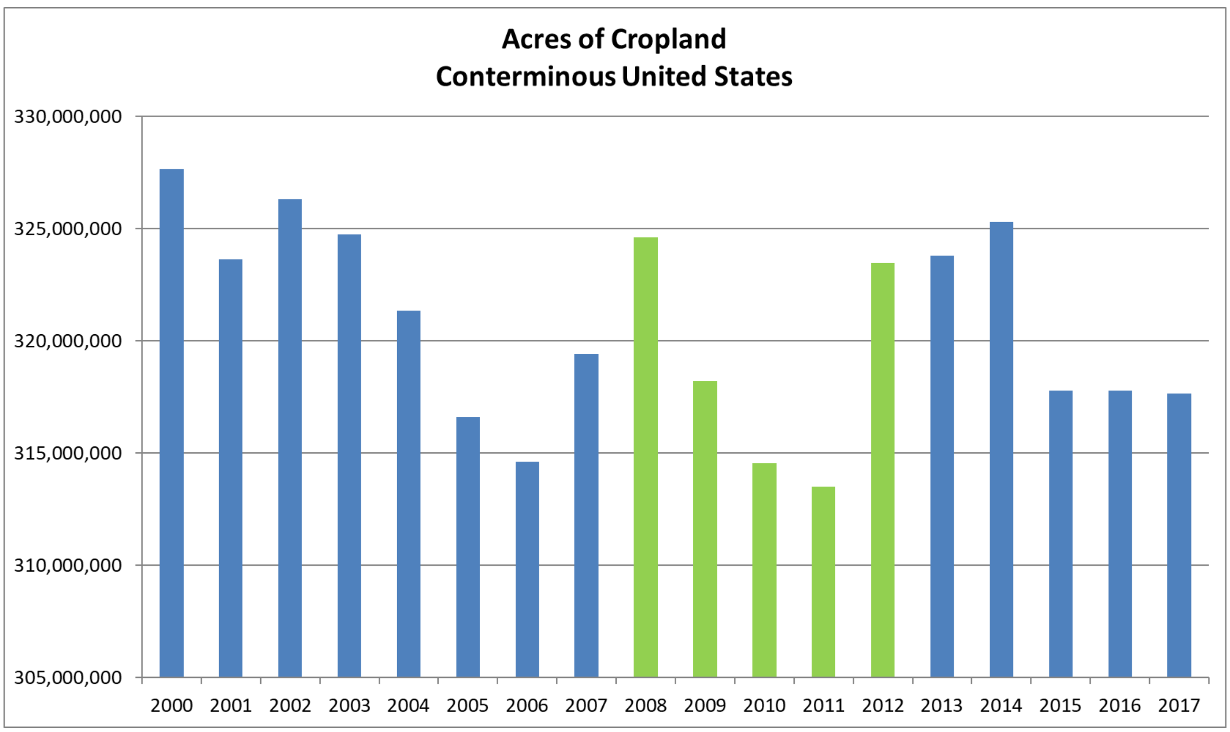

Fig. 2: NASS total croplands from 2000-2017 (NASS 2018a). Green bars highlight the Lark et al. (2015) study time-period.

Lastly, the use of the NLCD as a reference to help aid in establishing long-term crop or non-crop patterns and the mapping techniques used by Lark et al. (2015) will be discussed. The use of the NLCD to assist in modifying the CDL aggregated crop and non-crop classes can aid in better estimations of LCLUC

(Lark et al. 2015; Dunn et al. 2017; Lark et al. 2017; Wright et al. 2017; EPA 2018). However, Dunn et al. (2017) made it clear that accuracy assessments must be completed to give users a sufficient level of confidence in the resulting LCLUC maps/analysis. Moreover, Lark et al. (2015) did not provide an accuracy assessment and also made an assumption that the NLCD 2001 and 2006 data sets were accurate starting points in their analysis to assess classifications of crop/non-crop and change/no change. Lark et al. (2015) presented no evidence that supported this assumption of accuracy surrounding the NLCD data sets (this will be discussed further in following sections). Next, the mapping techniques used by Lark et al. (2015) raised several concerns. Some of the questionable mapping techniques used were:

1. the gross and net conversion maps were aggregated to 5.6 km resolution for display, but used a color scheme that did not adequately distinguish between the low ends of abandonment and expansion.
2. the relative cropland expansion map was assumed to be at 10 km resolution, with a scale bar that did not indicate the exclusion of values equal to zero, but indicated exclusion of values equal to 100.
3. the choropleth map identifying uncultivated conversion rates was broken into 12 classes (with odd break points) that made it difficult to discern which class certain ecoregions belonged.
4. the map of most common breakout crop by region did not specify the spatial resolution and was confusing about what breakout truly means.

Generally, the mapping techniques utilized were misleading due to changes in spatial resolutions (or the lack of identified spatial resolution), ramping techniques and color schemes used, and ambiguity.

Overall, Lark et al. (2015) introduced methods that attempted to correct issues in the Wright and Wimberly (2013) study. Many of these methods were interesting attempt to deal with inconsistencies in the CDL temporal sequence, but many issues were also present that did not validate or give high confidence in the results presented. The main issues with this study were:

1. the aggregation process that tried to mitigate the CDL's inability to differentiate between grassland types (e.g., native prairie, CRP, grass hay, grass pasture, fallow/idle grasslands, etc.).
2. the lack of evidence that supported the claim that aggregation mitigated between-class error.
3. the lack of an accuracy assessment for the LCLUC data set created in this study.

The presence of assumptions in the methods and the lack of more robust evidence to support the claims presented by Lark et al. (2015) should be kept in mind when utilizing this research.

Wright et al. 2017

The third study's methods that will be discussed were conducted by Wright et al. (2017). In this study, the major discussion will surround the use of the Lark et al. (2015) data set along with the accuracy assessment and bias correction factor implemented by Wright et al. (2017). First, Wright et al. (2017) used high-resolution NAIP as a ground-truth mechanism (or reference images) for the Lark et al. (2015) data set. This is a common practice in remote sensing, especially since the study area was the entire conterminous United States. The potential of randomized sample locations being chosen from inaccessible locations or a variety of long-distance locations for assessment makes the use of NAIP an effective measure. However, it is problematic that Wright et al. (2017) did not specify how many NAIP products (e.g., a single image from one year or a single image from multiple years) were used in the accuracy assessment. Nonetheless, the accuracy assessment presented in the supplemental documentation by Wright et al. (2017) gave producer and user accuracies between four classifications, with an overall accuracy reported at 97.5 percent (Figure 3).

Before further discussion of the Wright et al. (2017) accuracy assessment, it would be good to define producer and user accuracy. First, producer accuracy can be best understood as the accuracy of a classification map from the perspective of the map maker and deals with classification errors that are omitted from a given class. Producer accuracy (as a percentage) deals with how well each class can be identified based on comparisons with the reference map. However, user accuracy, which is often referred to as the reliability of the land use map, is concerned with the utility of a map from the perspective of the end-user and deals with classification errors of commission into other classes. User accuracy (as a percentage) deals with how well the land use map represents what is actually on the ground.

		NAIP LCLUC						
		Non-crop	**Crop**	**Convert**	**Abandon**	**Sum**	**User's Accuracy**	**Bias**
Lark et al. LCLUC	**Non-crop**	0.8255	0.0172	0.0000	0.00000	0.8427	**98.0%**	2%
	Crop	0.0019	0.1435	0.0010	0.00000	0.1464	**98.0%**	-10%
	Convert	0.0006	0.0005	0.0027	0.00003	0.0038	**70.4%**	3%
	Abandon	0.0005	0.0007	0.0000	0.00098	0.0023	**43.2%**	125%
	Sum	0.8285	0.1619	0.0037	0.00101		*Overall*	
	Producer's Accuracy:	**99.6%**	**88.6%**	**72.7%**	**97.5%**		**97.5%**	

Fig. 3: Agreement/disagreement matrix with accuracies and bias reported (Wright et al. 2017).

The easiest way to understand the agreement/disagreement matrix is to consider that non-crop and crop were classified as no change areas and converted and abandoned were both evaluated as change areas. When assessing the accuracy of no change areas (non-crop and crop), both producer (99.6 and 88.6 percent, respectively) and user accuracies (98.0 and 98.0 percent, respectively) were relatively high, but no change for crop areas had a moderate bias (-10 percent) to underestimate these true locations.

Next, and of more importance since this study was focused on assessing LCLUC, were the accuracies related to change areas (converted and abandoned). With converted areas, the producer accuracy was moderate at 72.7 percent, which means the data set accurately identified 72.7 percent of the land converted to crop in the reference NAIP. However, the user accuracy was slightly lower at 70.4 percent, which means that only 70.4 percent of the identified lands converted to crop were actually converted change areas on the ground (with a small bias to overestimate conversion by 3 percent). Lastly, the producer accuracy to identify abandoned croplands in the reference NAIP was high at 97.5 percent, but the user accuracy was only correctly identifying abandoned croplands 43.2 percent of the time (with high bias to overestimate abandonment by 125 percent).

Several factors were important to recognize in this accuracy assessment:

1. although the overall accuracy assessment of the entire data set was high at 97.5 percent, the accuracy assessment of change areas (converted and abandoned) resulted in high user errors (approximately 30 to 57 percent, respectively).
2. much of the error in identifying change areas was confused by both types of no change areas (non-crop and crop).
3. this accuracy assessment presented descriptive statistics, but gave no further statistical evidence that would suggest high levels of confidence in these accuracy levels or if the assessment was based on chance agreements.
4. none of these issues were addressed in the study or the supplemental documentation.

Based on the accuracy assessment, Wright et al. (2017) used the bias assessment to implement a bias correction factor to the Lark et al. (2015) data set. In this process, Wright et al. (2017) only issued a bias correction factor to the abandoned change areas since the bias was so high (125 percent). In doing so, the authors applied a bias correction factor in a uniform fashion across the entire conterminous United States. The assumption that this bias was distributed evenly across the United States was problematic. It is well documented that the CDL has variability in the errors associated with different crop and non-crop classes across different regions of the United States (Dunn et al. 2017; NASS 2018b). Since no spatial assessment was provided by the authors of the distribution of their errors and no further evidence was provided to support this assumption, this approach may not have actually corrected the bias issue, but rather potentially moved the error to other locations.

In closing, Wright et al. (2017) attempted to add robustness to the Lark et al. (2015) data set through a much-needed accuracy assessment and modification process. Part of this modification process identified and eliminated 12 percent of cropland expansion from the original Lark et al. (2015) data set due to this expansion occurring on non-arable lands. This phenomenon was identified as being problematic and was most likely what spurred the implementation of an accuracy assessment. The use of NAIP products as a reference to ground-truth was a solid approach to establish accuracies of classification. However, the exact use of NAIP as a reference to ground-truth was not clearly outlined. Moreover, based on the accuracy assessment provided by Wright et al. (2017), there was an indication that the Lark et al. (2015) data set was more adept at mapping areas of no change (non-crop and crop) as opposed to areas of change (converted or abandoned) based on the agreement/disagreement matrix (Figure 3). The attempt to adjust for bias was implemented in a spatially uniform manner, which is problematic since CDL classification mapping errors tend to occur in a non-uniform manner. Because of the lack of a more robust accuracy assessment, many of the issues that were present in the Lark et al. (2015) study were maintained in this study.

Evaluation of Data Utilized

The following sections will begin with a discussion on the data sets utilized in the reviewed studies (Wright and Wimberly 2013; Lark et al. 2015; Wright et al. 2017), specifically focusing on the evolution of the CDL and NLCD satellite-derived products. Next, further consideration will be discussed regarding the CDL's ability to map LCLUC over time since this data set was the primary data input in the reviewed studies. This discussion will be focused on establishing comparisons between CDL information and NASS information. Specifically, small scale comparisons will be made between the CDL and NASS data to assess the quality of the CDL as an input to monitor and map LCLUC in the Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) studies. Further visual assessments that were randomly selected to highlight issues will accompany these analyses.

CDL and NLCD Data Improvements

As this report and other researchers have alluded, the CDL has undergone constant changes to implement classification and mapping improvements over time (Lark et al. 2015; Dunn et al. 2017; Lark et al. 2017; Wright et al. 2017; EPA 2018; NASS 2018b). The CDL has historically had issues with mapping grassland-related categories and NASS (2018b) has advised that researchers instead use the NLCD for studies involving non-agricultural land. The CDL has even reprocessed and reissued revised data sets for 2008 and 2009 products (NASS 2018b) since the Lark et al. (2015) study.

Accuracy assessments from the CDL of these products have shown a wide range of overall accuracies (NASS 2018b). For example, 2008, 2012, and 2017 overall accuracy for South Dakota were 83.5, 35.0, 86.6 percent, respectively; however, Kansas, over the same three years, had overall accuracies of 87.5, 88.9, and 86.9 percent, respectively (NASS 2018b). These overall accuracies show high variability in South Dakota, with fairly high and consistent accuracies in Kansas, but overall accuracy is only part of the story when assessing classifications in the CDL products. Beyond the overall accuracies, it is critical to understand how errors are distributed across the agreement/disagreement matrix.

Even when classes of non-crop and crop are aggregated together, the assumption that between-class errors were accounted for (Wright and Wimberly 2013; Lark et al. 2015; Wright et al. 2017) needs to be further tested and validated. In some cases, and in certain regions, this could be accurate, but without evidence to support this claim across a national data set it would also be a fair assumption that errors are still present between non-crop and crop aggregated classes. Another factor to consider is that independent researchers have also shown that certain CDL reported errors can sometime be underestimated, such as in the 2009 and 2010 CDL errors for North and South Dakota (Sandler and Rashford 2018). Overall, non-uniform error in the CDL must be assessed and reported when large-scale studies use this data set to assess LCLUC so that the end-user can understand the strengths and limitations of these types of analyses.

The NLCD has also been assessed and results have shown improvements in classification capabilities over time (Wickham et al. 2010; Wickham et al. 2013; Wickham et al. 2014; Homer et al. 2015; Danielson et al. 2016; Wickham et al. 2017). Due to the improvements to these products, the NLCD has issued revised products from the legacy data set of 2001 to the LCLUC products from 2006 and 2011 (MRLC 2018). It is unknown if Lark et al. (2015) used the revised and amended 2001 and 2006 NLCD products from 2014 that were reissued when the NLCD 2011 was released. If the non-revised 2001 and 2006 NLCD products were used by Lark et al. (2015), then the potential for increased errors to establish long-term land use patterns for their study could have been present.

Considering the improvements to the NLCD over time, the newest revisions to the NLCD 2016 are currently under production to release in 2019 (Yang et al. 2018). Initial reports on overall accuracy assessments were high (ranging from 71 to 97 percent) and the outlined objectives from the NLCD 2016 are promising. Furthermore, the NLCD will release cloud-free Landsat imagery of the entire conterminous United States and LCLUC products in 2 to 3-year increments from 2001-2016 (Yang et al. 2018). These products could allow users to investigate LCLUC on a similar trajectory-based approach since a more robust temporal sequence would be available from the NLCD.

Overall, the CDL and the NLCD have committed to increasing accuracy over time and ensuring products are updated as data sources and classification models are improved (Wickham et al. 2010; Wickham et al. 2013; Wickham et al. 2014; Homer et al. 2015; Lark et al. 2015; Danielson et al. 2016; Lark et al. 2017; Wickham et al. 2017; NASS 2018b). Due to the efforts to improve these data sources, any longitudinal study may be problematic and should proceed with caution because comparisons of products with lesser degrees of accuracy (in early years, such as 2008 or 2009) with higher degrees of accuracy (in later years, such as 2012 or beyond) will produce results with false change, either in reversion or conversion totals. This issue would tend to be associated with the CDL as opposed to the NLCD since the NLCD is designed for direct comparability of their temporal products.

Evaluation and Comparison of the CDL with NASS Data

To begin this section, an evaluation of the 2008 and 2012 CDLs was performed in Iowa. This evaluation was initiated due to the conflicting results reported by Lark et al. (2015) about their findings being comparable with NASS figures that were presented earlier in this report (refer to the "Assessment of Applicable Methods" of Lark et al. 2015 section, specifically Figure 2). This evaluation considered how the CDL individual classification acreages compared to specific NASS (2018a) field crop totals. Furthermore, the comparison investigated totals at different geographic levels: state and agricultural districts.

Iowa was selected as a case study area for several reasons:

1. the large amount of agricultural production throughout much of the state with the marginal areas of grassland in the southern portion of the state.
2. the changing physical landscape and topography from northern to southern Iowa
3. the large amount of net conversion (5th highest of all states at 263,468 acres) reported by Lark et al. (2015) from 2008-2012.

It must be noted that Wright et al. (2017) utilized the Lark et al. (2015) data set, so these comparisons presented here are applicable to the Wright et al. (2017) findings as well.

Iowa state-level totals from 2008-2012 considered the following field crops from NASS (2018a): alfalfa, corn, hay, oats, soybeans, and wheat. Interestingly, NASS (2018a) included hay as a field crop as opposed to how Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) classified hay as non-cropland in their studies. As a result, the findings presented in this report will consider that hay is unique because it is defined differently by NASS (2018a) and the reviewed research. NASS (2018a) reported a net increase to field crop totals of only 38,000 acres without including hay as cropland in Iowa from 2008-2012. These NASS (2018a) totals showed that corn increased by 900,000 acres; however, these corn acres predominately replaced the decreasing acreages in other field crops (mostly alfalfa and soybeans). It is also worth mentioning again that U.S. corn acres (and in Iowa) were at a relatively low mark in 2008, so any comparison with this low mark as the base year would misrepresent any change. If 2007 would have been used as the base year any temporal comparison would have been considerably different since the national and Iowa corn acres were much higher for that year. With this said, even when compared with Lark et al. (2015) totals in Iowa from 2008-2012, this net increase was only approximately only 14 percent of the total net conversion that was reported by these researchers.

Analysis of the NASS (2018a) field crop totals at the agricultural district level revealed a similar spatial distribution of change as identified by Lark et al. (2015), but the magnitude of change identified by NASS from 2008-2012 was far less (Figures 4 and 5). Furthermore, Lark et al. (2015) identified south central Iowa as one of the areas with significant LCLUC; however, due to the drastic difference in total net change, it was suspected that the CDL was potentially having classification errors among certain crops/non-crops, and that this misclassification could be occurring at different levels within Iowa.

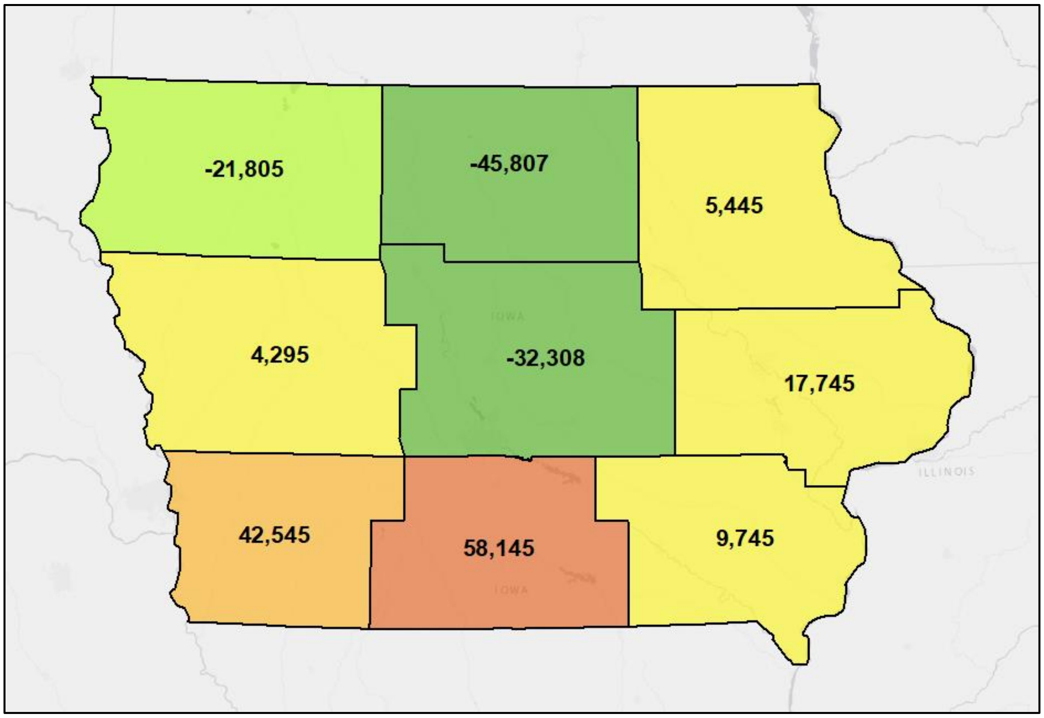

Fig. 4: All field crop changes in Iowa by agricultural district from 2008-2012 (NASS 2018a). Negative values indicate loss of planted cropland and positive values indicate gains of planted cropland. The north central and south central agricultural districts had the highest decrease (-45,807 acres) and increase (58,145 acres), respectively. Total net change (without hay) based on NASS (2018a) totals was 38,000 acres for Iowa from 2008-2012.

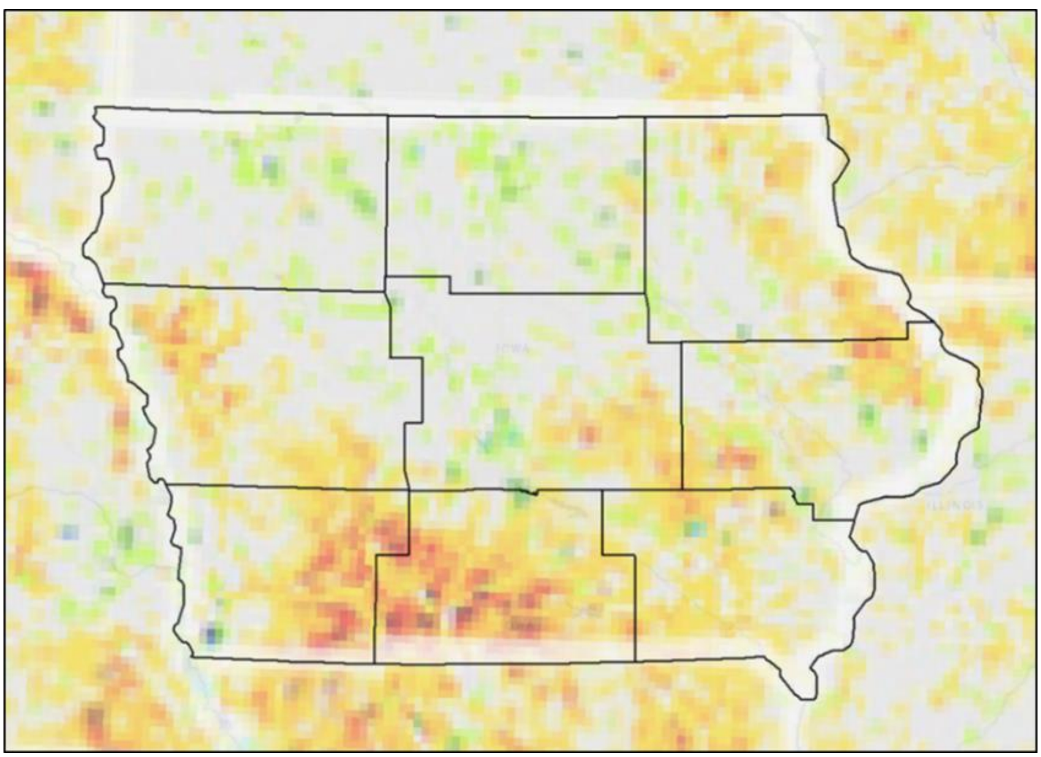

Fig. 5: A generalized version of the Lark et al. (2015) map of percent of landscape that was converted to and from cropland from 2008-2012 (blue to green represents reversion, gray represents no change, and yellow to red represents conversion). In this map, Iowa's agricultural districts are overlaid for a reference to compare to the NASS (2018a) field crop changes in Iowa by agricultural districts in Figure 5. Total net conversion reported by Lark et al. (2015) was 263,468 acres.

Testing of the CDL was conducted on two distinctly different agricultural districts (north central and south central) in Iowa from 2008-2012. These two agricultural districts were drastically dissimilar in their conversion and reversion totals, and they are physiographically different landscapes as well. The tests conducted were simple area calculations of the CDL by crop type via pixel counting method in each agricultural district, which were then compared to the NASS (2018a) totals for the corresponding crop type (Table 1).

Results from the 2008 comparison revealed that the CDL was analogous with the NASS (2018a) totals for corn (94.5 percent of estimated NASS total) and soybeans (96.1 percent of estimated NASS total) in the north central agricultural district. However, the south central agricultural district displayed less comparable totals for soybeans (81.2 percent of estimated NASS total) and for corn (83.3 percent of estimated NASS total). Hay and alfalfa were grossly underestimated by the 2008 CDL in both the north central and south central districts. Of interest, the total difference in acreage for corn and soybeans was similar in both the north central and south central, but the total acreage difference for alfalfa was significantly higher in south central Iowa (just over 175,000 acres) for 2008.

Table 1: Comparison of CDL acres vs. NASS acres for specific crop types in north central and south central Iowa from 2008-2012.

North Central	CDL 2008	NASS 2008	Difference 2008	Percent 2008	CDL 2012	NASS 2012	Difference 2012	Percent 2012	Change in Percent
Alfalfa	9,673	46,000	36,327	21.0	11,790	26,100	14,310	45.2	**24.1**
Corn	1,849,324	1,957,000	107,676	94.5	1,902,721	2,020,000	117,279	94.2	**-0.3**
Hay	599	10,200	9,601	5.9	3,275	9,100	5,825	36.0	**30.1**
Soybeans	1,210,203	1,259,000	48,797	96.1	1,117,177	1,172,000	54,823	95.3	**-0.8**
South Central									
Alfalfa	49,528	226,000	176,472	21.9	63,864	156,800	92,936	40.7	**18.8**
Corn	422,510	507,000	84,490	83.3	578,291	582,000	3,709	99.4	**16.0**
Hay	16,248	146,100	129,852	11.1	515,778	144,900	-370,878	356.0	**344.8**
Soybeans	463,517	571,000	107,483	81.2	616,330	618,000	1,670	99.7	**18.6**

*Columns labeled “Difference XXXX” are the NASS totals minus the CDL totals. Columns labeled “Percent XXXX” are the CDL totals divided by the NASS totals. The final column labeled “Change in Percent” is “Percent 2012” minus “Percent 2008”.
** Only alfalfa, corn, hay, and soybeans were used in this table (oats and wheat were omitted) because these categories had entries for all agricultural district for both years. These four crops accounted for over 99 percent of the NASS field crop totals.

When 2008 was compared with 2012, the north central district had no change at estimating soybeans and corn (95.3 and 94.2 percent, respectively). The south central district saw a significant improvement in the CDL estimates at 99.7 percent for soybeans (2008 was at 81.2 percent) and 99.4 percent for corn (2008 was at 83.3 percent). Hay and alfalfa saw increases in CDL estimates in the north central, but were still less than 50 percent of the NASS (2018a) totals. Furthermore, the south central district saw a drastic overestimation in hay, which was due to the 2008 CDL classification of grass/pasture changing to hay in the 2012 CDL (463,959 acres, approximately 90 percent, of 2008 grass/pasture was classified as hay in 2012). This is a prime example of the CDL’s inability to differentiate between grassland types (e.g., native prairie, Conservation Reserve Program, grass hay, grass pasture, fallow/idle grasslands, etc.). Overall, this comparison between 2008 and 2012 CDLs and NASS (2018a) totals identified that the CDL improved over time at estimating certain field crop totals. However, this analysis also raised concerns surrounding the CDL’s ability as an input data set for measuring land use change between years since certain land types were poorly classified.

Based on the 2008 Iowa CDL accuracy matrix (NASS 2018b) at the state-level, alfalfa was mostly confused with non-crop classes, such as hay and grass/pasture (lesser amounts of confusion with corn, soybeans, and oats). Corn and soybeans were predominantly confused with each other, and to a lesser degree with non-crop classes, such as hay, grass/pasture, and fallow/idle lands. The CDL and NASS comparison would indicate that a similar pattern may have occurred in the north central district, but a different and intriguing phenomenon was suggested in the south central district of Iowa.

The diverse physiography between the north central and south central districts in Iowa results in uniquely different crop field shapes in these two areas (Figure 6). These districts are within two distinct Major Land Resource Areas. The majority of crop fields in north central Iowa are large rectangular or square—shapes with well-defined boundaries that do not have much, if any, intermixing with other land use types. Whereas, south central Iowa has many relatively small irregular shaped crop fields that are overwhelmingly intermixed with other land use types.

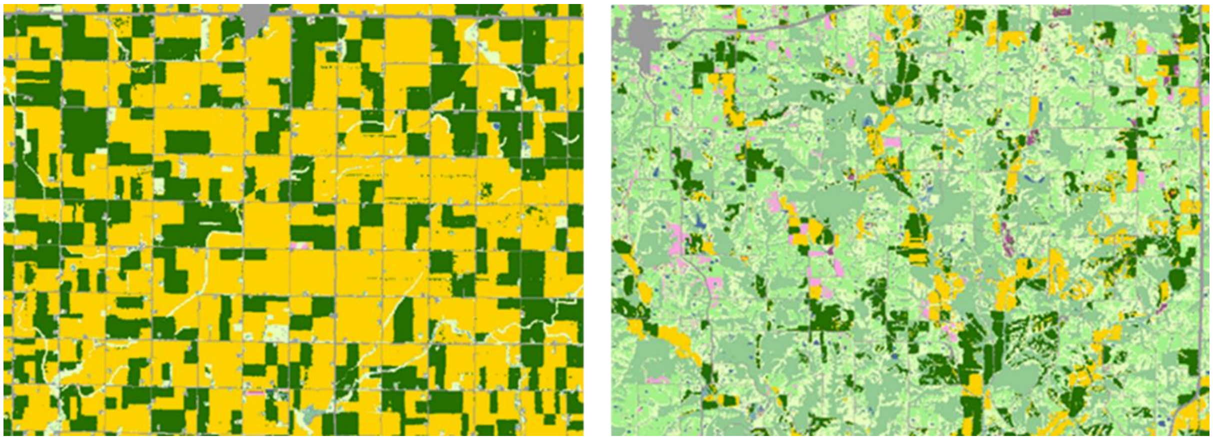

Fig. 6: Example from the 2012 CDL of corn (yellow) and soybean (dark green) fields in north central Iowa (left) and south central Iowa (right). North central is blocked crop fields on flatter terrain and the overwhelming majority of the land use, while the south central crop fields are disjointed and irregularly shaped, with a scattered pattern across more undulating terrain.

In the north central district, the 2008 landscape was dominated by corn and soybean, with minimal amounts of alfalfa and other non-crops, such as hay, grass/pasture or fallow/idle lands. Due to this, most misclassification that was occurring in this district was between corn and soybeans being confused with each other (Figure 7). This misclassification was identifiable by the presence of corn pixels speckled throughout a well-defined soybean field or soybean pixels speckled throughout a well-defined corn field.

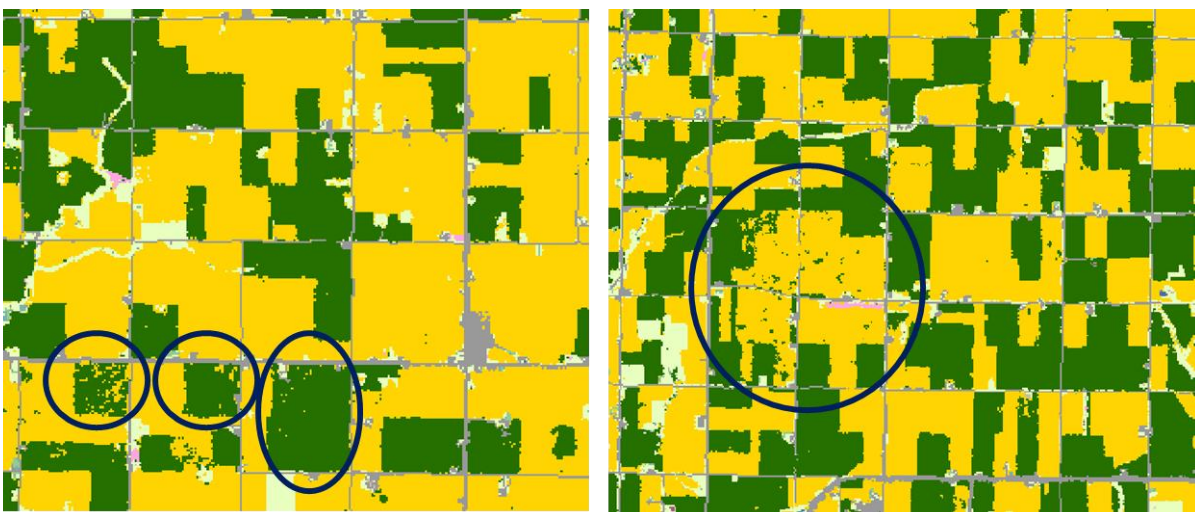

Fig. 7: Examples in the north central district of corn (yellow) and soybeans (dark green) being confused with each other in the 2008 CDL. Left images highlights corn pixels within soybean fields and right images highlights soybean pixels within corn fields.

However, in the south central district, the 2008 landscape was dominated by grass/pasture (just over 1.6 million acres). There were lesser amounts of corn and soybeans, and an increased amount of alfalfa compared to the north central district. Visual assessment suggested that much of the CDL misclassification in the south central district was between alfalfa (and also corn and soybean) being confused with grass/pasture or hay due to their lower estimated percentages when compared to NASS (2018a) totals in this district (Figure 8). This misclassification was evident by the fragmentation and speckling of crop or non-crop classes intermixed or in close proximity to one another.

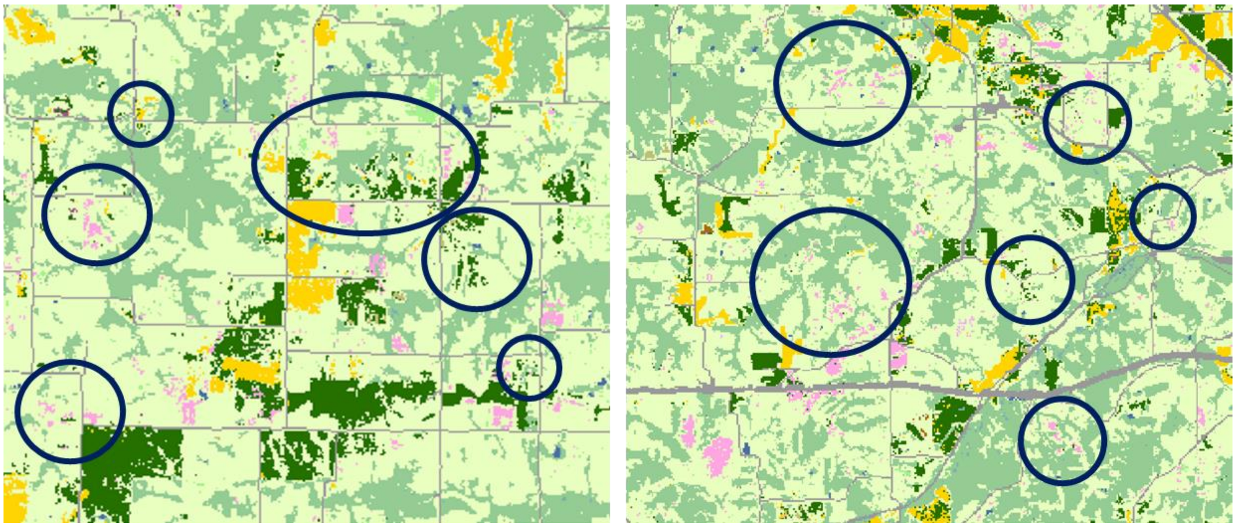

Fig. 8: Examples in the south central district of alfalfa (pink), and also some corn (yellow) and soybeans (dark green), confused with non-crop grass/pasture in the 2008 CDL. This confusion is noticeable via the fragmentation and speckling of these crop classes within non-crop classes.

Figure 9 exemplifies the implications of comparative analysis using the 2008 and 2012 CDLs. The dark and light blue boxes in the satellite imagery highlight areas that contained cultivated lands in 2008. These areas were managed croplands that showed the evolution of cultivated lands over a growing season. These cultivated lands and their associated management practices were represented by: (1) the indication of high biomass on June 14, then the lack of biomass on June 30, and finally high biomass again over the course of the other images (dark blue boxes in Figure 10) or (2) the growth of biomass throughout the growing season and then the loss of biomass by the end of the temporal sequence by September 27 (light blue box in Figure 10). However, the 2008 CDL did not fully capture these croplands since most of these areas were misclassified as grass/pasture. Furthermore, the 2012 CDL had these areas classified as cultivated croplands, so a comparison with the 2008 CDL would indicate that these areas changed from non-cropland to cropland. However, this change from non-cropland to cropland would actually be false change.

This is only one detailed and randomly selected visual assessment of the implications of LCLUC analysis using an early-year CDL (like the 2008 CDL). Moreover, it is suspected that this is a common theme in agriculturally marginal areas, such as southern Iowa where croplands can be misclassified as grass/pasture, hay, or other grassland types.

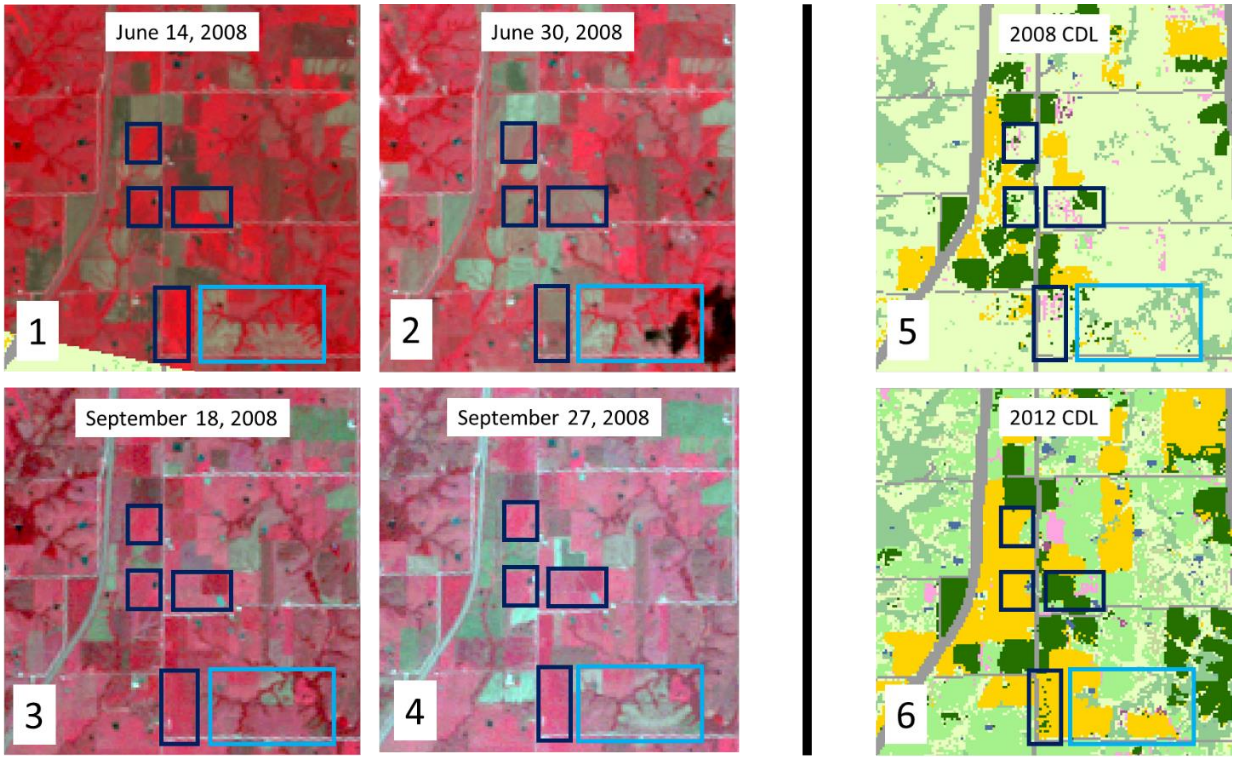

Fig. 9: Images 1-4 are color-infrared Landsat 5 TM. Images 5-6 are the 2008 and 2012 CDLs. Dark and light blue boxes highlight several examples of areas for misclassification comparison (all fields in these boxes are greater than 30 acres). The temporal sequence of Landsat 5 TM imagery shows the evolution of managed croplands over the growing season within the dark and light blue boxes.

Further visual assessments of a later-year CDL product in southern Iowa showed that misclassification was still an issue. The 2017 CDL was compared with one randomly selected panel of 2017 NAIP imagery from July 1, 2017 (Figure 10). The CDL was vectorized and turned completely transparent with a red outline to be able to see the NAIP imagery land type(s) that corresponded with the CDL classifications. Comparisons of the 2017 CDL with NAIP imagery showed: (1) general misclassification; (2) certain land classes were omitted due to how 30-meter pixels handle discrete classification; and (3) multiple land classifications could occur in only one known land class (Figures 11-14). This small visual assessment was done to show that even in more recent years the CDL still has issues with classification in these marginal areas in southern Iowa. Even though the CDL has committed to increasing accuracy over time (due to improved satellites, ancillary data for testing and validating, and classification modeling), the 2017 CDL was still showing confusion in the classification product.

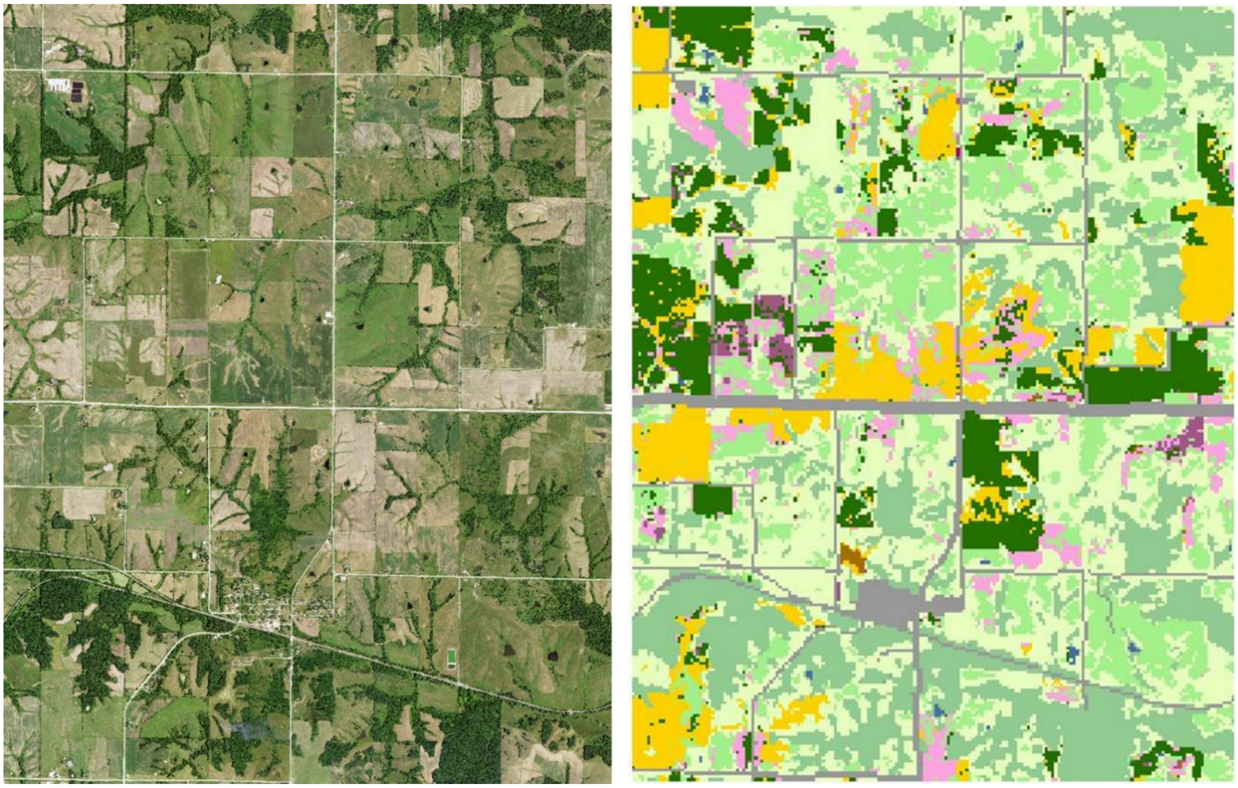

Fig. 10: 2017 NAIP Image (left) and 2017 CDL (right) used for comparison.

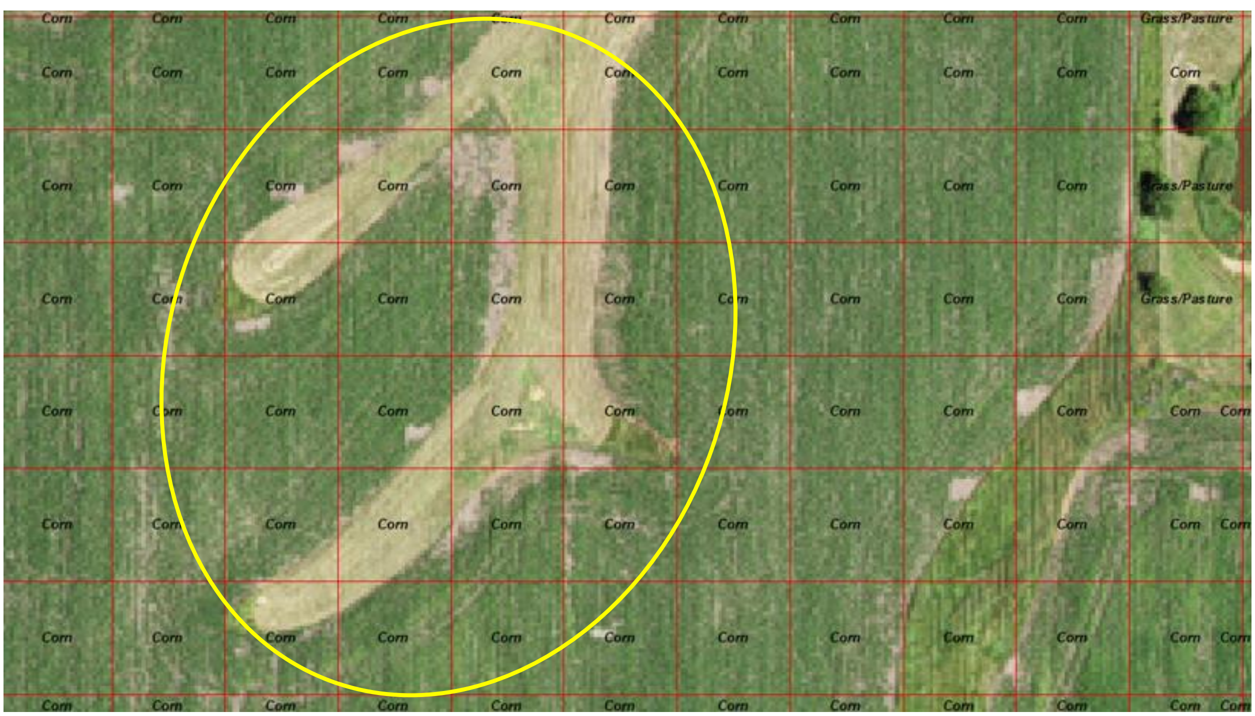

Fig. 11: 30-meter pixels omitted grassland from the 2017 CDL.

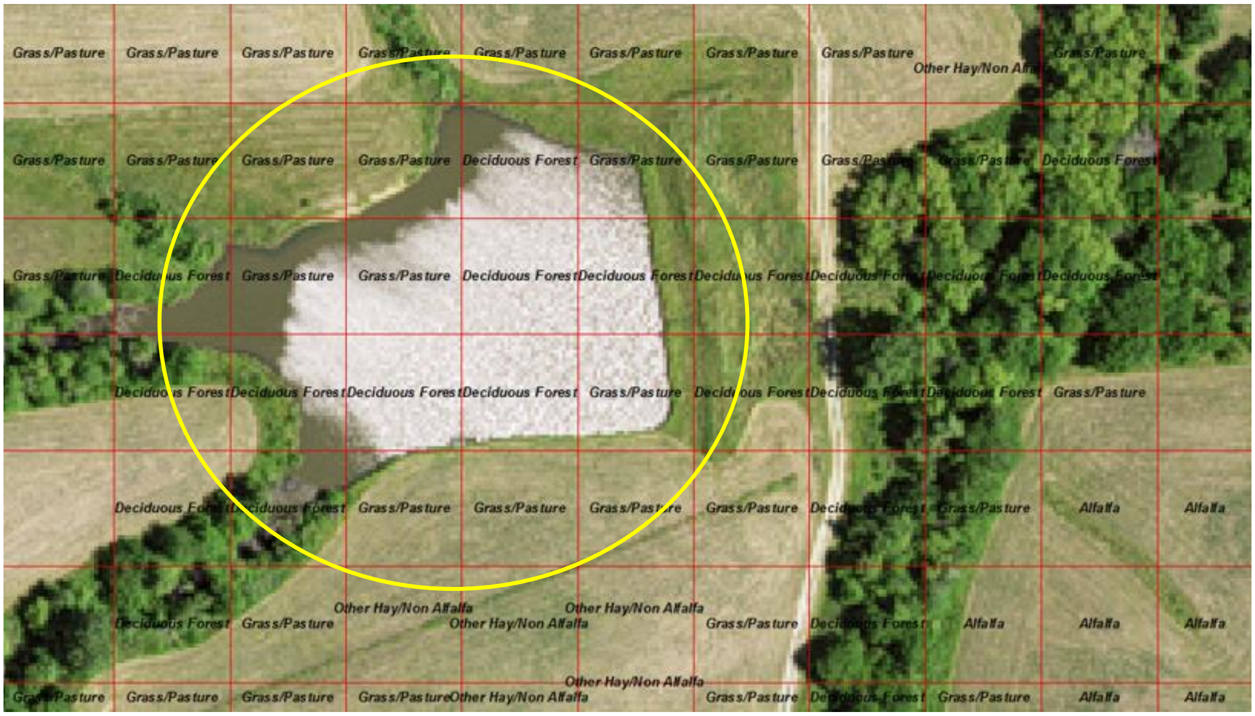

Fig. 12: General misclassification of water as deciduous forest and grass/pasture.

Fig. 13: General misclassification of hay and grass/pasture as deciduous forest.

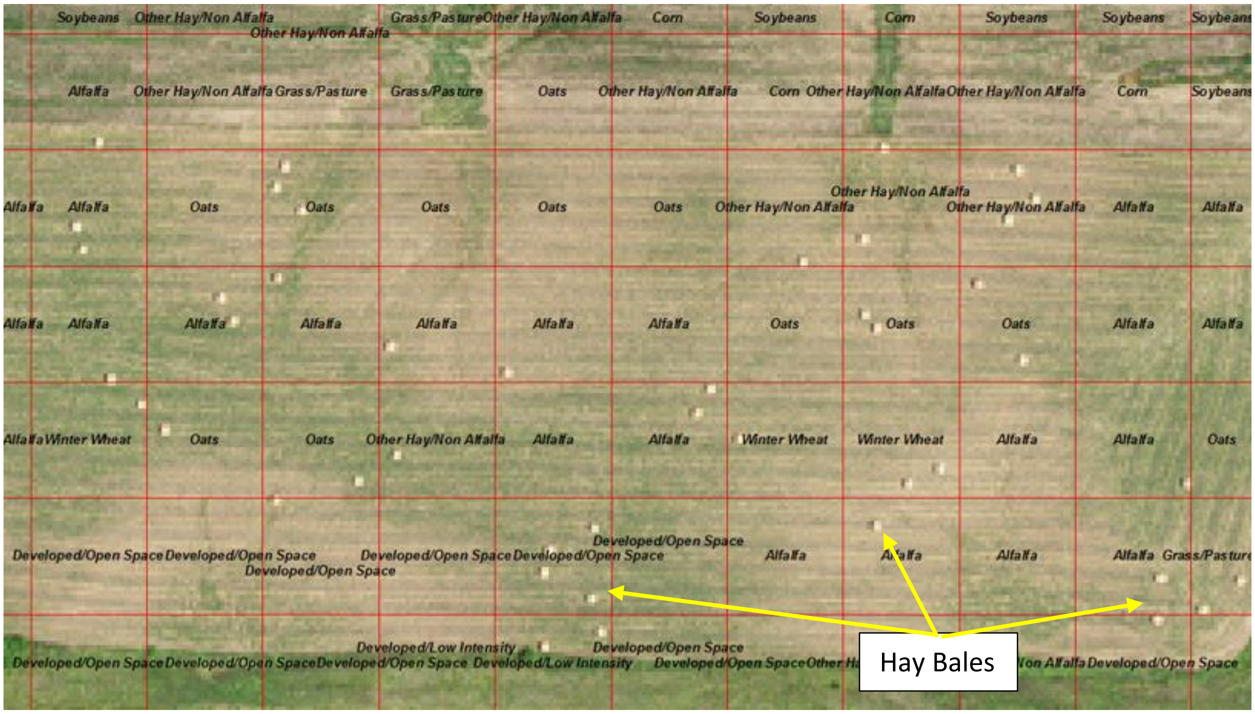

Fig. 14: Multiple classification types (crop and non-crop) in a hay field (identifiable by the presence of hay bales).

In summary, the providers of the CDL (and the NLCD) have maintained that accuracy in mapping land cover has been increasing over time. This assessment of the 2008 and 2012 CDLs showed improvements over time, but also indicated that there were discrepancies in cropland totals when compared with NASS (2018a) totals in Iowa. Furthermore, analyses of how the CDL mapped certain land classifications showed that separate agricultural districts in Iowa displayed different misclassification issues. The implications of comparing an early-year CDL product (such as 2008) with a later CDL product (such as 2012) that displayed better classification capabilities revealed that false change is present in these analyses. This is especially true in marginal areas, such as southern Iowa, where Lark et al. (2015) and Wright et al. (2017) indicated high conversion. Lastly, this report does not suggest that conversion or reversion was not occurring across the United States, but rather the magnitude of conversion reported by Lark et al. (2015) and Wright et al. (2017) is almost certainly overestimated due to misclassifications representing false change in certain areas.

Conclusion and Recommendations

When considering the research by Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) as one continuum, it is evident that certain challenges and successes have presented themselves in gaining a better understanding of using the CDL to investigate LCLUC. Moreover, there are still vital issues and challenges that remain and, as with any body of research, should be further investigated based on data input and methodological improvements. Based on the review of these studies (Wright and Wimberly 2013; Lark et al. 2015; Wright et al. 2017), it would be beneficial to highlight the major concerns with the data sources and methods presented in this report.

First and foremost, there were fundamental data issues that call into question the findings from the studies. The CDL, which was the primary data set used in all the reviewed studies, has several shortcomings, including the inability to differentiate between grassland types (e.g., native prairie, Conservation Reserve Program, grass hay, grass pasture and fallow/idle grasslands). As mentioned earlier in this document, even NASS (2018b) recommends that researchers use the NLCD for all non-agricultural land cover studies. Due to these critical accuracy issues with the CDL, a comparative analysis using a less-accurate 2008 CDL as the base year and comparing it with more-accurate 2012 CDL will result in false change. This was identified as being the most problematic in marginal areas, such as south central Iowa, where misclassification was likely to occur based on smaller crop field sizes, irregularly shaped fields, and closer proximity to other non-crop land uses (e.g., grasslands, hay, CRP, pasture, etc.).

Additionally, while the reviewed studies presented interesting approaches to estimating LCLUC, critical challenges remain in using these approaches. The most significant challenge was most of these approaches lacked accuracy assessments, which did not give the end-user a high-level of confidence in the resulting LCLUC mapping. When Wright et al. (2017) did include an accuracy assessment, it lacked a full discussion of the agreement/disagreement matrix that was only presented in a supplemental report. A detailed discussion of the reference process and the agreement/disagreement matrix would fully disclose the true utility of the analysis and give the end-user a higher level of confidence in the resulting LCLUC analysis.

Lastly, Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) insinuated that cropland expansion was attributable to the RFS program. However, this assumption was not quantified and even the EPA (2018) warned about the issues with attributing causation. When one considers the inaccuracy in the CDL and the methodological issues in the reviewed studies, this jump to causation has no scientific merit.

Going forward, with regard to the proposed objectives of the NLCD 2016 products (Yang et al. 2018), it may be a of interest to consider how the NLCD could be used to conduct LCLUC in a more robust manner (with the CDL as a supporting data set), especially since the reviewed researchers (Wright and Wimberly 2013; Lark et al. 2015; Wright et al. 2017) have all aggregated CDL classes in an attempt to reduce error. Furthermore, the development of a consensus among researchers regarding best practices (e.g., how to define and categorize croplands) have the potential to facilitate more accurate longitudinal studies. However, given the serious shortcomings of the reviewed studies, policy makers would be advised to remain skeptical of the findings to date regarding LCLUC.

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Attachment 2:

GHG Reductions from the RFS2 – A 2020 Update

Stefan Unnasch and Debasish Parida
Life Cycle Associates
February 2021

Life Cycle Associates

GHG Emissions Reductions due to the RFS2- A 2020 update

LCA.6145.213.2021
February 11, 2021

Prepared by:
Stefan Unnasch
Debasish Parida

DISCLAIMER

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Life Cycle Associates, LLC performed this study under contract to the Renewable Fuels Association. Scott Richman was the project manager.

Contact Information:

Stefan Unnasch
Life Cycle Associates, LLC
1.650.461.9048
unnasch@LifeCycleAssociates.com
www.LifeCycleAssociates.com

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Contents

Tables

Figures

Terms and Abbreviations

ANL	Argonne National Laboratory
ARB	California Air Resources Board
Btu	British thermal unit
BD	Biodiesel
CI	Carbon Intensity
CNG	Compressed Natural Gas
CRF	Corn Replacement Feed
LNG	Liquefied Natural Gas
DGS	Distillers Grains with Solubles
DDGS	Dry Distillers Grains with Solubles
EPA	Environmental Protection Agency
EIA	Energy Information Agency
FAME	Fatty Acid Methyl Ester
GHG	Greenhouse gas
GREET	Greenhouse gas, Regulated Emissions and Energy Use in Transportation (Argonne National Laboratory's well-to-wheels model)
kWh	kiloWatt-hour
LCA	Life cycle assessment
LCFS	Low Carbon Fuel Standard
LHV	Lower heating value
MGY	Million gallons per year
MJ	Mega joule
mmBtu	Million Btu
RFS	Renewable Fuel Standard (U.S.)
NERD	Non-Ester Renewable Diesel
Tg	Terra gram (10^{12}g)
TTW	Tank-to-wheels
UCO	Used Cooking Oils
U.S.	United States
VOC	Volatile Organic Compound
WDGS	Wet Distillers Grains with Solubles
WTT	Well-to-tank
WTW	Well-to-wheels

Executive Summary

The RFS2 has resulted in aggregate GHG emissions reductions from the use of biofuels, which exceed the original projections from the final Rule for the first 13 years of its implementation. The RFS2 has resulted in significant GHG reductions, with cumulative CO_2 savings of 980 million metric tonnes over the period of implementation to date. The GHG reductions are due to the greater than expected savings from ethanol and other biofuels. These emissions savings occur even though cellulosic biofuels have not met the RFS2 production targets. In addition, EPA underestimated the petroleum baseline in the Rule. Studies by Life Cycle Associates and the Carnegie Institute have shown that the GHG emissions from U.S. petroleum are higher than the EPA calculated in 2005 (Boland, 2014; Gordon, 2012, 2015). This study calculates the annual U.S. petroleum GHG intensity based on the changing trends in feedstock availability over time and determines the GHG savings calculated from the aggregate mix of renewable fuels. The GHG intensity for each category of ethanol plant and biodiesel feedstock is estimated for the resource mix over the past 13 years and combined to determine an aggregate estimate. Figure 1 shows the total emissions reductions from the RFS2 compared with the GHG reductions projected from the rule.

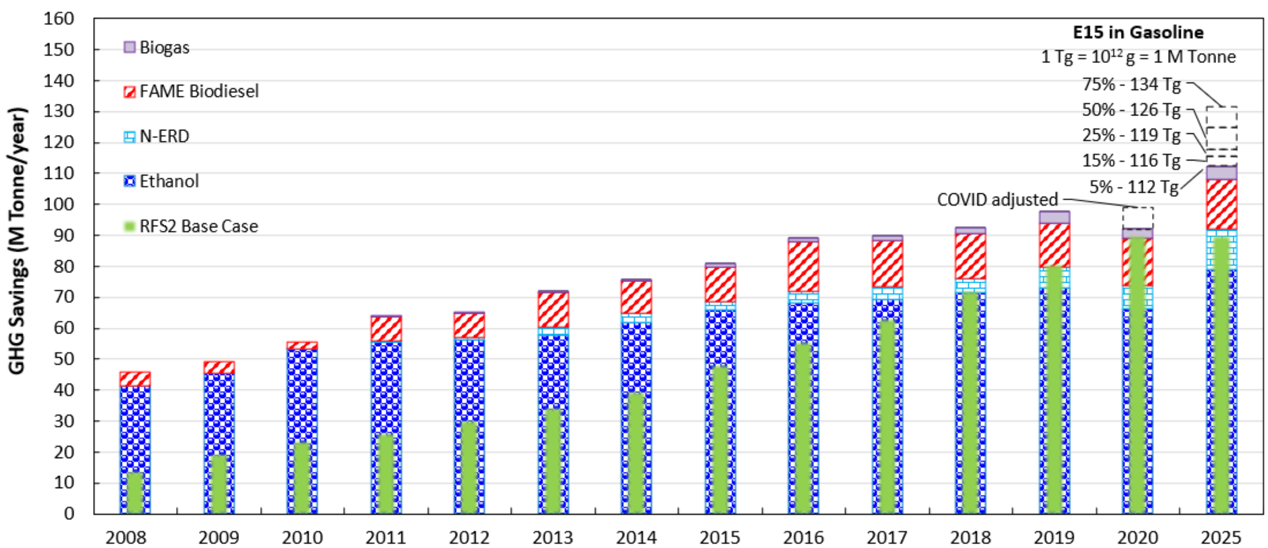

Figure 1. GHG Emissions Reductions due to the RFS2.

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1. Introduction

This study builds upon the 2014 Carbon Intensity of Marginal Petroleum and Corn Ethanol Fuels report and subsequent updates (Boland, 2014) (Boland 2015, Unnasch 2019)) released by Life Cycle Associates under contract to the Renewable Fuels Association. The Marginal Emissions report examined the trends in the greenhouse gas (GHG) emissions, termed Carbon Intensity (CI) of U.S. petroleum and corn ethanol transportation fuels. The CI is measured in grams of carbon dioxide emitted per megajoule of fuel (g CO_2 e/MJ). This work includes all renewable fuels sold under the RFS2 and their corresponding CI values.

The U.S. Renewable Fuel Standard (RFS2) requires the addition of 36 billion gallons of renewable transportation fuels to the U.S. slate by 2022. The RFS2 established mandatory GHG emission thresholds for renewable fuel categories based on reductions from an established 2005 petroleum baseline. Within the total volume requirement, RFS2 establishes separate annual volumes for cellulosic biofuels, biomass-based diesel, advanced biofuels, and renewable fuels. Figure 2 illustrates the RFS2 volume requirements per fuel category. To comply with the standard, obligated parties must sell their annual share (as calculated by EPA) within each category.

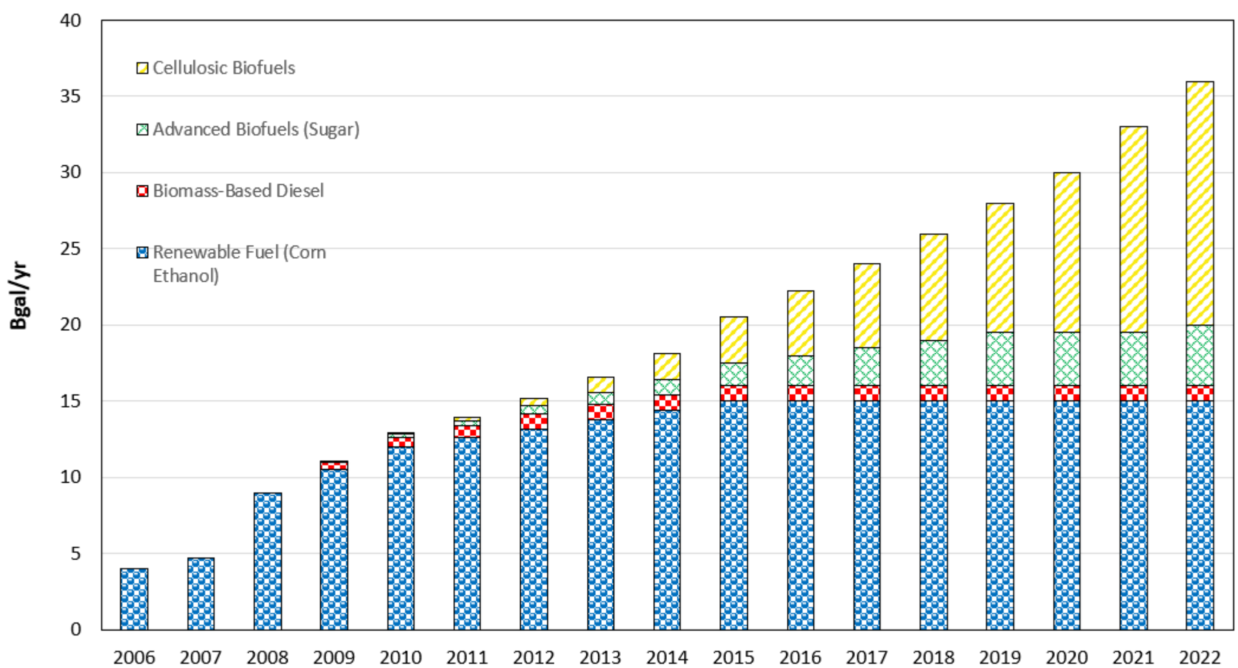

Figure 2. RFS2 renewable fuel volume requirements for the United States.

The 2005 petroleum baseline developed by EPA is based on the aggregate emissions from the production of petroleum fuels consumed in the U.S. during 2005. The methodology and assumptions for the petroleum baseline are contained in the EPA Regulatory Impact Analysis

(EPA, 2010). The baseline remains constant throughout the statutory timeframe of the RFS2 (2005 to 2022). However, the mix of crude slates used to develop the baseline has changed since 2005, and the advent of new crude extraction and processing technologies has raised the aggregate CI of petroleum fuels above the 2005 baseline. Furthermore, the baseline refining emissions were underestimated and have since been revised in LCA models (ANL, 2014; El-houjeiri, 2012). The 2014 Marginal Emissions study (Boland, 2014) re-examines the mix of crude slates and U.S. consumption trends to develop the annual aggregate U.S. petroleum CI. The annual aggregate CI provides a more accurate estimate of the aggregate U.S. petroleum CI.

Figure 3 shows the weighted carbon intensities of petroleum fuels consumed in the U.S. alongside the EPA 2005 baseline. This revised estimate results in an aggregate petroleum CI that is higher than the 2005 EPA average gasoline baseline of 93.08 g CO_2 e/MJ. The median CI of aggregate U.S. petroleum gasoline is 96.8 g CO_2 e/MJ.

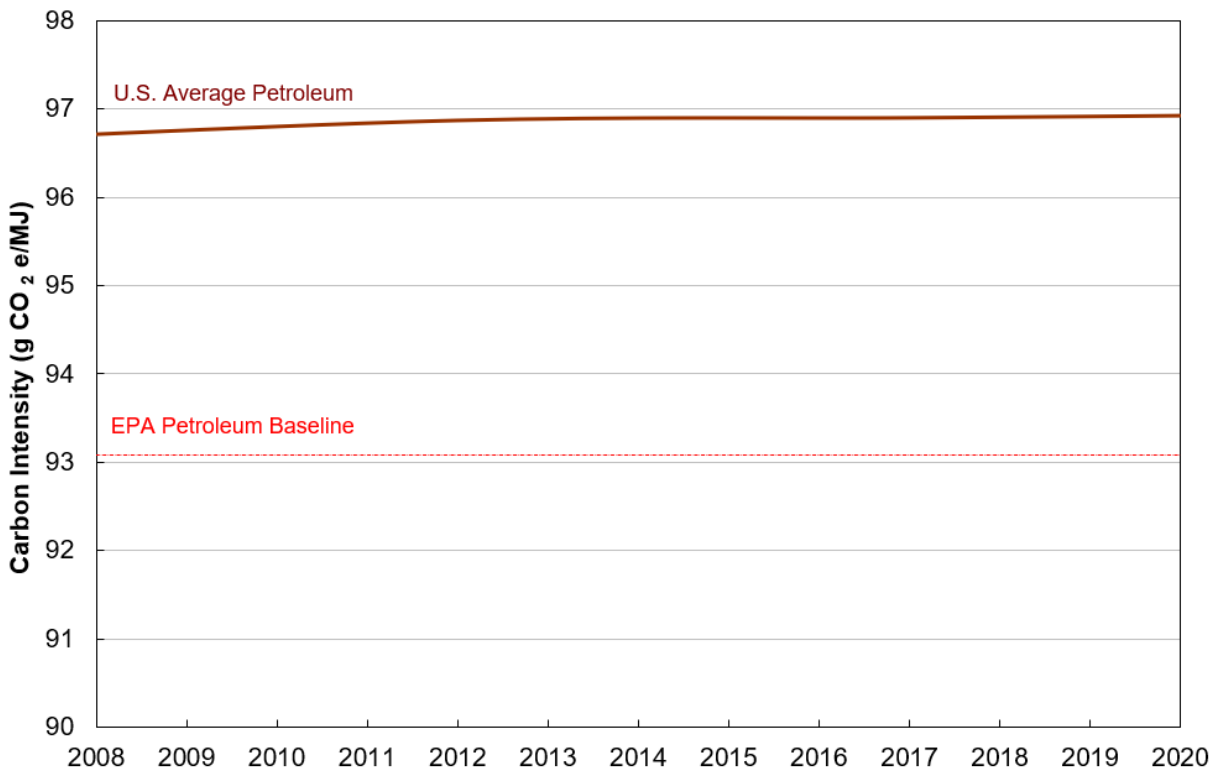

Figure 3. Weighted carbon intensity (g CO_2 e/MJ) of petroleum fuels consumed in the U.S.

1.1 RFS Renewable Fuel Categories, Production Volumes and RINS Generated

Table 1 shows the U.S. renewable fuel categories, the fuel type and the typical feedstocks used to produce each fuel. Also shown is the RIN D Code. The RIN code is the Renewable Identification Number (RIN), used to track fuel production and sales. Each type of renewable fuel generates a RIN when produced. Each D code applies to a specific RIN category.

EPA reports fuels sold by D-code type, which are further categorized as shown in Table 1. EIA reports the types of feedstocks used in biodiesel production.[1] This study matched the fuel/feedstock combinations with fuel volumes. Some fuel categories achieve GHG reductions that are consistent with the 50% and 60% GHG reductions in the RFS2, while other fuels such as corn oil biodiesel achieve even lower GHG reductions than the RFS requirements. The CI for each feedstock and fuel is matching in the following analysis.

Table 1. U.S. Renewable Fuel Categories, Fuel Type, Feedstock Source and RIN D-Code

RIN code	Fuel Category	Fuel Type	Feedstock
D6	Renewable Fuel	Ethanol	Corn, Grain Sorghum
D6	Renewable Fuel	Biodiesel	Palm Oil
D6	Renewable Fuel	NERD[a] (EV 1.7)	Palm Oil
D5	Advanced Biofuel	Ethanol	Grain Sorghum, Sugarcane, Beverage Waste
D5	Advanced Biofuel	Biogas	Landfill, Wastewater Treatment
D5	Advanced Biofuel	NERD (EV 1.6)	Tallow, Used Cooking Oils, Soybean, Distillers' Corn & Sorghum Oil, Food Waste
D5	Advanced Biofuel	NERD (EV 1.7)	Tallow, Used Cooking Oils, Soybean, Distillers' corn & sorghum oil, Food waste
D5	Advanced Biofuel	Bio-Naphtha	Used Cooking Oils, Distillers' Corn & Sorghum Oil
D4	Biomass-Based Diesel	Biodiesel	Soybean, Canola/Rapeseed, Tallow, Distillers' Corn & Sorghum Oil
D4	Biomass-Based Diesel	NERD (EV 1.5)	Tallow, Soybean, Distillers' Corn & Sorghum Oil
D4	Biomass-Based Diesel	NERD (EV 1.6)	Tallow, Soybean, Distillers' Corn & Sorghum Oil
D4	Biomass-Based Diesel	NERD (EV 1.7)	Tallow, Soybean, Distillers' Corn & Sorghum Oil
D3	Cellulosic Biofuel	Ethanol	Corn Kernel Fiber, Biomass Stover
D3	Cellulosic Biofuel	RCNG	Landfill, Wastewater Treatment, Animal Waste
D3	Cellulosic Biofuel	RLNG	Landfill, Wastewater Treatment, Animal Waste
D3	Cellulosic Biofuel	Renewable Gasoline	Forest Waste, Crop Residue, Food Waste
D7	Cellulosic Diesel	NERD (EV 1.7)	Forest Waste, Crop Residue, Food Waste

[a]NERD = Non-Ester Renewable Diesel

Table 2 shows the U.S. renewable fuel volumes generated (million gallons of fuel) from 2008 - 2020 (i.e., the period of RFS2 implementation). The study also evaluates the effect of the RFS extended through 2020 with fuel volumes shown as indicated.

[1] EPA categorizes renewable diesel by equivalence value EV. The equivalence value represents the ratio of heating value of a biofuel to the heating value of a gallon of denatured ethanol. NERD EVs may vary with data submitted by different fuel developers with petitions to EPA.

The GHG emissions for each category of fuel in Table 2 are calculated based on estimates of the composite carbon intensity (CI) for each of the fuels. The CI varies among all of the fuel technologies. Grain-based ethanol production uses a range of process fuels. Ethanol plants also produce distillers' grains, corn oil, and other food and feed products. Ethanol also is a higher-octane blending component which reduces the GHG emissions associated with crude oil refining.

Note that the RIN data is categorized by the Equivalence Value (EV) which corresponds to the different in energy content of diesel, naphtha, and jet fuel relative to ethanol which are typically associated with the production of non-ester renewable diesel (NERD) fuels as well as pyrolysis-based fuels. Biodiesel and NERD also use a range of feedstocks including vegetable oils and waste oils. The CI depends on the mix of these feedstocks.

Many sources of biogas generate RINs under the RFS including landfills as well as food waste and manure anaerobic digesters. The latter source of renewable natural gas (RNG) result in the avoidance of methane emissions, which further reduce GHG emissions. RNG is a feedstock for compressed natural gas (CNG) and liquefied natural gas (LNG) as well as a process fuel for some ethanol plants.

Table 2. U.S. Renewable Fuel Volumes used in Transportation[2]

D-code	Fuel Type	Fuel Volumes (Million Gallons) [a]							
		2008	**2010**	**2012**	**2014**	**2016**	**2018**	**2020[b]**	**2025**
6	Ethanol	9,309	13,298	12,987	14,022	14,725	14,967	12,566	15,310
6	Biodiesel	0	0	1	53	113	0	0	0
6	NERD (EV 1.7)	0	0	0	151	166	107	76	80
5	Ethanol	530	16	603	90	61	102	185	650
5	Biogas	0	0	3	20	0	1	0	10
5	NERD (EV 1.6)	0	5	2	0	0	0	0	0
5	NERD (EV 1.7)	0	3	10	9	5	24	38	107
5	Bio-Naphtha	0	0	0	12	18	21	21	40
4	Biodiesel	678	343	1,056	1,436	2,194	2,030	1,998	2100
4	NERD (EV 1.5)	0	0	1	0	0	0	0	0
4	NERD (EV 1.6)	0	0	9	7	0	0	5	14
4	NERD (EV 1.7)	0	1	80	320	421	485	824	1,400
3	Ethanol	0	0	0	1	4	8	30	102
3	RCNG	0	0	0	15	117	222	344	443
3	RLNG	0	0	0	17	72	83	83	165
3	Renewable Gasoline	0	0	0	0	0	0	0	0
7	NERD (EV 1.7)	0	0	0	0	1	0	0	0
	Anhydrous Ethanol	9,642	13,047	13,318	13,831	14,494	14,776	12,525	15,741
	Denaturant	197	266	272	282	296	302	256	321
	FAME Biodiesel	678	343	1,057	1,501	2,325	2,052	2,019	2,140
	Total N-E RD	0	9	103	488	591	615	943	1,587
	Total Biogas	0	0	3	53	189	304	427	618
	Total	**10,517**	**13,665**	**14,753**	**16,155**	**17,895**	**18,049**	**16,169**	**20,407**

[a]Fuel volumes correspond to total net generation EPA RIN data divided by the fuel's equivalence factor.

[b]2020 is the assumed 12-month production total of biofuels based on the 9 months (January – September 2020) data available.

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[2] Fuel volume is derived from the RIN generation data provided by EMTS.
https://www.epa.gov/fuels-registration-reporting-and-compliance-help/rins-generated-transactions

2. Land Use Change

The Land Use Change (LUC) reflects the net change in carbon stocks associated with expansion of crop production as well as indirect effects that are induced by the demand for feedstocks. LUC is an important, but controversial, element of a biofuel's life cycle impact, including the direct emissions associated with land conversion to agricultural fields and indirect emissions associated with economic impacts induced by the change to land use.

EPA, ARB and ANL have developed estimates for LUC estimates from biofuels production. These are summarized in Table 3. The development of LUC estimates is discussed in detail in the 2014 Marginal Emissions report (Boland, 2014). This analysis uses the best estimate for each biofuel category shown here to calculate the total emissions from the production of that biofuel.

Table 3. LUC Emissions Estimates from Biofuels

Policy	Corn EtOH	Sorghum Ethanol	Corn Stover	Sugarcane Ethanol	Soybean BD/RD	Canola BD/RD	Palm BD	Tallow BD/RD	Corn BD
					LUC (g CO_2e/MJ)				
2009 ARB	30	n/a	0	46	62	31	n/a	0	0
2010 EPA	28	13.1	-1.3	5.41	18.3	~15	48.2	0	0
2014 ARB	19.6	19.4	0	11.8	29.1	14.5	71.4	0	0
ANL/CCLUB	7.6	n/a	-1.1	n/a	n/a	n/a	n/a	0	0
Best Estimate	**7.4**	**7.6**	**-1.1**	**11.8**	**18.3**[a]	**14.5**	**48.2**	**0**	**0**[b]

[a] The ILUC associated with soy BD is consistent with the crop yield per acre. If ILUC per acre of corn is the same as ILUC per acre of soybeans, then ILUC for soybean-based BD or RD is about twice that of corn ethanol depending upon the displacement value of co-products from ethanol and soybean meal. The RFS and LCFS values for soybean and canola ILUC are used as a conservative assumption. The ILUC values for BD and RD should differ slightly depending on oil to fuel yield but these values are assumed invariant with biomass-based diesel type.

[b] Several approaches are available to assigning ILUC to ethanol and corn oil used for biodiesel production. The California ARB assigns all of the ILUC to ethanol and this approach is followed here.

3. Carbon Intensity of Corn Ethanol and Biofuels production

Ethanol represents the largest volume of renewable fuel produced and consumed in the U.S. The Marginal Emissions report (Boland, 2014) developed aggregated weighted CI estimates for the corn ethanol produced in the U.S. based on the installed capacity shown in Table 4. The installed capacity is based on the production cases described in the EPA Regulatory Impact Analysis (EPA, 2010). The capacity per plant type (including projections for capacity expansions) was used to model the trend in corn ethanol production for RFS operational years of 2008 through to 2020.

Important developments in the mix of corn ethanol technology include the following:

- Rapid adoption of corn oil extraction for dry mill plants (95% by 2020)
- Introduction of corn fiber/kernel fiber/stover in 38 plants by 2020[3]
- Growth in the use of low CI biogas as process fuel
- Elimination of coal as fuel for dry mill ethanol plants

[3] While EPA has not approved corn fiber petitions, 38 pathways have been approved by the California ARB. This technology results in about a 3% increase in ethanol production capacity. The adoption rate should grow to 50 plants by 2025.

Table 4. Corn Ethanol Production Capacity and Technology Aggregation

Plant Energy Source,	**Capacity (Million Gallons per Year)**						
Aggregated data[a,b]	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**	**2020**
Wet Mill, Coal	1,888	1,877	1,893	1,474	1318	1162	745
Wet Mill, NG	107	328	473	854	1,100	1312	538
Dry Mill, Coal	54	36	19	15	0	0	0
Dry Mill, NG, DDGS[c]	2,919	2,366	1,812	1,613	1,600	500	522
Dry Mill, NG, WDGS[c]	1,442	1,178	913	903	900	230	183
Dry mill, corn oil DDGS	1,946	4,617	5,471	5,336	7,000	8,500	9,917
Dry mill, corn oil, WDGS	961	2,145	2,728	2,589	2,700	3,000	3,484
Dry Mill, CRF/green corn[d]	325	361	397	461	700	800	965
Dry Mill, Biogas/Biomass[e]	195	250	305	360	415	470	525
Corn Stover/Fiber[f]	0	0	0	0.73	4	10	55
Total Corn Ethanol	9,837	13,158	14,011	13,606	15,737	15,984	16,883

[a] EPA Regulatory Impact Analysis (RIA)for the final Transport Rule.(EPA, 2009)

[b] Projections in consultation with industry experts.

[c] The rapid adoption of corn or extraction in dry mill ethanol plants has penetrated most of the market due to the improvement in energy consumption, reduction in GHG emissions, and production of corn oil. Total corn oil biodiesel from EIA data corresponds to 0.13 lb of corn oil per gallon of ethanol, which is about half of the potential yield. The balance of corn oil is used as animal feed.

[d] Corn replacement feed (CRF) and low GHG corn farming can reduce GHG emissions by producing additional co-product credit and implementing low impact farming practices. The introduction of lower emission corn is projected based on projections from industry analysts. (ACE, 2018).

[e] 6 ethanol plants with biogas or biomass process fuel have approved LCFS pathways.

[f] 38 corn fiber/stover/kernel fiber ethanol pathways were approved under CA LCFS in 2020. Assume corn fiber ethanol is an additional 3% of plant capacity.

Other emission reduction strategies include the use of corn replacement feed from stover and improved farm practices. Practices such as no till and precision farming have reduced GHG emissions from corn and these technologies are expanding.

Table 5 shows the representative CI of ethanol produced at each type of production facility described in the RIA. The CI reflects the ILUC values from the latest GREET model (ANL 2020).

Table 5. Carbon Intensity of Corn Ethanol

Corn Ethanol Production Type	Carbon Intensity ($g\ CO_2e/MJ$) 2008 [a]	2015 [a]	2018 [a]	2020[b]
Wet Mill, Coal	97.35	93.07	90.44	88.69
Wet Mill, NG	77.35	73.34	70.84	69.17
Dry Mill, Coal	67.61	63.38	N/A	N/A
Dry Mill, Average	64.27	56.04	54.55	54.11
Dry Mill, NG, DDGS	60.80	58.72	58.72	58.67
Dry Mill, NG, WDGS	54.38	48.78	48.78	49.88
Dry mill, corn oil DDGS	63.82	58.26	57.35	56.74
Dry mill, corn oil WDGS	54.92	49.79	49.79	49.78
Dry Mill NG, CRF	49.37	41.14	39.65	38.36
Dry Mill, Biomass/Biogas	38.00	34.14	30.00	28.15

[a] CI values from 2018 RFS Update (Unnasch 2018). CI of corn, electricity mix, and other life cycle factors have changed since then.

[b] Based on GREET1_2020 model. Data from GREET1_2020, provided energy inputs data to these calculations. Data from California LCFS pathways provide insight to corn fiber and biomass based – based pathways. GREET CCLUB estimates for ILUC included in this table.

Similar to ethanol, estimates for the production of bio- and renewable diesel were based on the feedstock use per fuel. The U.S. Energy Information Agency (EIA) provides inputs on the U.S. feedstock inputs into biodiesel production (EIA, 2015). The production volumes for modelled for the years 2008 through to 2020. The biodiesel feedstock production volumes are shown in Table 6.

Table 6. Feedstocks for U.S. Biodiesel Production

Product	2008	2010	2012	2014	2016	2018	2020
Total BD[a]	678	343	1,056	1,501	2,325	2,052	2,019
Canola oil	59	30	91	130	133	149	126
Corn oil	72	36	111	158	153	245	176
Palm oil	16	8	26	37	56	0	0
Soybean oil	360	182	561	797	1,619	1,212	1452
Tallow/Poultry	42	21	65	92	133	151	118
UCO	130	66	202	288	231	295	147

[a]Total BD volumes based on EPA-reported RINs. Split among oil types based on EIA data.

Similar estimates for the renewable diesel feedstocks were developed from the study of hydrogenation derived renewable diesel as a renewable fuel option in North America (Lambert, 2012). The biogas feedstocks are primarily landfill gas and wastewater treatment facility biogas. Biogas from anaerobic digestion of food waste and manure is also a source of biogas for CNG.

Table 7 shows the volumetric weighted carbon intensity estimates (developed by weighting the production capacity with the CI for each technology/feedstock) for the each of the biofuel categories included in the RFS2. The table also shows the assumed minimum reduction threshold CI for the RFS2 for each fuel type.

More recent studies of petroleum GHG emissions also indicate that the estimates for the original 2005 petroleum baseline in fact somewhat higher (EIA, 2013; Elgowainy, 2014; Unnasch, 2009).

3.1 Fuel Impacts

In addition to displacing higher GHG fossil fuels, alternative fuels have several other impacts on the transportation system. High octane ethanol allows to produce less energy intense hydrocarbon blending components and results in higher efficiency in high octane fuels. Renewable diesel results in an ultra-low sulfur fuel with a high cetane number that helps refiners meeting fuel specifications. These factors contribute to the overall GHG benefit of renewable fuels.

Fuel Efficiency and Octane

Reformulated gasoline is produced by blending a hydrocarbon component for oxygenate blending (BOB) with ethanol. To produce regular gasoline with an Anti-Knock Index (AKI) (R+M)/2 octane of 87 an 84 octane BOB is blended with ethanol[4]. Refiners take advantage of ethanol's octane produces a BOB with few high-octane components. Typically, the reformer is operated at a lower severity or less blending from alkylation units contribute to the octane of gasoline (Hirshfeld, 2015; Kwasniewski, 2015). Kwasniewski presents the different scenarios on a GHG intensity basis with a difference of 1 g CO_2e/MJ of gasoline between E10 and zero ethanol blending cases. The result is consistent with the energy intensity in a paper from Argonne National Laboratory (Elgowainy, 2014)[5].

[4] The AKI for ethanol is 99.3 (Pearson, 2015) but its blending octane number at 10% level is 114.

[5] For example, alkylation units require 1.2 MJ input per MJ gasoline compared with 1.03 MJ/MJ for crude distillation. Displacing the higher energy intensity component with ethanol reduces the CI of the BOB.

Table 7. Carbon Intensity Estimates of All Biofuels and RFS GHG Reduction Threshold (g CO_2e/MJ)

Fuel	Threshold	2008	2010	2012	2014	2016	2018	2020[a]	2025
Ethanol, D6	74.5	66.3	63.6	62.0	58.6	56.5	55.1	53.2	53.2
Biodiesel, D6	74.5	71.8	71.5	71.5	71.5	90.0	90.0	90.0	90.0
Non-Ester RD, D6	74.5	90.0	90.0	90.0	90.0	90.0	90.0	90.0	90.0
Ethanol, D5	46.5	41.9	42.1	42.1	42.2	39.6	39.6	38.0	38.0
Biogas, D5	46.5	25.6	24.4	24.4	23.8	23.3	23.3	21.0	21.0
Non-Ester RD (EV 1.6)	46.5	46.4	46.4	46.5	46.2	46.2	46.2	44.4	44.4
Non-Ester RD (EV 1.7)	46.5	46.4	46.4	46.5	46.2	45.9	45.9	43.8	43.8
Bio-Naphtha	46.5	46.4	46.4	46.5	46.2	45.9	45.9	33.1	33.1
Biodiesel	46.5	42.5	42.1	42.3	42.2	41.9	41.9	38.5	38.5
Non-Ester RD (EV 1.5)	46.5	35.0	35.0	35.0	35.0	35.0	35.0	34.8	34.8
Non-Ester RD (EV 1.6)	46.5	35.0	35.0	35.0	35.0	35.0	35.0	34.8	34.8
Non-Ester RD (EV 1.7) Soy/Tallow	46.5	35.0	35.0	35.0	35.0	35.0	35.0	34.8	34.8
Ethanol, Cellulosic	37.2	37.2	37.4	37.8	38.4	33.5	30.0	28.5	28.5
RCNG[b]	37.2	25.6	24.4	24.4	23.8	23.3	23.3	16.9	12.0
RLNG	37.2	29.6	28.3	28.3	27.6	27.0	27.0	20.6	15.7
Renewable Gasoline	37.2	28.0	27.0	27.0	26.6	26.1	26.1	22.6	22.6
Non-Ester RD, D3	37.2	28.0	27.0	27.0	26.6	26.1	26.1	26.1	26.1
US Electricity		204.6	182.5	182.5	170.3	159.9	159.9	159.9	159.9
Denaturant		81.0	81.0	81.0	81.0	81.0	81.0	81.0	81.0
Gasoline Blendstock	93.08	96.7	96.8	96.9	97.0	97.2	97.3	97.5	97.5
Diesel	93.08	98.7	98.8	98.8	99.0	99.2	99.3	99.9	99.9

[a]CI for Biodiesel (D6) and NERD (D6) is constant and rounded to equal 90 as CARB gives palm oil diesel the high CI equal to gasoline.

[b]CI for RCNG and RLNG is associated with the growing swine manure farms and digesters.

The benefit of blending ethanol on the BOB produced at the oil refiners is examined for E10 and E15. For 87 octane fuels the E10 BOB results in a 1.0 g CO_2e/MJ reduction while a BOB formulated for E15 receives a 1.5 g CO_2e/MJ GHG reduction, which is proportional to the GHG savings from the ethanol in E10. In this case of E15 a lower octane BOB is possible to produce 87 AKI blended gasoline.

In the case of E15 that results in a higher octane, the BOB is assigned the same 1 g CO_2e/MJ savings as the E10 BOB as it is the same refined product. The balance of E15 and E85 are estimated to result in higher octane fuels the same gasoline BOB used for E10 blending. All of the BOB for E10 or higher-octane blends is assigned 1 g CO_2e/MJ GHG reduction due to the effect on oil refineries. A 5% increase in ethanol will result in an extra octane point while E85 can have an octane number close to 93.

Several studies examine the effect of octane on fuel economy. Higher octane allows for an advance in ignition timing and higher turbocharger boost in engines with knock sensors. A 1% to 3% increase in energy economy is consistent with data from the EPA fuel economy guide where fuel consumption is reported or both E10 and E85 vehicles. The improvement in fuel economy from engine testing studies also indicates an efficiency improvement on the order of 1% for a 2-point increase in octane (Shuai, 2013; Stradling, 2015; Leone, 2017). Energy-economy ratio values of 1.005 and 1.02 were estimated for E15 and E85 respectively. The EER represents the energy economy of gasoline (E10) relative to the alternative fuel.

3.2 GHG Calculation Methods

GHG emissions were calculated based on the displacement of petroleum fuels. The aggregate mix of biofuels as well as crude oil resources provided the basis for GHG calculations. Displaced gasoline and diesel are calculated for each category of biofuel. In the case of ethanol, the effect on octane blending is also calculated. The net change in GHG emissions corresponds to the aggregation of each component fuel in the RFS. GHG emissions were calculated for each fuel category in equations 1, 2, and 3.

GHG from alternative fuel = Fuel volume × LHV × CI for each fuel (1)
The denaturant component of ethanol is calculated separately along with the biofuels

Displaced emissions correspond to severe effects including:

Alternative fuel volume × EER × LHV × CI for each fuel (2)

In the case of E15, E85, and CNG the EER values in this study are 1.005, 1.02, and 0.9 respectively

BOB volume associated with achieving 87 octane fuel × LHV × 1 g CO_2e/MJ savings (3)

For biodiesel and renewable diesel, the petroleum baseline fuel is diesel. Biogas displaces a mix of gasoline and diesel with a more conservative EER of 0.9 assumed for diesel displacement.

Net GHG emissions are calculated based on the CI of the renewable fuel minus the displaced fuel. In the case of ethanol, additional octane blending benefits are included as part of the impact. Table 8 provides an example for 1 billion gallons of ethanol with two CI value deployed either as E10 or E15. In the case of E10, 1 billion gallons corresponds to 81,224 TJ of energy and displaces the same energy in the BOB. For the E15 example here, half the ethanol displaces a proportional quantity of BOB. The other half of the E15 (500 million gallons) results in an EER of 1.005 and displaces more BOB. The effect on octane blending is also shown for each fuel volume.

Table 8. Carbon Intensity Estimates of All Biofuels plus EPA Minimum Threshold

	E10 87 Octane		**E15 87 Octane**		**E15 88 Octane**	
	TJ	**Gg GHG**	**TJ**	**Gg GHG**	**TJ**	**Gg GHG**
Energy Inputs and Emissions[a]						
10% Wet Mill Coal Ethanol	8,122	720	4,061	360	4,061	360
90% Dry Mill WDGS						
Ethanol	73,101	3,639	36,551	1,819	36,551	1,819
Total Ethanol	81,224	4,359	40,612	2,180	40,612	2,180
EER	1		1		1.005	
Displaced BOB	-81,224	-7,862	-40,612	-3,931	-42,515	-4,115
Total BOB	1,080,000		340,000		340,000	
Refinery Octane	1,080,000	-1,080	340,000	-510	226,667	-227
Net Emissions		-4,583		-2,262		-2,162
Fuel Volume						
Ethanol (B gal)	1		0.5[b]		0.5[b]	
RFG (B gal)	10		3.33		3.33	

[a]CI of Wet Mill Coal, Dry Mill WDGS, and BOB are 88, 49, and 96.8 g CO_2e/MJ respectively. Octane blending effect of E10 and E15 are 1 and 1.5 g CO_2e/MJ respectively.
[b] 50% of the billion gallons of ethanol in the E10 example are calculated for an 87 octane and 88 octane strategy. In the 88 octane calculation the BOB receives a lower octane blending credit while displacing more BOB.

3.3 Avoided GHG Emissions

The avoided GHG emissions are calculated from the reduction in CI from the revised petroleum baseline, as developed by Boland et al. (Boland, 2014). Figure 4 shows the total CO_2 savings, in million metric tonnes per year (Million tonne/yr) from the inclusion of ethanol in the RFS2.

Key changes in fuel volume include a growth in the production capacity of renewable diesel and biogas from animal waste.

The effect of different levels of E15 in 2025 are also examined using the approach outline previously assuming that 50% is blended at 87 octane and the balance results in higher octane fuel. 51% E15 in a gasoline pool of 138 billion gallons per year could be achieved with the current corn ethanol capacity in the U.S. of 17.4[6] billion gallons per year[7]. Note that the scenario for E15 shown here for 2025 uses more than the 15 billion gallons of D6 ethanol required under the RFS2. E15 results in additional GHG reductions because more ethanol is consumed as fuel and it enables the production of a lower octane BOB.

Figure 5 shows the CO_2 saving from all other biofuels. Since ethanol is thus far the major component of the RFS2, the majority of CO_2 savings are due to the ethanol fuels. Figure 6 shows the total CO_2 reductions of the RFS2 based on the analysis presented here. The base RFS assumptions are also shown in the graph, where the biofuels meet the minimum CI threshold mandated in the RIA (EPA, 2009) and as shown in Table 7. The RFS2 has resulted in the cumulative CO_2 savings of 980 million metric tonnes over the period of implementation (till 2020). The CO_2 savings as calculated from the minimum CI threshold base assumptions outlined in the RIA (EPA, 2009) results in the cumulative CO_2 savings of 593 million metric tonnes of CO_2.

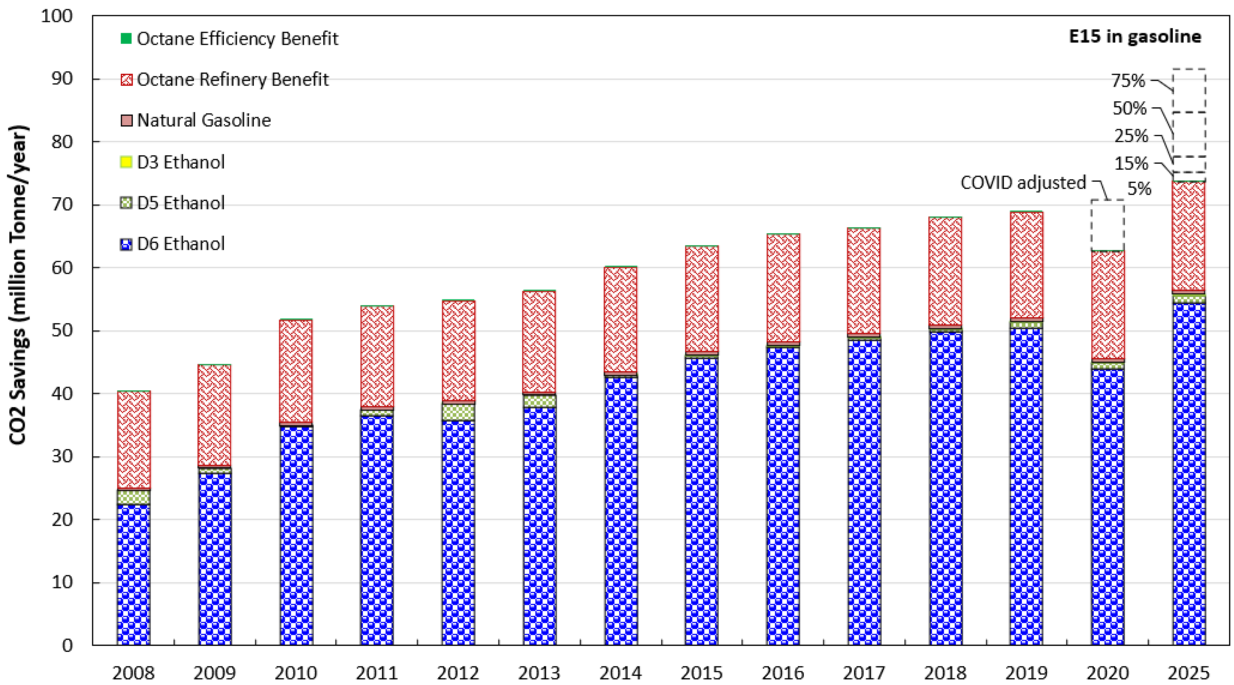

Figure 4. GHG Savings from Ethanol

[6] US fuel ethanol production capacity for the year 2020. https://www.eia.gov/petroleum/ethanolcapacity/index.php

[7] EIA projects 9 million bbl/d of gasoline consumption in 2022 or 138 billion gallons per year. 29% of ethanol as E15 could be achieved with U.S. ethanol production capacity for 150 billion gallons per year of gasoline consumption.

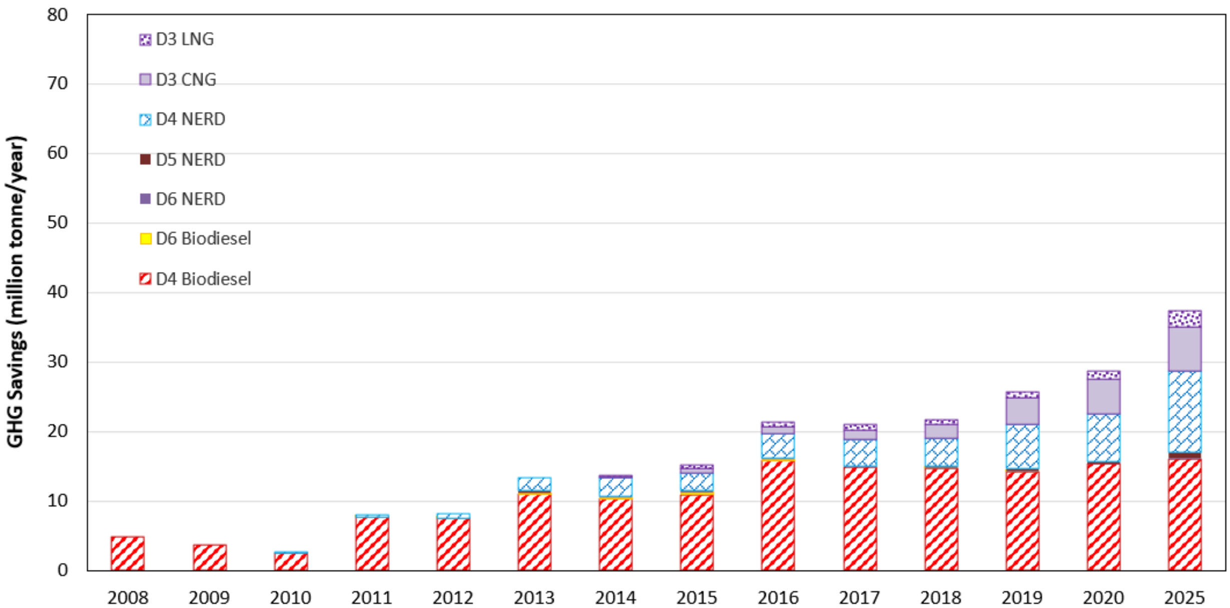

Figure 5. GHG Savings from Other RFS2 Biofuels (Excluding Ethanol).

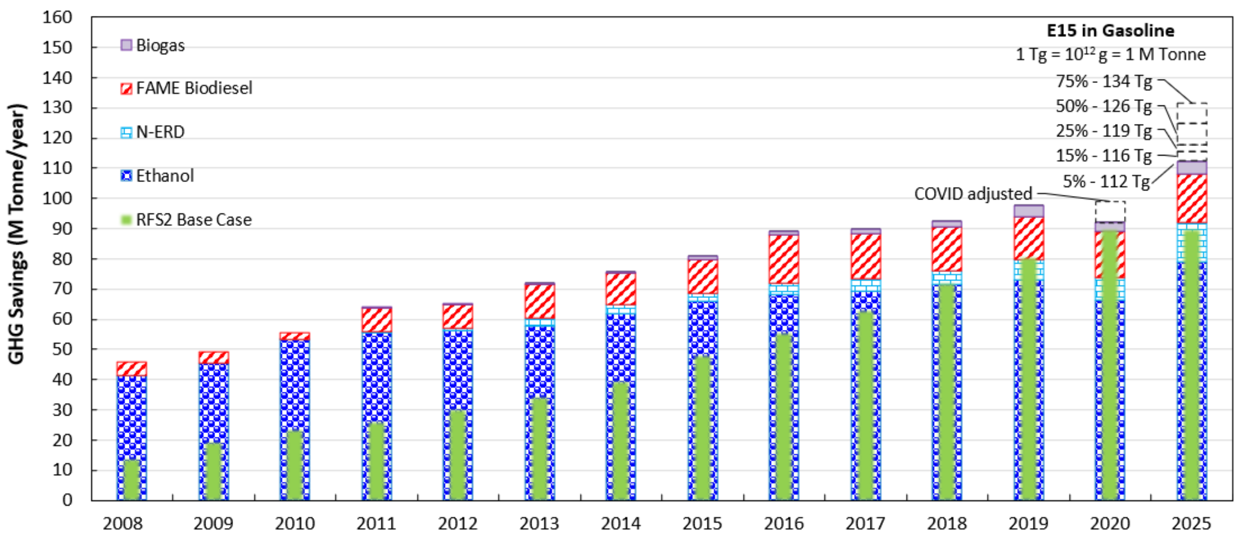

Figure 6. GHG Savings from the RFS2 Program

4. Conclusions

The RFS2 has resulted in GHG emissions reductions, which exceed the original projections from the 2010 final Rule. The increased GHG reductions are due to the following:

1. Corn ethanol has adopted technology improvements, which results in greater than the 20% reduction in GHG emissions originally required under the RFS.
2. Petroleum GHG emissions are higher than the baseline projected by EPA.
3. The mix of other renewable fuels has also contributed to additional GHG reductions even though cellulosic ethanol targets in the original rule have not been met.

Biofuels have achieved and exceeded the GHG reductions estimated by EPA. The reductions are greater than the categories within the RFS2 because technology improvements have resulted in reductions in energy use and the RFS categories characterize typical renewable fuels. These categories were not intended to represent the weighted GHG reductions of all fuels produced under the rule.

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