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

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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.

Major Concerns with Data Inputs:
- 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.

Major Concerns with Assessed Methods:
- 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).
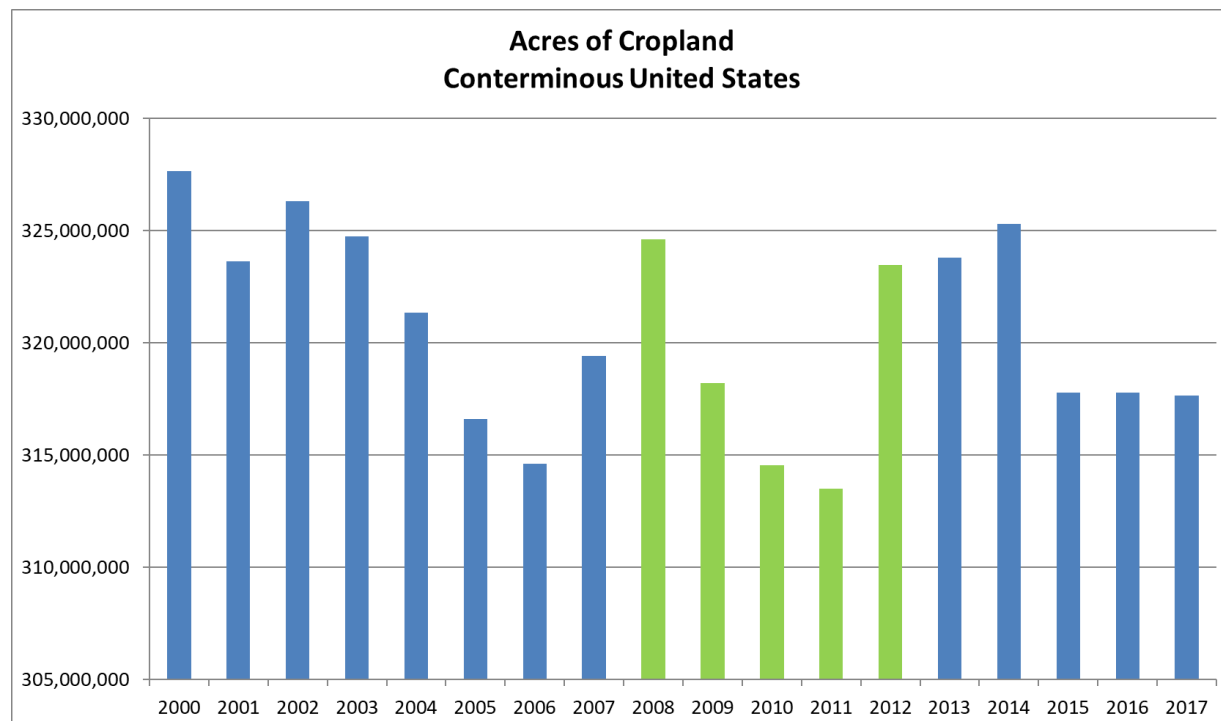

Fig. 2: NASS total croplands from 2000-2017 (NASS 2018a). Green bars highlight the Lark et al. (2015) study time-period.

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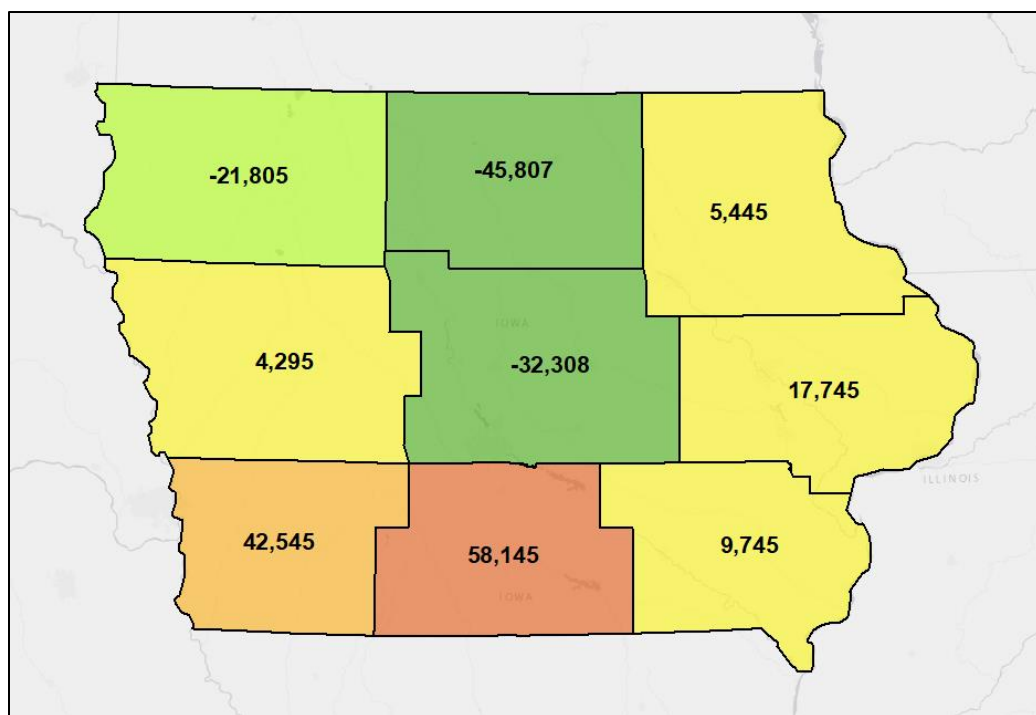
Fig. 4: All field crop changes in Iowa by agricultural district from 2008-2012 (NASS 2018a). Negative values indicate loss of planted cropland and positive values indicate gains of planted cropland. The north central and south central agricultural districts had the highest decrease (-45,807 acres) and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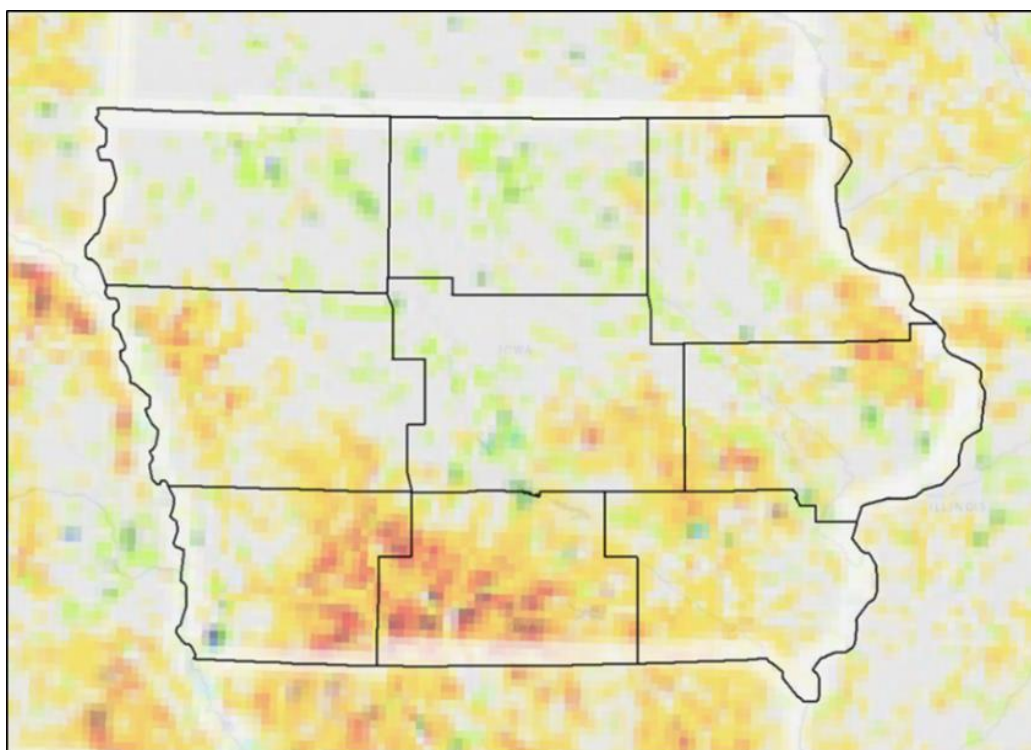

Fig. 5: A generalized version of the Lark et al. (2015) map of percent of landscape that was converted to and from cropland from 2008-2012 (blue to green represents reversion, gray represents no change, and yellow to red represents conversion). In this map, Iowa's agricultural districts are overlaid 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.
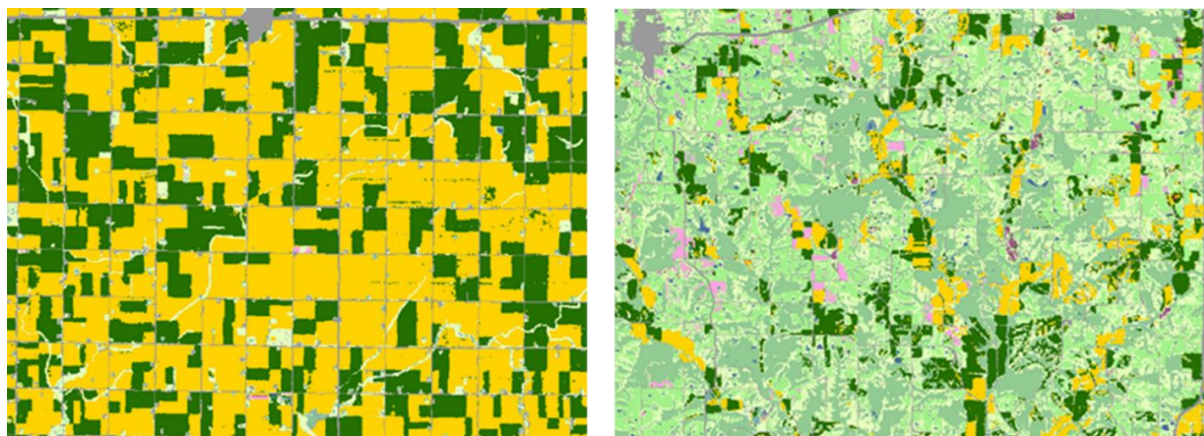
Fig. 6: Example from the 2012 CDL of corn (yellow) and soybean (dark green) fields in north central Iowa (left) and south central Iowa (right). North central is blocked crop fields on flatter terrain and the overwhelming majority of the land use, while the south central crop fields are disjointed and 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.
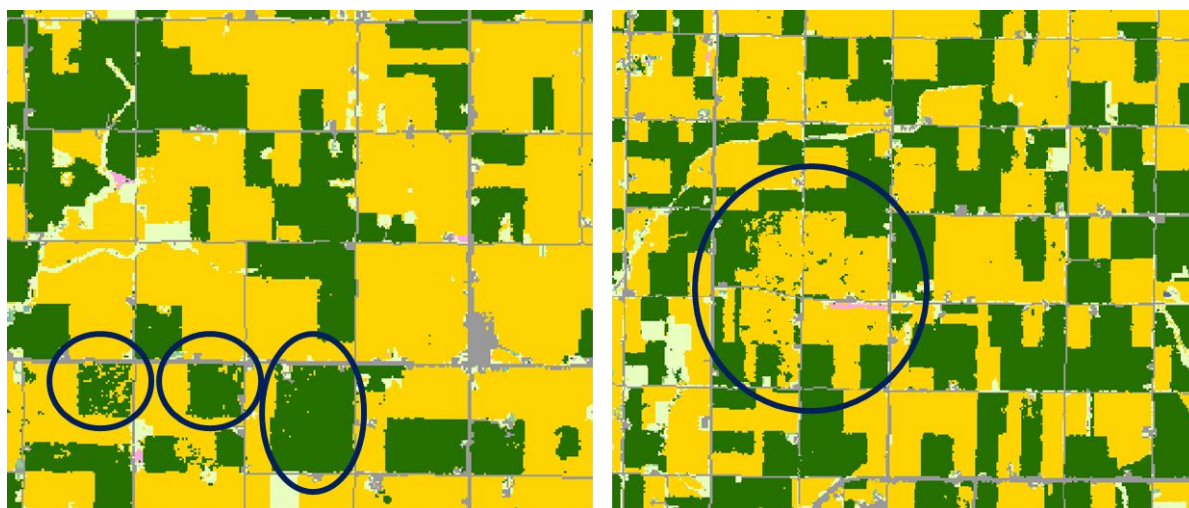

Fig. 7: Examples in the north central district of corn (yellow) and soybeans (dark green) being confused with each other in the 2008 CDL. Left images highlights corn pixels within soybean fields and right images highlights soybean pixels within corn fields.

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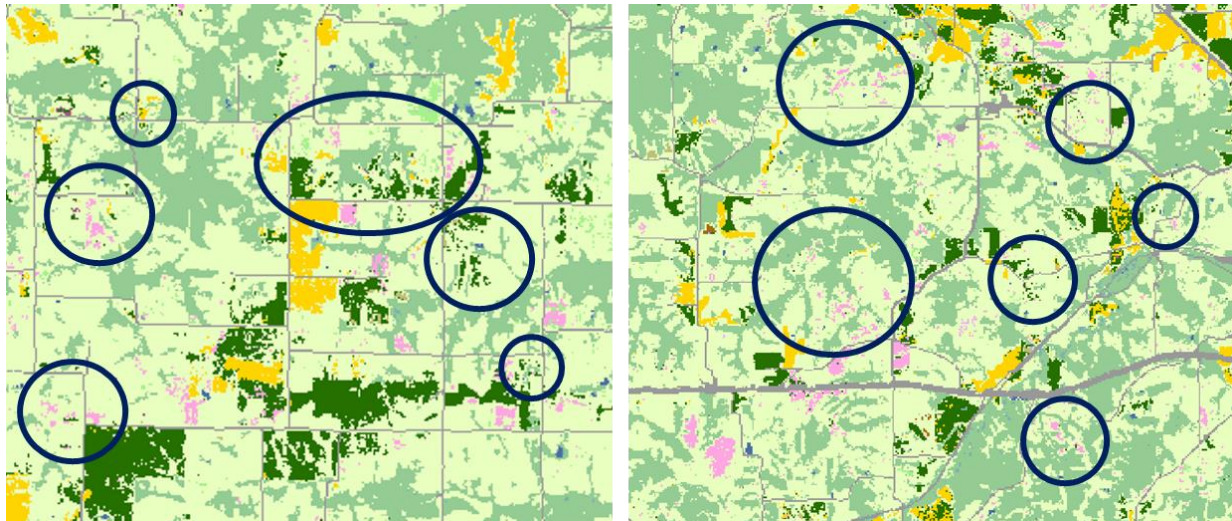
Fig. 8: Examples in the south central district of alfalfa (pink), and also some corn (yellow) and soybeans (dark green), confused with non-crop grass/pasture in the 2008 CDL. This confusion is noticeable via the fragmentation and speckling of these crop classes within non-crop classes.

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.
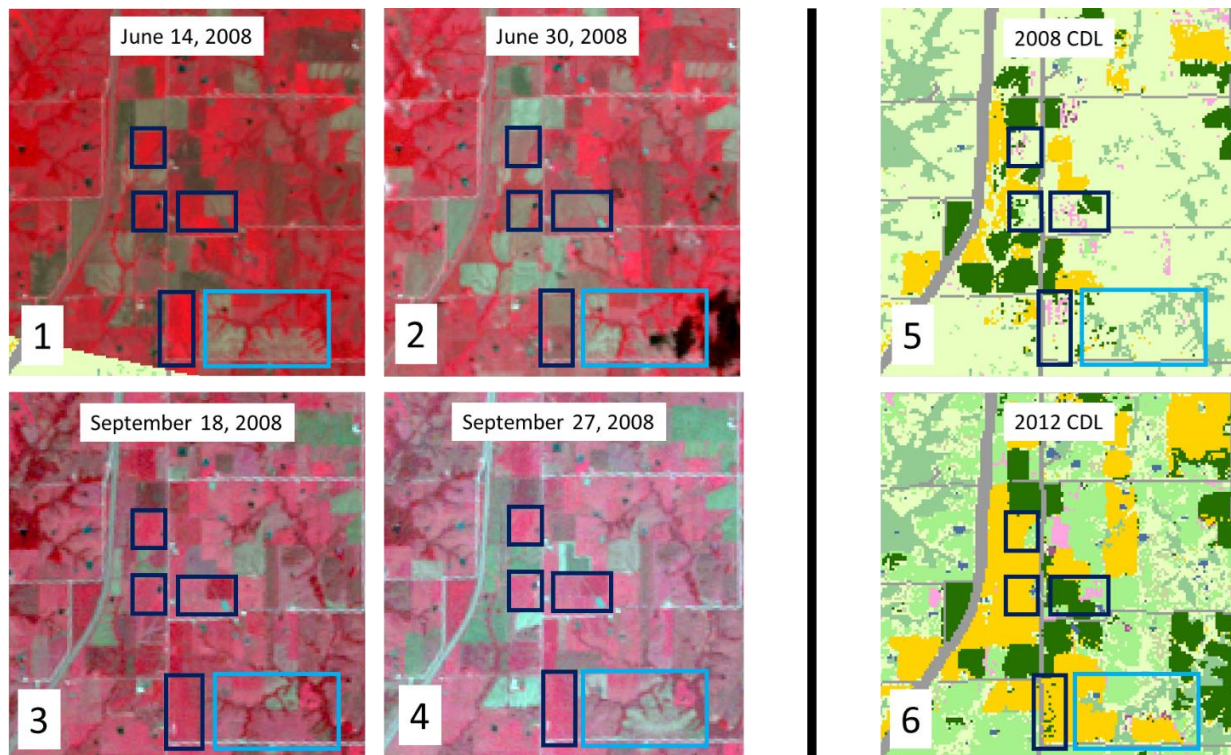
Fig. 9: Images 1-4 are color-infrared Landsat 5 TM. Images 5-6 are the 2008 and 2012 CDLs. Dark and light blue boxes highlight several examples of areas for misclassification comparison (all fields in these boxes are greater than 30 acres). The temporal sequence of Landsat 5 TM imagery shows the evolution 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.
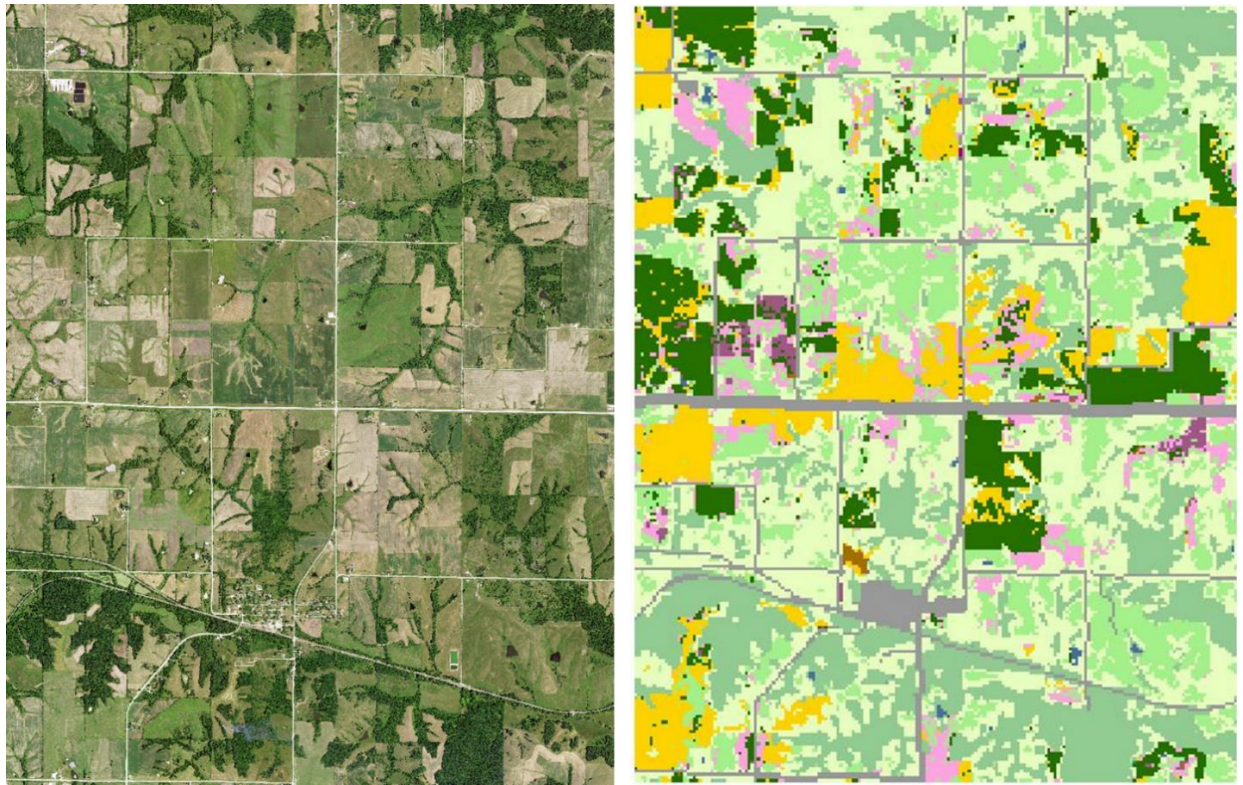
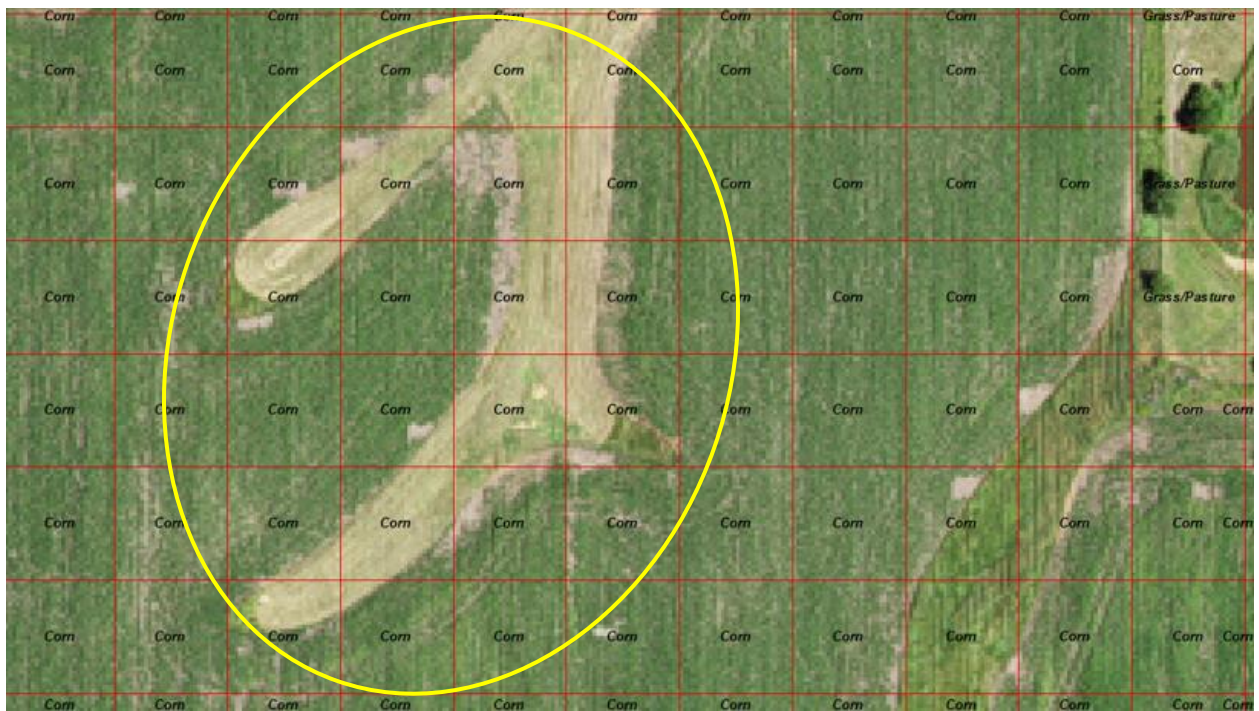**Fig. 10**: 2017 NAIP Image (left) and 2017 CDL (right) used for comparison.

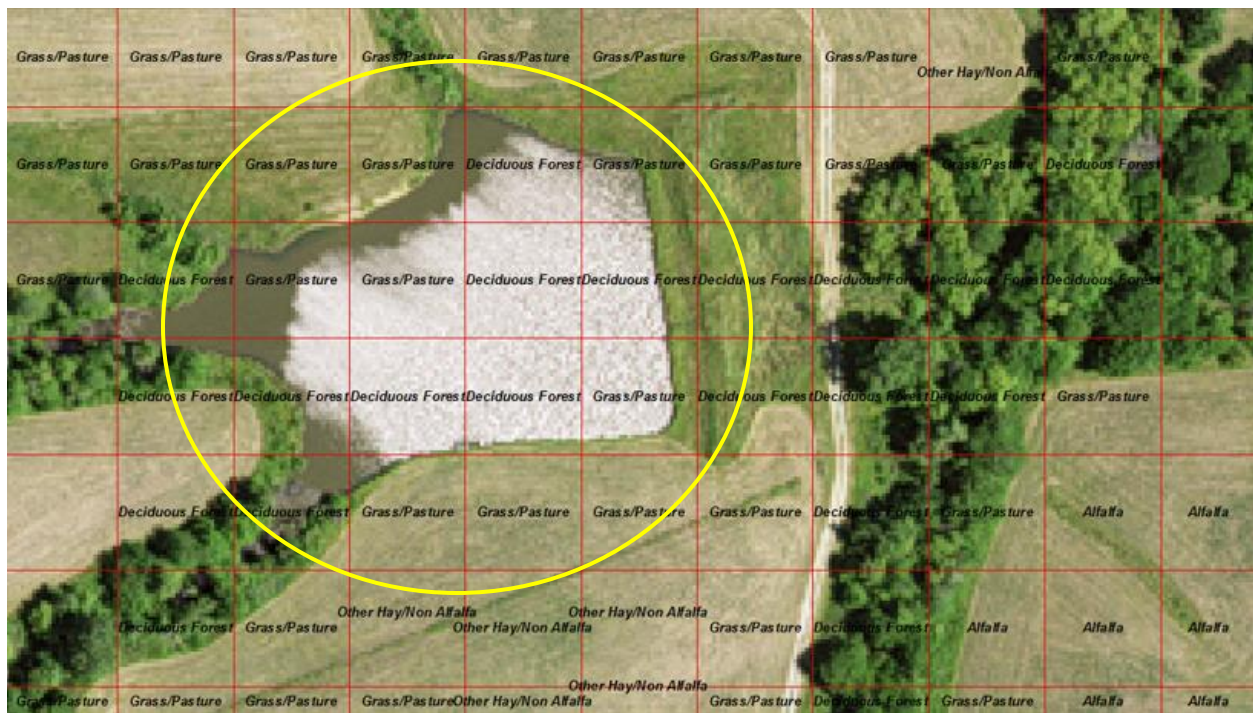**Fig. 11**: 30-meter pixels omitted grassland from the 2017 CDL.

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

Fig. 13: General misclassification of hay and grass/pasture as deciduous forest.
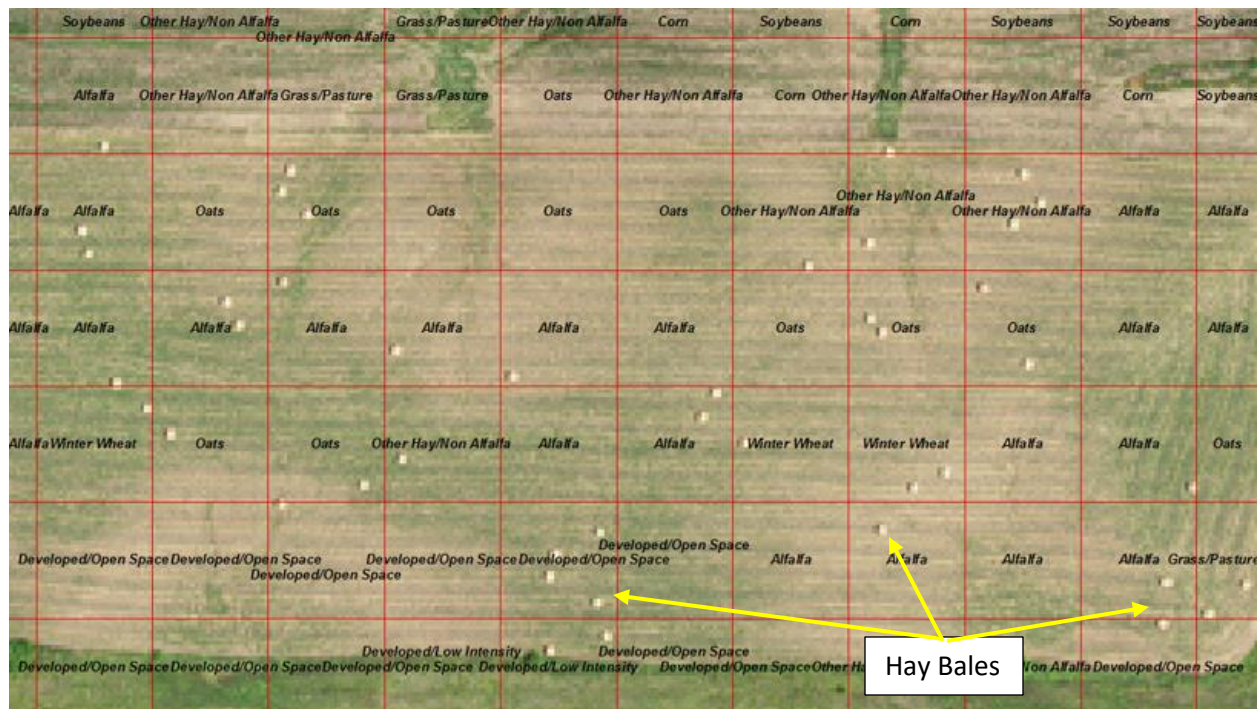
Fig. 14: Multiple classification types (crop and non-crop) in a hay field (identifiable by the presence of hay bales).

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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