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Measuring land-use and land-cover change using the U.S. department of agriculture's cropland data layer: Cautions and recommendations

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ABSTRACT

Monitoring agricultural land is important for understanding and managing food production, environmental conservation efforts, and climate change. The United States Department of Agriculture's Cropland Data Layer (CDL), an annual satellite imagery-derived land cover map, has been increasingly used for this application since complete coverage of the conterminous United States became available in 2008. However, the CDL is designed and produced with the intent of mapping annual land cover rather than tracking changes over time, and as a result certain precautions are needed in multi-year change analyses to minimize error and misapplication. We highlight scenarios that require special considerations, suggest solutions to key challenges, and propose a set of recommended good practices and general guidelines for CDL-based land change estimation. We also characterize a problematic issue of crop area underestimation bias within the CDL that needs to be accounted for and corrected when calculating changes to crop and cropland areas. When used appropriately and in conjunction with related information, the CDL is a valuable and effective tool for detecting diverse trends in agriculture. By explicitly discussing the methods and techniques for post-classification measurement of land-cover and land-use change using the CDL, we aim to further stimulate the discourse and continued development of suitable methodologies. Recommendations generated here are intended specifically for the CDL but may be broadly applicable to additional remotely-sensed land cover datasets including the National Land Cover Database (NLCD), Moderate Resolution Imaging Spectroradiometer (MODIS)-based land cover products, and other regional, national, and global land cover classification maps.

1. Introduction

Humans have altered earth's landscape more than any other species, with agriculture representing the largest anthropogenic use of land area (Foley et al., 2005; Ramankutty et al., 2008). As such, agricultural land use and land-use change are widely recognized as key drivers of the global environment (Tilman et al., 2001; Turner et al., 2007). Monitoring changes to our agricultural landscapes is critically important for understanding and managing food production, conservation, and climate change as well as informing and evaluating policies focused on addressing these grand environmental challenges (Byerlee and Janvry, 2007).

In the United States, the Department of Agriculture's (USDA) Cropland Data Layer (CDL) provides an annual publicly available land cover classification map tailored toward crop identification (Boryan et al., 2011). Produced by the statistical arm of the USDA–the National Agricultural Statistics Service (NASS)–the CDL covers the conterminous 48 states with field-level resolution and crop classification accuracies typically upwards of 90% for major commodities like corn, cotton, rice, soybeans, and wheat (USDA-NASS-RDD Spatial Analysis Research Section, 2016). Compared to other sources of agricultural land use data, including NASS's 5-year epoch Census of Agriculture and annual county-level surveys, the CDL's spatially explicit identification of land use and land cover makes it a particularly powerful tool for understanding and studying agricultural landscapes at fine detail.

Detecting landscape changes over time using the CDL has become increasingly enabled as the program ages, creating a temporal archive of annual data now spanning nine years nationwide and up to twenty years for select states. The number of peer-reviewed journal articles utilizing the CDL has also grown substantially following the release of wall-to-wall US coverage beginning in 2008 (Fig. 1). This growth likely stems from increased product availability and awareness, improved accuracy and associated utility, and greater ease of use through integration with affiliated products, such as the CropScape online portal, which allows users to perform online queries and simple analyses without the need for a desktop geospatial program (Han et al., 2012).

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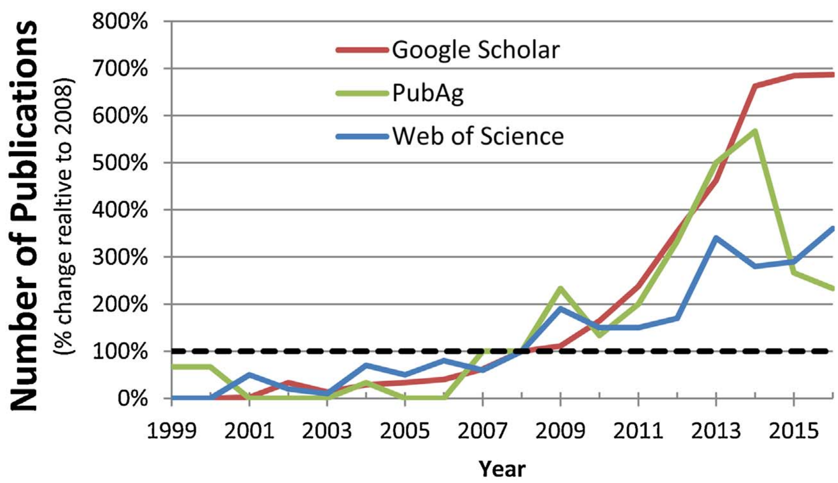

Fig. 1. Number of annual peer-reviewed journal articles or published conference proceedings that utilized the CDL, relative to 2008 totals. Applications of the CDL in academic and industry research have boomed since nationwide areal coverage began in 2008. Citation counts retrieved from searching for publications with the exact phrase "Cropland Data Layer" via Google Scholar, PubAg, and Web of Science; number of publications in 2008 from each portal were 43, 3, and 10, respectively. Google Scholar and Web of Science indices include all articles; PubAg is the portal to full-text journal articles authored by USDA staff.

However, with increased use and availability comes a need to develop accompanying best practices. Thus far, there have been no recommended guidelines or suggestions for use of the CDL from either the producers of the dataset or its user communities. As a result, a unique method for processing and analyzing the CDL is typically developed for each study or application. While this approach has led to a creative divergence among scholars and practices, the inconsistency among analyses limits practical comparisons and hinders successive building of methodology. The lack of explicit discussion regarding methodologies and best practices can also potentially propagate problematic approaches throughout the literature. In addition, methodologically unique analyses of the same study region and timeframe can occasionally produce widely different results and suggest conflicting conclusions (Kline et al., 2013; Sahajpal et al., 2014; Wright and Wimberly, 2013a, 2013b). This variation—originating from processing decisions rather than data discrepancies—can also falsely evoke uncertainty in the underlying data, hindering policy and scientific applications from moving forwards.

Here, we propose a set of recommended practices for utilizing the CDL for studying land-use and land-cover change (LULCC). Because the CDL is designed and produced with the intent of monitoring annual land cover and not changes over time, these guidelines are particularly geared towards multi-year change analyses, where additional precautions are necessary to reduce the probability of error and misanalysis. Many of the considerations and potential pitfalls we highlight, however, also apply to analyses based on a single year of data such as those measuring future land availability or the geospatial distribution of existing crops.

We begin with an overview of the relevant methodology used in the production of the CDL as well as a summary of its uses for measuring LULCC reported in the literature. Subsequently, we provide a list of cautions and associated techniques to mitigate some of the challenges to measuring LULCC. We then detail a problematic issue of crop area estimation bias in the underlying CDL data and outline multiple solutions to correct for this bias. Lastly, we propose a set of additional recommendations to consider during any application of the CDL for measuring LULCC. While the set of cautions and recommendations provided here cannot address every situation that arises, we hope it serves as a launching point for further discussion and common ground from which to build and refine.

2. BACKGROUND & APPLICATIONS

2.1. CDL production

The CDL products are annually released each January with the purpose of identifying crop-specific land cover circa mid-summer of the previous year's growing season. Non-crop areas are also identified but with less specificity and concern over accuracy. Satellite imagery inputs, based on availability and cost effectiveness at the time, have included the Resourcesat-1 Advanced Wide Field Sensor (AWiFS), Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced TM Plus (ETM +), Landsat-8 Optical Land Imager (OLI), and Deimos-1 and UK-2 from the Disaster Monitoring Constellation. The multispectral imagery is classified by leveraging the USDA Farm Service Agency (FSA) crop administrative database for the training and accuracy assessment of crops, and the Multi-Resolution Land Characteristics (MRLC) consortium's National Land Cover Database (NLCD) for all other non-crop classes. Note that the CDL does not simply revert to nor default to the NLCD in areas of non-cropland, but rather incorporates NLCD information for non-cropland as training data into the CDL's own, unique classification decision tree. The processing is performed at a state-level for all but the biggest and smallest states.

The first available US-wide product was released for year 2009 (Johnson and Mueller, 2010) with nationwide 2008 coverage completed retrospectively soon afterwards. Most state CDLs during these two years were at 56 m resolution based on the native pixel size of the AWiFS data, which was the primary input source. 2010 to present has been consistently at Landsat's 30 m resolution. For certain states, particularly those in the Corn Belt region, the CDL history goes farther back in time with North Dakota being the most historical example having started in 1997. States available 2005 and earlier were also generated at 30 m as Landsat imagery was the sole input source. A full listing of years available by state are listed within the NASS CDL metadata (USDA-NASS-RDD Spatial Analysis Research Section, 2016).

From that initial single state product two decades ago, the research and development effort expanded organically and improved steadily to what is considered state-of-the-art today. However, there are two notable eras to the underlying methodology (beyond the noted pixel size differences). In 2005 and prior only two images (ideally early and late in growing season) were used over a given pixel, training data was limited to that manually collected and digitized by NASS, and the classification was based on a maximum likelihood methodology. The work from 2006 onward has instead relied on multiple images throughout the season (and some even prior), the more encompassing FSA and NLCD data for training, and an ensemble decision tree classification methodology. As a result, there is a significant change in look and feel from 2005 to 2006 with the more contemporary products considered more robust.

Lastly, it is worth noting that the primary goal of the CDL is, and always has been, to provide supplemental information in helping corroborate and refine NASS mainline crop area survey estimates through a technique known as "regression estimation" (Battese et al., 1988). As such, CDL-like products are generated and analyzed by NASS typically multiple times within the growing season with a sole focus on intensively cropped regions. The final CDL land cover product that is ultimately provided to the public is thus in some sense a byproduct of the original area estimation work. Nonetheless, it is recognized by NASS that the public CDL contains significant value for a broad host of land cover applications, whether directed at agriculture or otherwise.

2.2. Applications and uses of the CDL for measuring LULCC

Typical studies utilizing the CDL in research range from static characterization of current land cover to projections about future land use, and most recently, analyses of changes over time. Mueller and Harris (2013) provide a synopsis of the many reported ways in which the CDL has been applied to date. Most analyses focus on agricultural applications, but use has also spread to broader ecological, industrial, and planning analyses, which draw upon the high spatial resolution and land cover specificity provided by the CDL.

Agricultural LULCC studies utilizing the CDL can typically be broken into two categories—descriptive studies and predictive (modeling) studies. In descriptive studies, researchers frequently use the CDL to observe, describe, or characterize recent or current conditions and phenomena. In these applications, knowledge of existing agricultural practices and LULCC pathways are often used to provide context and a framework for understanding changes captured by the CDL. As such, studies have typically focused on either recent crop rotations (Han et al., 2013; Li et al., 2012; Long et al., 2014b, 2014a; Plourde et al., 2013; Sahajpal et al., 2014) or land conversion (i.e. cropland expansion/abandonment; Johnston, 2013, 2014; Lark et al., 2015; Wright and Wimberly, 2013a). In addition, a number of descriptive studies identify the current amount of land or crop resources available for a particular application, such as biofuels production or crop residue removal; however, many of these also serve as the input or basis for subsequent predictive modeling studies (Rashford et al., 2013).

In predictive applications, data from the CDL are often incorporated into a larger modeling framework to understand the effects recent or hypothetical conditions or changes to the landscape or environment may have on target metrics such as ecosystem services, biodiversity, or land use. Many of these studies have focused on bioenergy production potential or the effects of future bioenergy scenarios (Elliott et al., 2014; Gelfand et al., 2013; Li et al., 2012, 2013; Meehan et al., 2010; Muth et al., 2013; Muth Jr. and Bryden, 2013). Rashford et al. (2013) provide a thorough overview of the challenges in using CDL data for modeling purposes, particularly regarding the conversion of grasslands (Rashford et al., 2013). Similar to the limitations of the CDL for mapping LULCC that we discuss here, substantial considerations are necessary when using the CDL as input for modeling endeavors.

3. General cautions for use

Certain precautions should be taken to help reduce the probability of error in measuring LULCC using the CDL. A summary of common tasks and challenges is presented in Table 1, with details and potential solutions highlighted in the following subsections.

3.1. Land use, land cover, and grassland identification

Due to its reliance primarily on satellite-based data, the CDL is generally unable to identify land use and instead provides indication of land cover. In many ways, this can create challenges in comparing aggregated CDL data to that of inventory data such as the Census of Agriculture, which provides farmer-reported land use at county-level resolution. For example, the CDL delineates forests by cover type (deciduous, coniferous, or woody wetlands), whereas the Census of Agriculture delineates forests by use (grazing or managed for timber). It should be noted that through data fusion or dasymetric mapping approaches (Joshi et al., 2016; Monfreda et al., 2008; Ramankutty et al., 2008), the CDL can be used in combination with other data to give more spatially detailed insights into land use. Thus, while the CDL does not natively provide information on land use, it can still be utilized in analyses of land use and land-use change.

Similarly, the CDL has particular difficultly in accurately distinguishing between grassland types—e.g. native vs non-native—as well as grassland use, such as pasture vs hay. Part of this difficulty stems from the subtleties that exist across category types from a multispectral imagery standpoint (Schuster et al., 2015), and additional challenges stem from the inter-state inconsistences in how grass type crops are reported within FSA data used for training. Thus, individual analysts creating the CDL must decide how to use grass and pasture ground reference data in their particular state, region, and year. As a result, this can occasionally create observable differences across state boundaries and years. NASS is currently spending effort to improve the grass categories, which are typically seen as the weakest aspect of the product. In the meantime, to better reflect the difficulty of distinguishing

Table 1
Limitations of the USDA Cropland Data Layer for monitoring Land Cover and Land Use Change (LULCC). Presented is a list of common tasks performed during LULCC mapping, descriptions of related capabilities and constraints, and an example of each situation.

Task	Explanation of Limitation	CDL Example
Identifying land use	Like many satellite-derived remotely sensed data, the CDL only identifies land cover and does not provide information on land use.	Does not distinguish unmanaged forests from those used for timber production or livestock grazing.
Distinguishing grassland vegetation	Due to their spectral similarity during remote sensing classification, it is difficult to accurately discern among various grassland vegetation types and uses.	Cannot identify native vs. non-native vegetation, difficulty discriminating pasture from hay.
Assessing area using direct pixel counting	Because fields often do not align with pixels, there can be sub-pixel area biases and adjustments required to measure acreage.	In NASS's use of the CDL for acreage estimations, a regression-based pixel-area adjustment factor is used.
Measuring incremental or pixel-level changes	Resolution limitations (30 + m) hamper capturing small changes in area, and annual edge effect can falsely suggest incremental changes along field boundaries.	Rural roads are typically < 10 m wide, leading to inconsistency in their mapping and that of the adjacent field edges over time.
Measuring changing field sizes or other landscape metrics	Improvements in the CDL classifications over time have reduced the occurrence of within-field speckle and apparent heterogeneity, influencing many landscape metrics.	Fields previously mapped as a checkerboard of 2 crops appear more homogeneous when correctly mapped as a single crop.
Directly comparing results across multiple U.S. states	Independent processing and classification of the CDL for each state often leads to inconsistencies across states, particularly noticeable along boundaries.	The 2008 Kansas CDL classified almost all grassland as pasture/hay, generating higher estimates compared to its neighbors.
Measuring change between two isolated points in time	Assessing change using a bi-temporal "snapshot" methodology (i.e. using data only from the 2 years of interest without intermediate-year data) misses crop and cropland rotations and can multiply errors in the original data. Precludes temporal filtering.	CropScape online portal's web-enabled change analysis feature.

between types of grasslands and eliminate confusion among grass classes, the 1997–2013 CDLs were recoded and re-released in January 2014 using a collapsed category of Grass/Pasture (class 176) to capture all previous cover classes of Pasture/Grass (class 62), Grassland Herbaceous (class 171), and Pasture/Hay (class 181).

3.2. Area estimation using direct pixel counting

Directly counting pixels can produce imprecise estimates of area due to misclassifications as well as misalignment of field and pixel boundaries. As such, use of a pixel area adjustment factor may be required to measure acreage and account for a frequent crop underestimation bias. For NASS's internal application of the CDL for area estimation of individual crops, the CDL is compared to a sampling of ground reference data using a regression analysis to gain insights into the classification bias. An area multiplier factor is then applied to each pixel to adjust its acreage value. End users may be able to replicate this process by using the published NASS statistics from the Survey or Acreage reports to adjust individual CDL pixel values. Alternatively, using published NASS statistics or other data sources to calibrate the *change* in acreage over time may similarly correct for sub-pixel area and other biases (see section 4 "Crop area bias and methods for correction").

3.3. Measuring incremental changes, field size, and landscape ecology metrics

Spatial resolution limitations generally prevent capturing the small changes that occur at the boundaries of fields, such as when a fence, hedgerow, or windbreak is added or removed or when a field incrementally expands or contracts in its margins. Similarly, the induced edge effect that occurs from classifier uncertainty within mixed pixels (those centered on a transition between two land cover types) can falsely suggest incremental field contractions or expansions between various years of the CDL when in fact no change in field size occurred. As such, the CDL is more suited for detecting changes to whole fields or large plots of land–where the area-to-perimeter ratio is maximized–rather than incremental changes in landscapes.

Improvements to the CDL's methodology and accuracy over time have also led to concomitant improvements in the homogeneity of mapped fields. These improvements confound measuring changes to many landscape ecology metrics and configuration indices using CDL data. For example, because improved map consistency directly translates to decreased landscape diversity or heterogeneity, it can artificially give the appearance of increased patch sizes. If field size or other landscape metrics are to be measured, a more robust methodology should be used, such as one based on object recognition (Yan and Roy, 2016). In general, the CDL is best and most appropriately used for contextual or field-level and larger analyses where differences in pixel size, mixed pixels, and sub-pixel area issues become much less of a concern.

3.4. Comparisons across dissimilar products (states and years)

In production of the annual CDLs, NASS independently processes and classifies each state. Differences in the interpretation of remotely sensed image signatures and use of training data across states can lead to certain inconsistencies that are particularly noticeable along borders. This effect is most easily observed in the previously distinct (but now aggregated) grassland categories, but differences exist across crop and other non-crop classes as well. To help mitigate the issue, each state classification draws upon a certain level of reference data from outside the state's border; however, some residual state-to-state variation often remains.

Similarly, each year of each state's CDL is independently classified without reference to previous-year data. This differentiates the CDL from linked land cover classification products such as the National Land Cover Database, which instead generates updated classifications in reference to a base year. Advantages of annually-independent products like the CDL are that they better facilitate methodological changes and product improvements each year and avoid propagating potential errors temporally throughout multiple years of a dependent product. As a tradeoff, however, annual independence generates challenges for measuring changes across time, necessitating many of the additional precautions described here.

The effects of independence are especially salient when comparing across years that use dissimilar input data, since these products may exhibit additional differences including spatial and spectral resolution. In general, direct comparison across CDLs of different resolutions should be avoided or specially addressed to account for the change. If necessary, reclassification of 56- and 30-m CDLs should be resampled to the lower resolution raster. Results of the resampling should be closely inspected for any artifacts from the original resolution difference, and these artificial signals should be addressed or explicitly accounted for. Data along the edges of same-class pixel blocks or polygon-like features (e.g. field edges) and linear features (e.g. roads) are particularly susceptible to distortion or errors during resolution transformation. As a collective result of the spatial and temporal independence of each state CDL product, exceptional care should be taken in all multi-state or multi-year analyses to identify any larger issues and anomalies to ensure consistency of the analysis and continuity of the final product.

3.5. Bi-temporal change analyses

Analyses that directly compare two isolated points in time and that take a bi-temporal "snapshot" of change–without considering data from the intermediate years–should be used with strong caution. Due to the amount of noise and uncertainty in a single year of CDL classifications, these snapshot difference analyses often falsely elevate apparent change by multiplying the error found in each annual CDL layer. Furthermore, excluding intermediate-year data precludes the use of temporal filtering and reclassification techniques that can aid the identification and correction of misclassifications.

In spite of these limitations, straightforward snapshot-style or "naïve" change assessments can be useful for quickly screening research questions and identifying trends for further investigation without investing substantial time or processing into the effort. To facilitate these rapid inquiries, the CropScape web portal includes a change analysis feature that makes this bi-temporal snapshot approach widely accessible to novice and expert users alike (Han et al., 2012). However, if change is to be measured on a more robust level, the methodology should include *both* spatial and temporal approaches to correcting for likely misclassifications, as well as additional time-series consideration of how year-to-year variations in rotations among crops or between cropland and pasture can influence results.

4. Crop area bias and methods for correction

In pursuit of continuous product improvement, the accuracy of the CDL has continuously increased over time (USDA-NASS-RDD Spatial Analysis Research Section, 2016). Concomitantly there have been changes to the level of bias (over- or under-mapping) with which the CDL identifies total cropland extent. Historically, the CDL under-predicted total cultivated area relative to its reference data, however the magnitude of underprediction has lessened over time. As a result, unadjusted estimates of total cropland area based on the CDL alone suggest a substantially greater increase in total cropped area over time compared to other data sources (Fig. 2). In this section we characterize the identified crop underestimation bias and its change over time and outline a number of approaches to mitigate the issue.

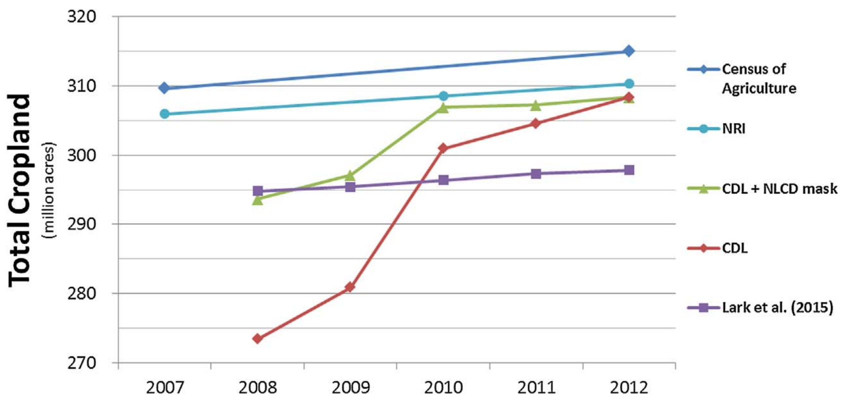

Fig. 2. Total cropland over time based on uncorrected CDL compared to other datasets. If not addressed, the CDL's tendency to increasingly capture cropland over time can skew change analyses towards crop and cropland expansion. Using a cultivated layer mask (e.g. CDL + NLCD mask, see section 4.4) or calibrating with external data (e.g. NRI data, see section 4.2) offer two methods to help correct for this issue.

4.1. Characterizing bias in the CDL

The bias of a remote sensing product gives an indication of the product's tendency to under- or over-map area of a specific class compared to reality. Estimates of a product's bias can be derived from published accuracy statistics and calculated as negative one plus the ratio of producer's to user's accuracy (Olofsson et al., 2013). If point-level results of an accuracy assessment are available, this statistic is equivalent to the number of sample points mapped as a given class divided by the number of sample points identified as the given class in the reference data. For the CDL, accuracy-derived biases are available for each class by state in tables available online (USDA-NASS-RDD Spatial Analysis Research Section, 2016).

To understand the collective bias of the CDL and how it has changed over time, we estimated the nationwide cropland over- or under-mapping for each year by calculating a weighted average across all crops accounting for differences in area of each class and each state. To compute this, we first multiplied the state-level bias for each specific class by the area of that class in that state. This result was subsequently summed for all states and divided by the total nationwide class area to estimate the national-level bias for each specific crop. A single consolidated cropland bias was then estimated by area-weighting each crop's specific bias by the crop's proportional contribution to total cropland area, defined according to the crop/non-crop categorization listed in Appendix A. Results for the estimated nationwide bias for total cropland 2008–2012 are shown in Table 2 below.

The negative bias value for total cropland signifies that the CDL generally undermaps cultivated area relative to its reference data, primarily from FSA (USDA-NASS-RDD Spatial Analysis Research Section, 2016). The reduction in magnitude of the bias over time suggests that the undermapping or amount of missed cropland has continuously decreased. This trend can skew results when trying to quantify or detect specific LULCC, and is likely to manifest as an exaggerated signal of cropland expansion. The issue can be mitigated, however, by a number of approaches including use of ancillary data from sources like the annual NASS Surveys, the NLCD, or published CDL accuracy statistics, as described below.

Table 2
Nationwide cropland area estimation bias of the CDL. Table reports the tendency of the CDL to generally underestimate (negative bias value) total crop area at the national level. The reduction in bias over time suggests more complete capturing of total cultivated extent each year, which can falsely indicate cropland expansion if not corrected. Data based on CDL accuracy statistics (USDA-NASS-RDD Spatial Analysis Research Section, 2016) consolidated across all crops using the crop/non-crop categorization listed in Appendix A.

Year	2008	2009	2010	2011	2012
Cropland Estimation Bias	−2.22%	−2.08%	−1.73%	−1.66%	−1.29%

4.2. Calibrating pixel-area values with independent data

One way to correct for the bias and the reduction in bias over time is to calibrate the area (or area of change) with published crop area estimates from NASS or other data sources. In this approach, the area value of individual pixels should be adjusted so that when totaled they agree with county- or state-level published statistics, such as those in the USDA Acreage reports. For example, if corn area is undermapped in the CDL by 20% in a given county, the area value of each pixel of corn in that county could be upward adjusted accordingly (in this case divided by 0.8), such that a single 30 m x 30 m resolution pixel of corn would receive an updated area value of 1125 m^2 instead of 900 m^2. The calibration is most straightforward when done for a single crop, such as corn, but can also be used for a combination of crops or total cropland if care is taken to assure that definitions and included crops are aligned between data sources. This approach is similar to the regression adjustments used by NASS when making official crop area estimates based on the CDL (USDA NASS, 2012; USDA-NASS-RDD Spatial Analysis Research Section, 2016).

Referencing user and producer accuracy data for each class or group of classes can provide an alternative indication of the areal biases and associated method for correction (Olofsson et al., 2013; Stehman, 2013). The bias for any specific class or combination of classes can be derived using the reported state-level crop accuracy rates from the CDL metadata or the published error supermatrices (USDA-NASS-RDD Spatial Analysis Research Section, 2016). Multiplying the calculated bias by the class area provides an estimate of the total area of over- or under-mapping by the CDL, which in turn can be used to derive an adjusted estimate of total area for the given class. If pixel-level correction is desired, these bias-adjusted estimates of class area can be used analogously to the NASS statistics in the previous paragraph to calibrate the area value of each individual pixel.

The pixel-level calibration techniques are most appropriate when pixel-level adjustments are made to individual years. However, this can create difficulties for assessing change if a given pixel is assigned different adjusted values across different years. For example, if a pixel with a native area value of 900 m^2 is adjusted to be worth 800 m^2 in year one and 850 m^2 in year two and the pixel underwent a class change between years one and two, it is not immediately clear whether the area of change should equal 800 m^2, 850 m^2, or some intermediate value.

In such cases, the amount of *change* between years in the CDL can be calibrated with the *change* in area derived from either published NASS estimates, the bias-adjusted area estimates from the CDL, or other sources of land change data like the National Resources Inventory (NRI; USDA, 2015). Calibrating the area of change across CDL years is admittedly less desirable than independently adjusting pixel area values for each year and then measuring change because the former accounts for discrepancies across the reference data's entire administrative boundary using only a select subset of the mapped class (the changed pixels) as opposed to distributing the bias adjustment across all pixels of the mapped class (the changed and unchanged pixels). Nonetheless, this approach is likely preferable to no adjustment at all, and will result in an estimate of change in line with the reference data and that is not conflated by improvements to the CDL over time.

4.3. Integrating spatial variation in uncertainty

One extension to the uniform pixel-area value adjustment technique is to incorporate information from the CDL confidence layers to identify which pixels are most likely incorrect and reclassify or adjust only those pixels accordingly, rather than uniformly debiasing. The CDL confidence layers are ancillary data provided by USDA NASS that provide a measure of how well a specific pixel fit within the decision tree ruleset used to classify it (Liu et al., 2004; USDA-NASS-RDD Spatial Analysis Research Section, 2016). Thus, the confidence layer gives an indication of the spatial variation of uncertainty within each CDL class.

Given a known amount of over- or under-mapping of a specific class within an administrative boundary (e.g. county or state), one can use the confidence layers to identify the pixels that were mapped with greatest uncertainty and replace those pixels with an appropriate countervailing classification such that the new summed totals equal the independent data. This approach is feasible when the data of interest are a binary choice (e.g. corn and not corn; or cropland and noncropland). However, if a complete accounting of the landscape is required and there exists more than two map classes, it becomes unclear to which class the uncertain pixels should be reclassified. In this case, one could imagine a hybrid approach where the area-value of pixels are adjusted in the manner of 4.2 but done so proportional to the uncertainty in each pixel, rather than uniformly across all pixels of a class.

4.4. Using a cultivated layer mask

An alternative method for addressing the CDL's improvement in capturing cropland over time is to use additional remote sensing-based data to identify cropland that was likely missed in early years. The MLRC's NLCD product is especially well-suited for this task as it provides coverage for the complete U.S. dating back to 1992 and boasts the same 30 m resolution as recent CDL years. In this approach, cultivated cropland extent from the NLCD or other products can be used to identify the footprint of total cropland in given years and flag areas likely to have been cultivated but not captured by one of the CDL's crop classes. A drawback of using the NLCD or most other products is that the crop specificity of the CDL is lost. However, the approach is effective for studies where the data of interest are total cropland or another broad land cover class. As always, adequate attention should be given to classification categories and definitions of the additional data to ensure a good fit between sources.

An example of this approach can be seen in the recent analysis of cropland expansion by Lark et al. (2015), where data on cultivated cropland from the 2001 and 2006 NLCD was used to identify areas likely to have been previously cropped but not captured by the CDL in its early years of full continental coverage (Lark et al., 2015). Results from this analysis, which also included additional corrections and adjustments, are graphed for reference in Fig. 2 along with an example isolating the impact of the cultivated layer mask (Fig. 2**; CDL + NLCD mask**). For the latter example, the amount of cropland at each time step was derived from the union of the NLCD 2006 cultivated crops footprint and the CDL cropland footprint for each year, using the same definition for cropland as Appendix A.

5. Recommendations for best practices

We next describe a set of additional recommendations to consider during application of the CDL for mapping LULCC (Table 3). Adhering to these broad guidelines while incorporating the previous cautions and cures will generally enhance the utility, accuracy, and consistency of analyses. Organized loosely by change detection processing steps, these guidelines are intended to provide starting advice on processing decisions that should ultimately be tailored for each specific analysis.

5.1. Combine classes

Consolidating the original 100+ raster classifications of the CDL into aggregated categories can significantly improve the accuracy of assessments by eliminating misclassification errors within the combined classes. This approach can be applied to both crop and non-crop categories, and is especially applicable for land covers in which the CDL has lower identification accuracies. In particular, all grassland classes should regularly be combined due to the inability to adequately discern grass-based pasture, hay, and non-agricultural uses. To this extent, the CDL has recently internalized this measure and retroactively combined all grassland-dominated covers into a single category to represent grassland/pasture.

Class consolidation is also effective for combining crop categories, where the approach reduces the effects of classifier confusion among the many crop classes, which may exhibit spectral similarities. As example, Table 4 shows the improvements in accuracy resulting from consolidation of the corn and soy classes in the 2012 South Dakota CDL. Similarly, consolidating all non-crop covers results in substantial accuracy improvement via elimination of misclassification between the non-crop classes.

CDL class consolidation is particularly useful for mapping total cropland extent (Johnson, 2013) and changes to cropland area or land conversions (Lark et al., 2015), as well as for facilitating comparisons with other datasets such as the NLCD. The collapsed classes can also subsequently be disaggregated after initial detection of land cover changes in order to benefit from improved change detection accuracy while retaining the original crop specificity of the CDL (Lark et al., 2015)

5.2. Utilize all available data

For studies analyzing changes over time, all data throughout time should be considered. For example, a study assessing changes between 2000 and 2004 should include the intermediate years of 2001, 2002, and 2003 as well as the endpoints in order to understand the full "trajectory" of land cover during the study period and take advantage of all available data. Studies of crop rotations inherently incorporate this practice; studies on land conversion, on the other hand, typically do not. By considering the full trajectories of land cover over time, it is possible to better characterize and differentiate change. The additional temporal information can be used in temporal filtering to help identify likely classification errors (Lark et al., 2015), and can also be used to help identify and delineate fields, since pixels of a given field tend to rotate crops in unison (Sahajpal et al., 2014; Yan and Roy, 2014).

Similar to using all available years of the CDL, ancillary data should be used wherever available. In this sense, the CDL can be used as "one of many" data sources. As shown in section 4.1 regarding the cropland underestimation bias in early CDL years, use of a single data source can potentially be problematic. Where available, additional data sources should be used in combination with or as validation for analyses based on the CDL. Other U.S. datasets that may prove useful include the USDA's Census of Agriculture (NASS, 2014), USDA NASS Survey data (NASS, 2016), the National Land Cover Database (Homer et al., 2015), the LandFIRE datasets (Zahn, 2015), and the NRCS's National Resources Inventory (NRI) (USDA, 2015).

The USDA's Census of Agriculture is frequently considered the best available "truth" for land use (Johnson, 2013), though its 5-year frequency can often limit its utility for direct comparison with CDL-based studies. NASS Survey statistics, which provide annual county-level data on crop area, can be valuable but should be closely interpreted to

Table 3
Summary of recommended practices for measuring LULCC using the CDL.

Recommendation	Details	Benefit	Example References
Combine classes	Reclassify all grassland classes, frequently rotated crops like corn and soy, or all crops into a single combined category where appropriate.	Reduces errors distinguishing among spectrally-similar land cover classes.	(Johnson, 2013) (Johnston, 2013) (Wright and Wimberly, 2013a)
Adjust for areal biases	Use ancillary dataset or a regression estimator to correct for frequent crop underestimation bias.	Reduces false signals and exacerbated change areas due to CDL product improvement over time.	(Johnson, 2013) (Lark et al., 2015)
Utilize all temporal data	When measuring changes over time, all available data should be used, including intermediate years.	Allows temporal classification and temporal filtering of likely misclassifications. Aids field boundary identification.	(Plourde et al., 2013) (Johnston, 2014) (Sahajpal et al., 2014) (Lark et al., 2015)
Integrate multiple datasets	Use additional remote sensing or ground-based data sources in combination with the CDL to measure LULCC.	Improves confidence of findings, enables correction of individual product biases.	(Lark et al., 2015)
Establish Minimum/Maximum Unit of Change (MUC)	Match change detection size to expected range of plausible changes.	Reduces mapping of spurious change. Improved signal to noise ratio.	(Cox and Rundquist, 2013)
Undertake post-classification processing	Use field segmentation, a Minimum Mapping Unit (MMU), or spatial filtering to remove likely misclassifications.	Improves consistency between map representation and reality (fields, etc.). Reduces speckle. Better alignment with CDL capabilities (when use MMU).	(Yan and Roy, 2014) (Lark et al., 2015) (Mladenoff et al., 2016)
Verify with independent data	Use published USDA statistics or other authoritative data to aid selection of processing and assessment methodology.	Improves selection of post-classification processing techniques. Corroborates findings.	(Johnson, 2013) (Plourde et al., 2013) (Sahajpal et al., 2014) (Lark et al., 2015)
Perform an accuracy assessment	Use confirmed ground data or high resolution aerial photography to conduct a site-specific accuracy assessment	Provides insights into the correctness of the change product. Allows calculating bias-adjusted estimates of areas of change.	(Reitsma et al., 2015) (Wright et al., 2017)

Table 4
Example state level accuracies for individual and consolidated classes in the 2012 South Dakota CDL. Table shows the producer's and user's accuracies for example individual crop and non-crop classes used in the CDL, as well as the improved accuracies resulting from consolidating similar land covers into aggregate classes. All non-crop covers consolidated according to the table in Appendix A.

CDL Class	Producer's Accuracy	User's Accuracy
Corn	94.73%	93.47%
Soy	94.32%	94.59%
Consolidated Corn/Soy	97.50%	96.87%
Other Hay/Non Alfalfa	53.07%	33.75%
Grassland/Pasture	86.12%	38.55%
All non-crop covers consolidated	99.20%	98.58%

ensure double cropped areas and definitional issues surrounding total cropland, principle crops, planted area and harvested area do not confound comparisons between survey acreage data and that of the CDL (Laingen, 2015). County-level FSA data on program crop acreage, collected as a producer requirement to receive federal assistance, can be useful as an additional reference point with the caveat that it is considered a “floor” value, since crops from producers not participating in an FSA program are excluded. Plot level FSA data from the Common Land Unit (CLU) would allow the most explicit comparison of LULCC analysis results; however, the FSA CLU is held confidentially and, similarly, by itself is not an exhaustive tabulation of crop area.

Comparisons to other satellite-derived data, such as the NLCD or even MODIS-derived land cover products like MCD12Q1 (Friedl et al., 2010) can be fruitful for identifying areas of bias in each product; however, users should be aware that problematic areas may be subject to the same trends or misclassifications. The NRI provides an independent ground-based dataset for comparison, but is only produced periodically, typically every 5 years. Based on statistical area sampling as opposed to full areal coverage, it is most applicable for benchmarking state and national levels of gross land conversion. Certainty of analyses can also be improved when the CDL is used in combination with ground-based or aerial photography such as the USDA’s National Agricultural Imagery Program (NAIP).

5.3. Use a minimum/maximum unit of change (MUC)

A Minimum and/or Maximum Unit of Change (MUC) can help improve the certainty of mapped changes by limiting allowed changes to those which match the biophysical, legal, or socially-expected size of the phenomenon being observed. For example, most crops in the U.S. are not rotated or converted as single sub-acre pixel-sized units, but rather operate on the scale of whole fields. Thus, in studies of agricultural land conversion and crop rotations, matching the size of allowable change with operable unit sizes can help remove spurious signals arising from classifier uncertainty and misclassifications.

Median field size in the U.S. is 58 acres, with 75% of fields at least 29 acres in size as of 2011 (White and Roy, 2015). Thus, a MUC of 5, 10, or even 15 acres is likely to capture most valid changes to whole fields. When choosing the size of a MUC, it should be noted that the certainty of identified change typically improves as the MUC size increases, resulting in a lower commission error. However, the risk of omission rises. Use of a large MUC (and thus high threshold for change) can therefore be implemented when certainty of identified observations is more imperative than capturing all potential changes.

5.4. Post-classification processing

Post-classification user modifications to the CDL such as spatial filters, minimum mapping units (MMUs), and field segmentation can help clean up apparent misclassifications in the raw data, especially in older years of the CDL. We do not propose a single best post-processing filter or refinement method; it is likely that no such universal best approach exists. Rather, each analyst should individually select the post-classification processing that produces results most appropriate for the analysis at hand.

To identify a suitable approach a variety of post-processing methods and parameters should be trialed (Table 5) and these should be tested against a set of reference data as well as visually inspected for their impact on mapping the landscape. For spatial filters–a common post-processing technique–parameters to explore include the size and type of spatial filter, applying the filter before or after measuring change (i.e. on the input vs the output), and applying the filter at the original thematic resolution or upon consolidated classes. Minimum mapping units (MMUs) provide an additional refinement mechanism particularly useful for removing small features on the landscape that can be challenging to distinguish or measure when changed. Similar options to investigate for MMU parameters include the size, number of neighbors considered in defining the size, and method for replacing removed pixels.

Table 5
List of common post-processing methods and considerations. Multiple techniques, parameters, and their permutations should be investigated to identify the most appropriate approach for mapping the desired LULCC phenomenon.

Post-processing technique	Parameters to consider
Spatial Filter	Size (e.g. 3 × 3, 5 × 5) Type (e.g. contiguous majority or moving window) Shape (e.g. square, radius) Number of neighbors (e.g. 4 or 8) Replacement threshold (e.g. half or majority)
Minimum Mapping Unit	Size (e.g. 10 or 20 pixel) Number of neighbors (e.g. 4 or 8) Replacement method (e.g. nearest neighbor or majority class within a moving window)
Field Segmentation	Input data (e.g. CLU boundary polygons or satellite imagery) Fill method (e.g. majority or center-of-field)

Similar to the selection of a MUC, the size and effects of post-classification processing adjustments should match the expected operable units of the study area and land cover or crop under consideration. For example in highly heterogeneous landscapes, smaller filter and MMU sizes may be needed in order to appropriately capture landscape features, whereas regions with primarily large, whole-field LULCC can take advantage of larger processing unit sizes (Mladenoff et al., 2016).

The strength of processing techniques and parameters should also be based on the level of expected error in the input data. In general, older CDL years will command larger MMUs and/or more aggressive filters or filling of segmented fields. For example, in Florida, a 20 acre MMU was found to produce the best results in 2004 (Boryan et al., 2011). In contrast, recent CDLs have progressed to the point where a 3 × 3 filter or one hectare MMU may suffice, or may not even be necessary. An additional method for refining classifications involves creating field segmentations from original Landsat imagery (Maxwell and Craig, 2008; Yan and Roy, 2014) or administrative field boundary data and spatially filling the segments with the majority or centroid CDL crop class.

5.5. *Verify with independent data and assess the accuracy*

Independent land change data can provide a helpful point of comparison to assess the effects of processing choices on measured change and aid in selection of post-processing techniques. Many of the datasets listed in section 5.2 provide info on net or gross land change at the county-level, and these counts can be charted against the outputs from different CDL-based change algorithms to identify overall congruence between the datasets as well as outliers, which can indicate locations of potential error in the original CDL time series data or the selected post-classification processing techniques.

While comparisons to other estimates of change can provide quick feedback for refining change detection algorithms and corroborating results, they are not sufficient for ensuring an accurate product. Aggregated amounts of change (e.g. at the county level) identified by CDL-based analyses can produce correct estimates of changed area while not correctly identifying locations of change on the landscape. Thus it is important to conduct additional verification of any LULCC product, which should include both visual inspection and site-specific accuracy assessment. In addition to quantifying the uncertainty associated with the product, a complete accuracy assessment can facilitate calculating error-adjusted estimates of total change area (Olofsson et al., 2013; Stehman, 2013)

As a related consideration, known error rates in the CDL (provided in the metadata) are frequently greater than the amount of land cover change intended for measurement. Thus, it is often a great challenge to pull out what is subtle actual change from within the inherent CDL noise. The cautions and recommendations presented here can help researchers overcome this challenge. However, even the most careful assessment of the CDL should be accompanied by comparison to other sources and at least some level of site-specific accuracy assessment to ensure adequate detection of the signal and minimization of noise.

6. Discussion

6.1. *Impact of recommended practices on observed LULCC*

Different practices for measuring LULCC can often produce substantial differences in resulting estimates of change. To illustrate this impact we consider the results from a recent analysis implementing some of the recommended practices with that of a naïve, bi-temporal snapshot approach which does not. As one example of the former, Lark et al. (2015) measure total land conversion to and from cropland in the conterminous U.S. 2008 through 2012 and utilize a subset of recommendations including class consolidation, integration of multiple datasets, temporal and spatial post-classification processing, and correction for changes in spatial and thematic resolution in the CDL over time.

Using their approach, Lark et al. estimated gross levels of cropland expansion and abandonment from 2008 to 2012 of 7.3 million acres and 4.3 million acres, respectively, for a net increase in cropland area of 3.0 million acres. In contrast, an analogous snapshot approach using the CDL and directly comparing cropland in 2008 to 2012 would suggest 63.6 million acres of expansion and 28.6 million acres of abandonment, for a net gain of 35.0 million acres–nearly twelve times greater net expansion than the example analysis utilizing recommended practices.

Nationally-aggregated and county-level assessment of the example results using recommended practices aligned well with other published estimates of gross and net conversion including those from the USDA Census of Agriculture and the NRCS National Resources Inventory—often considered the “gold standards” for measuring cropland change (Johnson, 2013; Laingen, 2015; Lark et al., 2015). However, while this alignment suggests the possibility of improved change detection, processing decisions can often produce correct results for incorrect reasons, particularly when aggregated. Though not included in the original publication, results of a follow-up site-specific accuracy assessment of the Lark et al., 2015 data showed an overall map accuracy of 97.7% (Wright et al., 2017). Alternatively, the naïve change assessment using the same consolidated CDL classes but no additional recommendations generates an expected 91.78% overall accuracy for the change product. Thus, the subset of additional recommended practices used by Lark et al. resulted in an estimated 72% (3.5x) reduction in overall map error. See Appendix B for details.

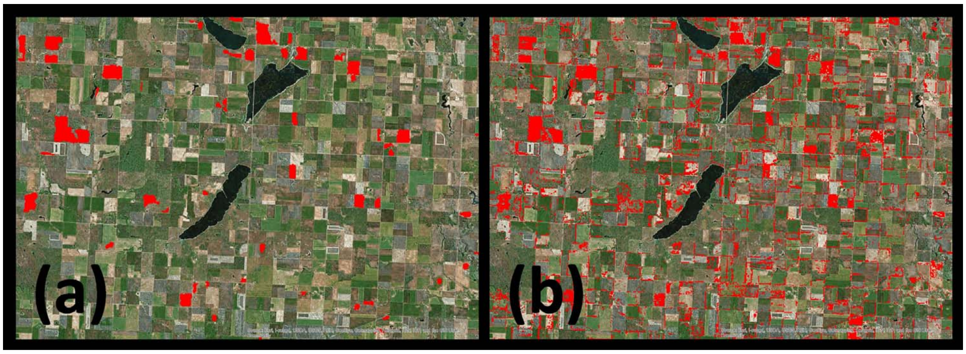

Fig. 3. Landscape-level impacts of recommended practices. Maps show recent LULCC in Potter County, SD, identified using a subset of the recommended practices from Lark et al. (2015) (**a**) versus that identified using a simple snapshot change analysis (**b**). Areas in red are those identified as conversion from noncropland to cropland and are overlaid on basemap imagery from ArcGIS online. Use of the recommended practices can help identify field-level features with greater uniformity and reduces the mapping of artifacts resulting from mixed pixels, misclassifications, and resolution changes in the input data, particularly noticeable along field edges and roads in **3b**. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The effects of using the recommended practices and improvements can be further observed by visually investigating the differences in mapped LULCC at the field level. For example, Fig. 3**a** shows a snapshot of recent cropland expansion identified using the recommended practices from the example above. In contrast, Fig. 3**b** identifies cropland expansion using the naïve change assessment 2008–2012 using the same CDL input but without additional considerations. In general, the LULCC identified using the refined approach more closely matches landscape features (e.g. fields) and reduces the mapping of artifacts that frequently result from mixed pixels, misclassifications, and resolution changes in the input data.

6.2. Additional applications and alternative approaches to measuring change

The guidelines developed here were targeted for analyses of change over time, but may be relevant to many analyses and applications for which the CDL or other land cover maps are an input. For example, those looking to map land availability or model the spatial variation of ecosystem services would benefit from ensuring that their single-year CDL input is free from state-level artifacts, crop area biases, or over-extending the CDL's capability in identifying grassland vegetation type or use. Any efforts to model environmental impacts or outcomes over time using the CDL as input should similarly consider how the cautions described here may influence results, particularly with respect to the change in mapped bias of total cropland area.

Though developed specifically for the USDA CDL, this set of cautions and recommendations might also serve as a guide to improving post-classification land change detection using remote sensing products in general. Other land cover maps to which the practices may be especially applicable include historic instances of the MLRC's National Land Cover Database (NLCD), the USDA Forest Service and Department of Interior's LandFIRE datasets, the USGS GAP analysis products, and other land cover classification maps such as those based on Moderate Resolution Imaging Spectroradiometer (MODIS) data.

Lastly, it should be noted that using a remote sensing product such as the CDL for post-classification measurement of changes to land cover and land use may not be as ideal as detecting changes directly from unclassified satellite imagery over the same time period. However, controlling for the dynamic nature of croplands can often confound other change detection methodologies, and most of these change assessments are unable to achieve the crop-specific detail of the CDL. More importantly, the time and resources required to perform such analyses on state and national scales is often prohibitive. In direct contrast, many environmental and policy-relevant issues frequently demand immediate attention and thus necessitate measuring change using the best available land cover classification product. As it stands, the CDL is the only annual, national-level, and timely-produced dataset that can deliver on these needs, and it does so on a continuously improving basis (Johnson, 2013; Wright and Wimberly, 2013b).

6.3. Summary and conclusions

Use of the CDL for measuring LULCC is on the rise, but there has thus far been limited guidance regarding appropriate methods and best practices. This has led to uncertainty among potential users, dissonance across applications in the literature, and hindrance of successive methods development. To address this knowledge gap, we drew from published analyses, user and producer experiences, and demonstrative examples to produce an initial list of cautions and recommendations, resulting in best practices guidance for future assessments and a collective basis for continued methodological development.

We found substantial opportunities for potential error in analysis when using the CDL, but that optimistically most obstacles can be adequately overcome by using appropriate caution. A prolific and perhaps the most significant source of error in CDL-based LULCC analyses is failure to account for crop area estimation bias and changes to the bias over time. However, even this challenge can be addressed by calibrating or correcting the CDL with ancillary data. When used appropriately and in conjunction with related information, the CDL is a valuable and effective tool for detecting diverse trends in agriculture. Adding knowledge of the common pitfalls and recommended practices presented here can help users create more reliable post-classification measures of LULCC, thus further enabling critical analyses that improve our ability to understand agriculture and successfully navigate rising environmental challenges.

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Appendix A. Consolidated crop and non-crop class membership

Original CDL categories were considered to be cropland or non-cropland according to the distinctions below, from Lark et al. (2015) and based on Johnson (2013). For the calculation of total cropland bias in Section 4.1, fallow/idle (class 61) was withheld from the cropland domain due to the ambiguous cultivated/uncultivated nature of this class in historic CDL years as well as to maintain consistency with other analyses (e.g. Lark et al., 2015, Wright and Wimberly, 2013). Note that in more recent years of the CDL, however, the fallow/idle class has shifted in intent towards capturing only actively cultivated fallow land.

ID	Crop	ID	Crop	ID	Crop	ID	Non-Crop	ID	Replaced or withheld
1	Corn	48	Watermelons	217	Pomegranates	37	Other Hay/Non Alfalfa	61	Fallow/Idle Cropland
2	Cotton	49	Onions	218	Nectarines	62	Pasture/Grass		
3	Rice	50	Cucumbers	219	Greens	63	Forest		
4	Sorghum	51	Chick Peas	220	Plums	64	Shrubland		
5	Soybeans	52	Lentils	221	Strawberries	65	Barren		
6	Sunflower	53	Peas	222	Squash	81	Clouds/No Data		
10	Peanuts	54	Tomatoes	223	Apricots	82	Developed		
11	Tobacco	55	Caneberries	224	Vetch	83	Water		
12	Sweet Corn	56	Hops	225	Dbl Crop WinWht/Corn	87	Wetlands		
13	Pop or Orn Corn	57	Herbs	226	Dbl Crop Oats/Corn	88	Nonag/Undefined		
14	Mint	58	Clover/ Wildflowers	227	Lettuce	92	Aquaculture		
21	Barley	59	Sod/Grass Seed	229	Pumpkins	111	Open Water		
22	Durum Wheat	60	Switchgrass	230	Dbl Crop Lettuce/Durum Wht	112	Perennial Ice/Snow		
23	Spring Wheat	66	Cherries	231	Dbl Crop Lettuce/Cantaloupe	121	Developed/Open Space		
24	Winter Wheat	67	Peaches	232	Dbl Crop Lettuce/Cotton	122	Developed/Low Intensity		
25	Other Small Grains	68	Apples	233	Dbl Crop Lettuce/Barley	123	Developed/Med Intensity		
26	Dbl Crop WinWht/ Soy	69	Grapes	234	Dbl Crop Durum Wht/ Sorghum	124	Developed/High Intensity		
27	Rye	70	Christmas Trees	235	Dbl Crop Barley/Sorghum	131	Barren		
28	Oats	71	Other Tree Crops	236	Dbl Crop WinWht/Sorghum	141	Deciduous Forest		
29	Millet	72	Citrus	237	Dbl Crop Barley/Corn	142	Evergreen Forest		
30	Speltz	74	Pecans	238	Dbl Crop WinWht/Cotton	143	Mixed Forest		
31	Canola	75	Almonds	239	Dbl Crop Soybeans/Cotton	152	Shrubland		
32	Flaxseed	76	Walnuts	240	Dbl Crop Soybeans/Oats	171	Grassland Herbaceous		
33	Safflower	77	Pears	241	Dbl Crop Corn/Soybeans	181	Pasture/Hay		
34	Rape Seed	204	Pistachios	242	Blueberries	176	Grassland/Pasture		
35	Mustard	205	Triticale	243	Cabbage	190	Woody Wetlands		
36	Alfalfa	206	Carrots	244	Cauliflower	195	Herbaceous Wetlands		
38	Camelina	207	Asparagus	245	Celery				
39	Buckwheat	208	Garlic	246	Radishes				
41	Sugarbeets	209	Cantaloupes	247	Turnips				
42	Dry Beans	210	Prunes	248	Eggplants				
43	Potatoes	211	Olives	249	Gourds				
44	Other Crops	212	Oranges	250	Cranberries				
45	Sugarcane	213	Honeydew Melons	254	Dbl Crop Barley/Soybeans				
46	Sweet Potatoes	214	Broccoli						
47	Misc Vegs & Fruits	216	Peppers						

Appendix B. Accuracy of Lark et al. (2015) versus a bi-temporal snapshot of change 2008–2012

A site-specific accuracy assessment of Lark et al. (2015) was recently performed using high-resolution aerial photography from the National Agricultural Imagery Program (Wright et al., 2017). Results showed relatively high and balanced user and producer accuracies for most categories with the exception of cropland abandonment, which had a high producer's accuracy but low user's accuracy. This ratio suggests substantial over-mapping of abandoned cropland area, which was likely a result of some abandoned locations becoming recultivated in subsequent years, as identified by aerial imagery at the time of the accuracy assessment. Overall accuracy for the 2008–2012 change product was estimated at 97.7%.

LULCC Class	Producer's Accuracy	User's Accuracy	Bias
Non-cropland	99.6%	98.0%	2%
Cropland	88.6%	98.0%	−10%

Expansion	72.7%	70.4%	3%
Abandonment	97.5%	43.2%	125%
Overall Accuracy	97.7%		

For comparison, the overall accuracy of a land change map based on two annual land cover maps can be estimated as the overall accuracy of the image from year 1 multiplied by the overall accuracy of the image from year 2 (Congalton and Green, 2008). For a naive bi-temporal snapshot of change between cropland and noncropland using consolidated CDLs that have crop vs non-crop accuracies of 95.7% for 2008 and 95.9% for 2012 (derived from USDA-NASS-RDD Spatial Analysis Research Section, 2016), the product would have an expected 2008–2012 change accuracy of 0.957*0.959 = .918 or 91.8%. This overall error rate (8.2%) is approximately 3.5 times larger than the overall error (2.3%) found for Lark et al. above.

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