Crop Sequence Boundaries (CSB): Delineated Fields Using Remotely Sensed Crop Rotations

Kevin A. Hunt
USDA-NASS, Washington, DC, USA – Kevin.A.Hunt@usda.gov

Jonathon Abernethy
USDA-NASS, Chicago, IL USA – Jake.Abernethy@usda.gov

Peter Beeson
Global Conservation Institute, Santa Fe, NM, USA – PBeeson@global-conservation.org

Maria Bowman
USDA-ERS, Washington, DC, USA – Maria.Bowman@usda.gov

Steven Wallander
USDA-ERS, Washington, DC, USA – Steve.Wallander@usda.gov

Ryan Williams
USDA-ERS, Washington, DC, USA – Ryan.Williams@usda.gov

Abstract

Gridded landcover datasets like the NASS Cropland Data Layer (CDL) provide a useful resource for analyses of cropland management. However, many farm operation decisions are made at the field level, not the pixel level. To capture relationships between land cover and field characteristics – size, contiguity, etc. – some method is needed to aggregate gridded data into crop fields. To provide a uniform and consistent approach for aggregation of gridded data at the field level over a series of years, this research project developed a set of Crop Sequence Boundaries (CSBs), which are polygons that delineate areas of homogeneous cropping sequences. The CSBs are open-sourced algorithm-based, geospatial polygons derived using historic CDLs together with road and rail networks to capture areas with common cropping sequences. Most efforts to delineate fields using algorithm-based polygons built from remote sensing data have focused on limited geographies or individual years. The CSBs were created to provide full coverage for the contiguous US and to be accurate and repeatable across years. Initial assessments of CSB accuracy find overall high accuracy according to corn and soybean acreage. This new expansion of crop field mapping is possible using cloud computing. The CSB approach used geospatial functions in Google Earth Engine (GEE) and in the ArcGIS Pro application. These geospatial functions are run in parallel, in Amazon Web Services (AWS), by sub-dividing the contiguous US into smaller regions based on road and rail boundaries to prevent overlaps or gaps in the data. The regions were merged after processing was complete. As a new set of algorithmically delineated field polygons, the CSBs enhance applications requiring large-scale crop mapping with vector-based data.

Keywords: Statistical analysis; Landcover; Cropland; Geospatial; CDL.

1.0 Introduction

The United States Department of Agriculture (USDA) has two of the thirteen federal principle statistical agencies: the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS). These two agencies continuously collaborate and coordinate on the compilation and analysis of data and the dissemination of information for statistical purposes [1].

One example is the NASS Cropland Data Layer (CDL). The CDL provides operational in-season crop type estimates at 30-meter resolution by utilizing multispectral imagery from Earth observational satellites and a classification algorithm trained on crop acreage reporting data maintained by USDA's Farm Service Agency (FSA). This gridded dataset is produced for the contiguous US and is disseminated annually to the public following the completion of the growing season. The CDL for the contiguous US has been available each year since 2008 [2].

The new, algorithmically delineated field polygons, called Crop Sequence Boundaries (CSBs), presented in this paper were developed in a collaborative effort between ERS and NASS by leveraging a time series of historical CDLs. The CSBs, which are scheduled for release summer 2023, are field-level boundaries for areas with homogenous crop rotation histories. The field boundaries are automatically and algorithmically, rather than manually, delineated. Other field boundary datasets are often manually delineated, represent legal or administrative boundaries, and, most importantly for analysis of gridded datasets, frequently do not necessarily correspond to the idea of a field as an area with a uniform crop rotation because legal land units are often split or combined into effective management areas, i.e., fields.

Geospatial research has been developing automated crop field delineations methodologies for over 30 years. Most studies have been published in the last three to five years, a reflection of recent improvements in data, computing power, and methods. Geographically, most studies focus on relatively small regions to demonstrate and test methodological advances. Within the United States, these studies have focused on multiple states [3], [4], Iowa [5], and Illinois [6]. Only one study to date has developed automatic crop-field delineated polygons for the contiguous US [7]. Among the other studies, the geographic scope have included study areas in China [8], [9], [10]; South America [11], [12]; Europe [13], [14], [15] [16]; Africa [17], [18], [19]; Southeast Asia [20], [21]; Turkey [22]; Saudi Arabia [23]; and Australia [24]. Only one study has implemented an automatic crop-field delineation methodology globally [25].

Two broad approaches are used in the automatic crop field delineations literature: the zone method and the edge intensity method. Most studies primarily rely on only one of these methods, although some studies use a mix of the two. The zone method uses contiguity of similar pixels (single crop or sequence) and can have multiple crops in a field polygon. An approach similar to the zone method was previously proposed for Iowa [5]. The edge intensity method implies one crop type or some physical separating boundary [7].

The objective of this project is to produce CSBs for the contiguous US. The CSB algorithm uses a novel approach to capturing crop fields by employing the zonal method to a stack of historical CDL years. By combining multiple years of historical CDLs, the zonal method can accurately identify homogenously cropped regions while maintaining information on their crop-specific sequences and acreages. To further improve the accuracy of the zonal method, the fields are masked with a spatial data layer of US roads and rails [26]. This maintains edges where homogenously cropped fields border each other with the same crop rotation but physically are separated by a road or rail line. The resulting CSBs were validated by comparing corn and soybean acreages to the NASS estimated total planted acres, for each contiguous state and nationally.

The paper is organized as follows: The study area and data are described in Section 2. The study methodology is introduced in Section 3 followed by results and discussion in Section 4. Finally, the conclusions are presented in Section 5.

2.0 Study Area and Data

2.1 Study Area - Contiguous US

The contiguous US is the study area (Figure 1), which does not include the non-contiguous states of Alaska and Hawaii or US territories. In terms of US agricultural production, corn and soybeans represent the two largest crops planted by acreage for this study area.

Fig. 1. The contiguous US, highlighted in black.

2.2 Cropland Data Layer (CDL)

The CDL is a 30-meter pixel-based gridded dataset that represents all landcover across the contiguous US. Currently, the CDL represents over 200 types of crops or cropping patterns with high levels of accuracy for major commodities, such as corn, soybeans, wheat, rice, and cotton. It has been published with complete contiguous US coverage annually since 2008. The two major commodities, corn and soybeans, have accuracies above ninety percent [2]. The CDL has been a useful dataset for agricultural analysis and statistics.

2.3 Cropland Sequence Boundaries (CSB)

Currently, each of the CSBs are comprised of 8 consecutive years of stacked CDLs. The sequence time frame indicates the range of years included in the dataset. For example, the 2015-2022 CSBs include the CDL years 2015, 2016, 2017, 2018, 2019, 2020, 2021, and 2022. The coverage of the CSBs consist of the contiguous US. The complete set of eight CBS, consisting of 2008-2015 CSBs to 2015-2022 CSBs, have been completed 2008 to 2022 and are assessed in this paper.

2.4 NASS Quick Stats Corn and Soybean Agricultural Estimate Data

NASS produces planted acreage estimates for corn and soybeans for most US states; these are considered the ground truth for total planted acres of corn and soybeans at the state and national levels. The planted acreage estimates are available at the end of the season on Quick Stats [26] and are used for validation purposes.

3.0 Methodology

The approach closely followed the steps described in Beeson et al. 2020, where the first generation of the CSBs (referred to as Crop Management Units) were developed.

By design, the CSB polygons are developed from only publicly available datasets: the NASS CDL [2] and the US Census TIGER line data [27]. The algorithms are an automated arcpy script utilizing typical GIS tools requiring no manual drawing of field boundaries. As fields may divide or combine over years, multiple CSB windows were examined. An eight-year window was used for the first release of the CSBs, but any duration can be used. The initial steps are to filter and simplify CDL classes on each historic CDL year to reduce noise and re-impose road and rail network line data lost when filtered. These steps are completed in Google Earth Engine (GEE). The resulting rasters are then brought into ArcGIS to be stacked and converted into polygons on a sub-region basis. Small polygons, under 10,000m^2, are eliminated into the next largest polygon to remove islands within fields and clean field edges using ArcGIS geospatial tools. Multiple processor environments allow for faster completion of this step as sub-region pools can be spawned to a core when available. Here, the AWS environment available to the USDA has 96 cores. The resulting CSBs represent areas of similar cropping sequences for the designated years. These steps can be repeated for the 8-year moving window to produce the contiguous US resulting in at least eight unique layers of CSB history for all lower 48 states (2008-2015, 2009-2016, 2010-2017, 2011-2018, 2012-2019, 2013-2020, 2014-2021, and 2015-2022).

3.1 CDL Pre-Processing

The primary data input to the CSBs is the NASS CDL [2], which is also the input for numerous other field delineation algorithms [3], [4], [5], [6], and [7]. In each of these, the CDL undergoes some degree of pre-processing two major reasons. First, noise reduction in the CDL is needed. The noise in the CDL is well documented [28] but has been less in the most recent years [29], making noise reduction less important but still useful in earlier years. Second, even in areas with limited noise, simplification is needed given the focus on cropland and the desire to limit the number of unique sequences with stacking multiple years.

Setting aside some of the important computing steps, four structural changes to the data are made during pre-processing: resampling, reclassifying, filtering, and masking known edge features (roads and railroads).

Resampling: The first change to the raw CDLs is a resampling from 30-meter resolution to 10-meter resolution. The purpose of this step is to improve the masking (reimplementation) of road and rail networks. Because many rural roads and rail routes are less than 30 meters in width, imposing them on a 30-meter gridded dataset introduces errors in field edges, particularly where the transportation features run diagonally across the gridded data. The edge noise, without resampling, leads to a downward bias in field areas by assigning too many pixels to roads and rail lines.

Reclassifying: The original CDLs have over 200 different classifications for land covers, so stacking multiple years of CDLs can lead to hundreds of thousands of different unique sequences. The reclassification step aggregates the land cover types into a smaller set of classes.

Filtering. A number of other projects have developed alternative methods for filtering and smoothing the CDL [30]. For the CSBs, the filtering process iterates though multiple steps. First the CDL is filtered using a focal mode based on patch sizes greater than 40 pixels with a radius of four pixels and run with eight iterations. Then the CDL is filtered again (without patch size limits) to eliminate speckled CDLs and exaggerate field boundaries.

Reimposing transportation features: To correct for any misclassification of roads and rails that may have been introduced by the filtering process, or that might have been misclassified in the original CDL, the CSB process uses publicly available transportation feature classes to impose road and rail networks, which are imported from Census Tiger files. The roads are available on GEE, but the rail network has to be uploaded as a local asset.

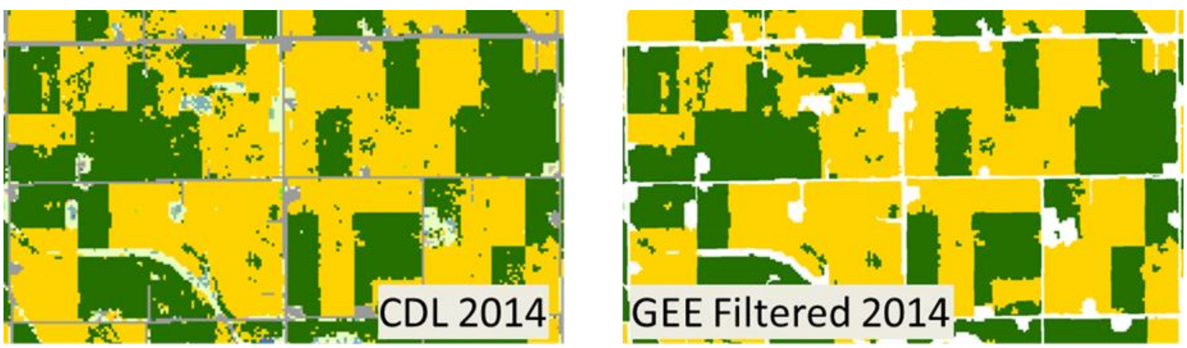

Figure 2. Comparison of 2014 CDL before and after filtering.

3.2 Zonal Identification

Using the modified CDLs for each crop year, the CSBs are developed through six steps: subregion definition, stacking, masking, polygon conversion, refinement, and crop code repopulation.

Subregion definition: Given the large processing requirements for the following steps, each processed CDL is split into subregions. These subregions are defined using the transportation network features. This avoids the problem of splitting fields along administrative boundaries (e.g., states and/or counties lines) or biophysical boundaries (e.g., watersheds). The size of the subregion and the number of subregions allows for efficient multi-core processing.

Stacking: The current CSBs are developed using a stack of 8 CDL years, but any duration could be used. A shorter window, using fewer years, will result in larger polygons that may not divide fields as much. A longer window, using more years, will result in smaller polygons that possibly divide the fields more than expected. If a project spans a 10 year period, it would be appropriate to use the same 10-year window CSB to match. If a project studies rotations on a 3-year basis, then a CSB window in multiples of three would be appropriate (e.g., 3, 6 or 9 years). The 8-year window was chosen as a good compromise for not over or under dividing fields.

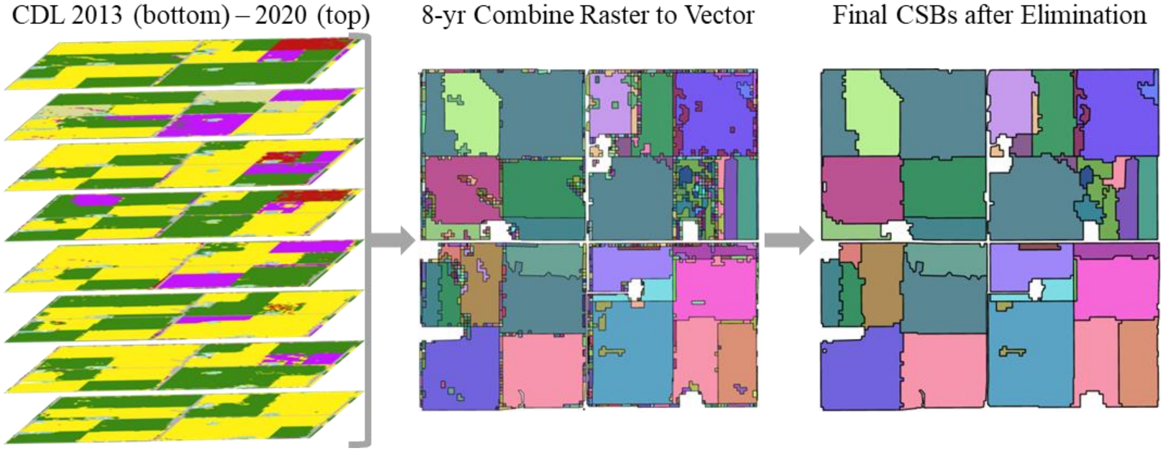

Figure 3. Creation of sequence zones by stacking eight filtered CDLs and using combine raster function, then edge artifact cleaning to final CSBs

Masking: All sequences that do not involve any crop classes or only one year of cropping are removed.

Polygon Conversion: Each zone of adjacent pixels with the same sequences are converted into polygons. In addition to aggregating (joining) similar pixels, the conversion step simplifies the polygons to reduce the number of extra vertices. The polygons are projected to Albers Conical to prevent adding artifacts that look like steps in otherwise straight lines while in raster format.

Refinement: The eliminate function is used to avoid downward bias in area, thus preserving the aggregate total area as much as possible, resulting in a continuous border between CSB polygons. The model runs elimination four times. The first time the selected polygons are less than $100m^2$; in the second they were less than $1{,}000m^2$; and for the last two, the polygons are less than $10{,}000m^2$.

Repopulating: Repopulating the attribute table uses zonal majority of CDL classes as well as county and state locations. A unique ID is added after all sub-regions were joined.

3.3 CSB Acreage Validation

One way of validating the accuracy of the CSBs is to compare the CSB derived acreage to the available ground truth planted acreage. Ground truth data are available for a wide range of crops on the USDA NASS Quick Stats website. Planted acreages on Quick Stats are available at the county, state, and national levels.

To calculate the CSB-based acreage, a crop type is assigned to each CSB based on the majority class of CDL pixels within each polygon. For a given county and crop, the CSB-derived, county-level planted acreage is the sum of the areas of each CSB within the county containing the crop of interest (1)

$$A_{crop} = \sum_{csb \in county} A_{csb}\, I_{csb}(crop) \qquad (1)$$

where,

A_{crop} = the area of the crop in the county, the sum is over CSBs contained in the county, A_{csb} is the area of the CSB, and $I_{csb}(crop)$ is equal to one if the CSB has the crop and zero otherwise. The same procedure can be conducted by state and for the contiguous US.

Once the county, state and national estimates are obtained from the CSBs, the error can be calculated using the percent error:

$$PE_{crop} = \frac{A_{crop} - T_{crop}}{A_{crop}}$$

where PE is the percent error and T_{crop} is the ground-truth planted acreage of the crop derived from Quick Stats. Since the CSBs represent a sequence of years, each CSB can be summarized by a sequence of percent errors, one for each year and crop type.

4.0 Results and Discussion

Initial 8-year CSB creation for the contiguous US took about five days using a 96-core AWS workstation. The process is fully automated, but the sizes of the 86 subregions are not balanced. Some sub-processing regions are completed in a couple hours while a few take five days. This could be improved to reduce the time to two days. A majority of the processing time was spent on the elimination step, which incrementally reduces the number of total polygons. This step is run four times by dissolving the selected polygons into the neighbor that shared the longest border. The first elimination process started at nearly 500 million polygons and dissolved about 100,000 that were less than 100 m^2. The second pass eliminated 250 million polygons that were less than 1,000m^2. The third pass eliminated another 100 million polygons that were less than one hectare. The last pass started with over 50 million polygons and reduced the remaining by 50 percent. After the elimination step, only polygons greater than one hectare were kept as final CSBs which reduced the resulting 25 million polygons to fewer than 20 million. Without incrementally increasing the elimination size, the tool often fails or takes days.

The area totals for each crop follow the accuracy of the initial CDL input. In general, compared to the Quick Stats national acreage, values produced by the CSB are higher (table 1). This is due to the elimination step forcing the polygons to match their neighbors' edges by expanding into non-cropland or edge noise.

	Corn			Soybean		
Year	Quick Stats (ac)	CSB (ac)	Error	Quick Stats (ac)	CSB (ac)	Error
2015	88,019,000	89,888,422	2.1%	82,660,000	87,120,721	5.4%
2016	94,004,000	96,665,222	2.8%	83,453,000	87,644,495	5.0%
2017	90,167,000	93,440,276	3.6%	90,162,000	96,119,359	6.6%
2018	88,871,000	92,904,634	4.5%	89,167,000	95,515,323	7.1%

2019	89,745,000	93,459,732	4.1%	76,100,000	80,548,849	5.8%
2020	90,652,000	95,060,605	4.9%	83,354,000	88,401,544	6.1%
2021	93,252,000	97,139,581	4.2%	87,195,000	93,138,351	6.8%
2022	88,579,000	93,071,290	5.1%	87,450,000	94,088,968	7.6%

Table 1. Percent error for CSB's compared to Quick Stats national planted acreage for corn and soybean.

When CSB acreage for corn at the state level is compared to Quick Stats reported planted corn acres, the results are generally the same nationally (figure 5). The CSB acreage is higher with a slope value above 1.0 with few outliers at the lower values. However, the earliest year, 2015, had a lower slope value at 0.888. The largest outlier is Nevada and has under reported values in 2015 and 2018.

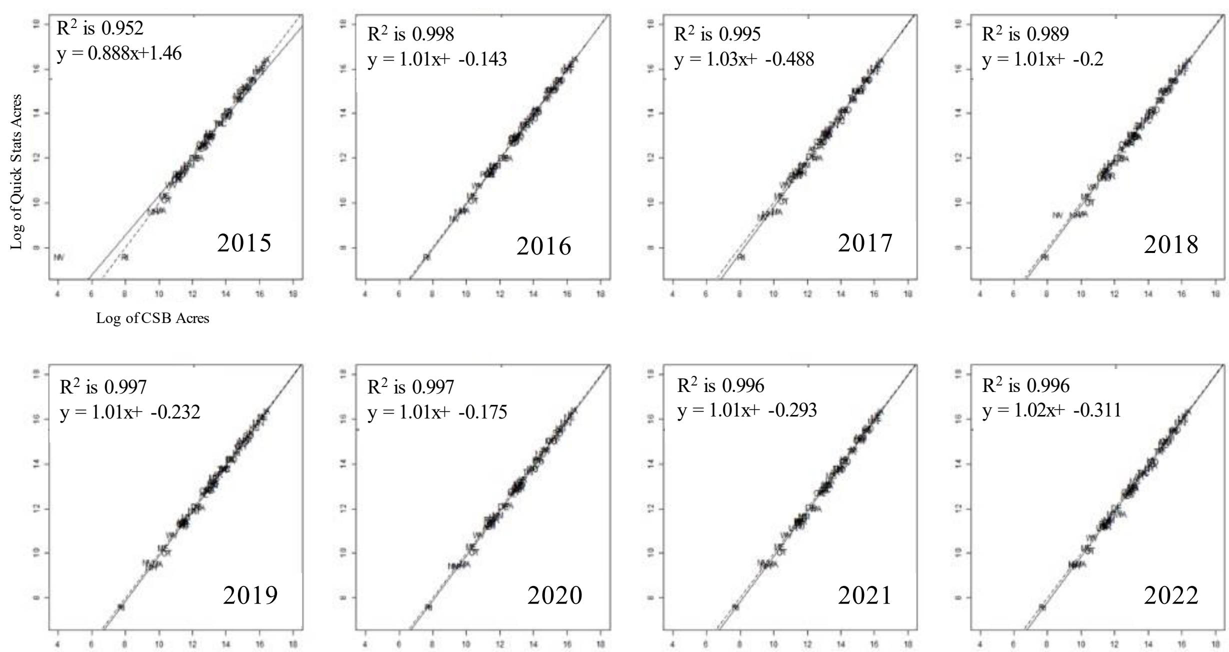

Figure 5. CSB corn planted acreage compared to Quick Stats by state (fit line is dashed and the one-to-one line is solid).

For soybean CSB acreage at the state level, the slope value has trended above 1.0 in the last several years (figure 6). Generally, soybeans have greater outliers in both higher and lower acreage than Quick Stats. Some of the outlier states with lower CSB areas are Texas, Oklahoma, and Florida. New Jersey and Delaware are outliers in the positive direction. Soybeans tend to have a wider range of results, and the r^2 value is slightly lower than that for corn.

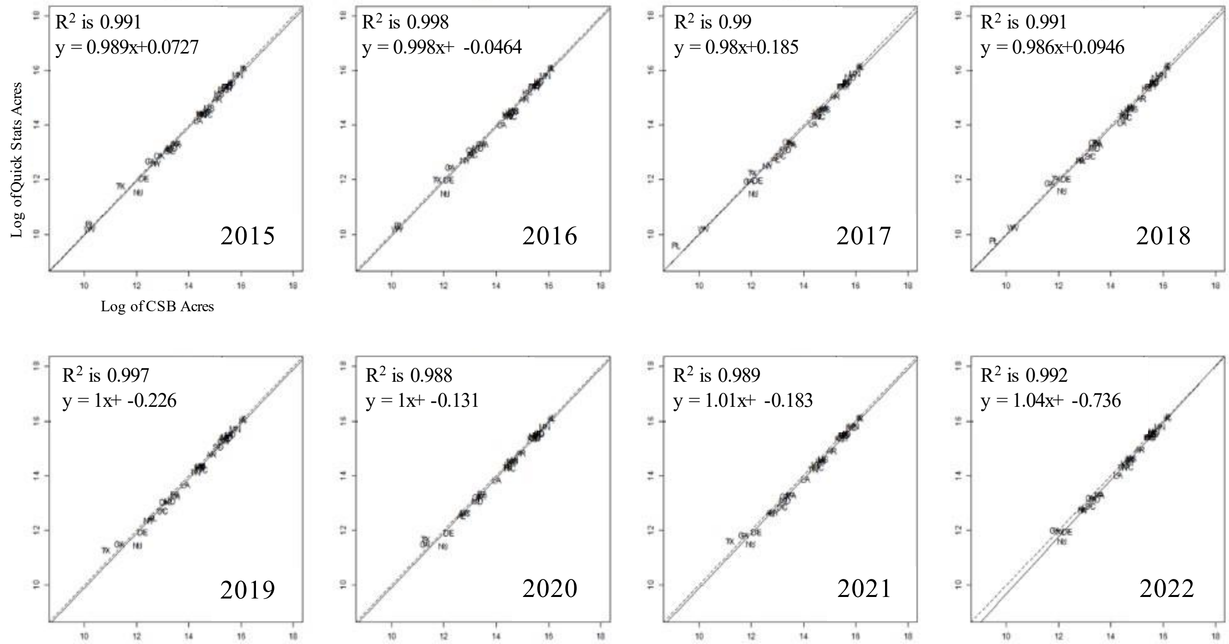

Figure 6. CSB soybean acreage compared to Quick Stats by state (fit line is dashed and the one-to-one line is solid).

5.0 Conclusions

Creation of the CSBs is a repeatable automated process for building crop field polygons with accurate representation of crop areas. Geospatial research into automatic crop-field delineation has been studied for many years; however, with advancements in accessibility to cloud computing and a growing historical CDL archive, it is now possible to produce the contiguous US products demonstrated in this paper using this method.

The CSBs may benefit from future refinement. The current version represents an early iteration, prioritizing a uniform spatial and temporal methodology. This produces a streamlined product but likely at the cost of accuracy for some geographical areas due to unique factors that vary across physical landscapes. Future CSB versions may need to incorporate new considerations and advancements that account for local variability.

This novel approach can provide a solid methodology for advancing automatic crop field delineation in the US and around the world. The CSBs have been extremely useful including predicting preseason planted acreage for corn and soybean [30], and georeferencing farms [31] and have fully utilized high performance computing cloud resources, including Google Earth Engine (GEE) and Amazon Web Services (AWS) in their creation [32].

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