A New Automatic Stratification Method for U.S. Agricultural Area Sampling Frame Construction Based on the Cropland Data Layer

Claire G. Boryan, Zhengwei Yang, *Member, IEEE,* Liping Di, *Senior Member, IEEE,* and Kevin Hunt

***Abstract*—This paper, for the first time, proposes to apply USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) geospatial data for stratifying U.S. agricultural land. A new automated method is proposed to stratify the NASS state level area sampling frames (ASFs) by automatically calculating percent cultivation at the primary sampling unit (PSU) level based on the CDL data. The NASS CDLs are 30–56.0 m raster-formatted, georeferenced, cropland cover classifications derived from satellite data. The CDL stratification experiment was successfully conducted for Oklahoma, Ohio, Virginia, Georgia, and Arizona. The stratification accuracies of the traditional (visual interpretation) and new automated CDL stratification methods were compared based on 2010 June Area Survey data. Experimental results indicated that the CDL stratification method achieved higher accuracies in the intensively cropped areas, while the traditional method achieved higher accuracies in low or nonagricultural areas. The differences in the accuracies were statistically significant at a 95% confidence level. It was found that using multiyear composite, CDL-based cultivated layers did not improve stratification accuracies as compared to the results of single-year CDL data. Two applications of the CDL-automated stratification method in official USDA NASS operations are described. The novelty of the proposed method was using geospatial CDL data to objectively and automatically compute percent cultivation of the ASF PSUs as compared to the traditional method that subjectively determines percent cultivation using visual interpretation of satellite data. This proposed new CDL-based process improved efficiency, objectivity, and accuracy as compared to the traditional stratification method.**

***Index Terms*—Area sampling frame (ASF), automated stratification, cropland data layer (CDL), cultivated data layer, land cover-based stratification.**

I. Introduction

AREA sampling frames (ASFs) are the foundation of the agricultural statistics program of the National Agricultural Statistics Service (NASS) and many other statistical survey programs. Since 1954, ASFs have been used as a primary tool for conducting surveys to gather information on crop acreage and other agricultural information. They are considered "the backbone to the agricultural statistics program of the National Agricultural Statistics Service (NASS)" [1]. NASS' primary area frame-based survey is the June Area Survey (JAS) in which approximately 11 000, 1 sq mi sample segments are visited by enumerators each year at the beginning of the growing season to collect crop type and acreage information. Estimates of crop acreage and livestock inventories are based on the data collected during the JAS. The NASS ASFs are based on U.S. land cover stratification, which classifies land cover into agricultural intensity groups or strata based on percent cultivation. This traditional stratification of land cover has been conducted using visual interpretation of aerial or satellite data or topographic maps since the 1950 s. This popular method requires a manual, subjective, and labor-intensive process. It does not utilize existing land cover data such as the cropland data layer (CDL) in an automated, objective, and efficient manner to stratify area frames. The accuracy of NASS' survey statistics depends on the quality of the ASF and subsequently the techniques used in its construction.

The USDA NASS' traditional state area frame stratification method has been widely used around the world [1]–[4]. There are different varieties of the area frame stratification method and its applications. The European Union's (EU's) Monitoring of Agriculture with Remote Sensing (MARS) project, in 1988, used the NASS traditional ASF construction method to conduct the Land Use and Cover Area Frame Statistical Survey (LUCAS) and proposed using a regular grid of square segments instead of natural boundaries for segment delineation to reduce cost [5]. The European CORINE Land Cover (CLC) 2000 map was tested for use in stratification in Spain, but difficulties were encountered when multiple CLC polygons crossed individual segment boundaries causing designation of segments to multiple strata. The CLC was evaluated as a covariable to define strata based on an agricultural intensity index [6]. Pradhan stratified $1\ \mathrm{km}^2$ segments based on agricultural intensity, using visual interpretation of SPOT-XS images and a land cover map to identify different types of agriculture for the Hamada province of the Islamic republic of Iran [7]. He encountered the same difficulties faced by Gallego *et al.* (segments assigned to multiple strata), but resolved the issue by assigning segments that crossed multiple strata on the land cover map to the stratum with which the segments most overlapped. This method obviously increased stratification errors. Hansen and Wendt tested using USGS National Gap Analysis Program (GAP) classifications for the stratification of USDA Forest Service's Forest Inventory Analysis (FIA) plots in Indiana and Illinois [8]. They noticed the increased precision of forest inventory estimates. McRoberts *et al.*

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C. G. Boryan, Z. Yang, and K. Hunt are with the Research and Development Division, USDA National Agricultural Statistics Service, Fairfax, VA 22030 USA (e-mail: claire.boryan@nass.usda.gov; zhengwei.yang@nass.usda.gov).

L. Di is with the Center for Spatial Information Science and Systems, George Mason University, VA 22030 USA.

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conducted postsampling stratification for the states of Indiana, Iowa, Minnesota, and Missouri forest area estimation based on the 1992 National Land Cover Dataset (NLCD 1992) [9] classes and observation of forest inventory plots. They concluded that the NLCD 1992 provided an effective means of postsampling stratification, which resulted in reduced variances for estimates of forest land area over postsampling stratification based on visual interpretation [10], [11]. Dunham *et al.* further evaluated stratifications using the NLCD 1992 and visual interpretation of photo imagery in western Oregon and concluded that forest inventory estimate accuracies were similar but cost was reduced using the automated land cover-based approach [12]. Liknes *et al.* used land cover classification results from MODIS for FIA stratification and found that the results were inferior to those based on NLCD data due to lower spatial resolution [13]. Liknes *et al.* further evaluated the use of USDA NASS 2005 Wisconsin CDL and the NLCD 1992 data for postsampling stratification of FIA plots. The results indicated that the 2005 CDL outperformed the NLCD 1992 for postsampling stratification [14]. These studies indicate that utilizing geospatial land cover classification data for area frame stratification could result in improved estimates and significantly reduce stratification cost.

To improve the efficiency, reduce the cost, and improve the precision of the estimates generated from the JAS, this paper proposed for the first time to modernize the NASS traditional ASF stratification process using CDL geospatial data. In this paper, a new automated method has been developed to objectively, consistently, and rapidly stratify U.S. land cover, based on percent cultivation, of the ASF primary sampling units (PSUs) using the 2010 CDL products. A performance comparison between the NASS traditional method and the new automated CDL stratification method was made. The effectiveness of the traditional and CDL-based methods in determining percent cultivation, at the Area Frame PSU level, was assessed using in situ validation data collected at the segment level as part of the 2010 JAS. Five states including Arizona, Georgia, Ohio, Oklahoma, and Virginia were selected because these states serve as a good reflection of the range (variety and quantity) of agricultural commodities grown in the United States. The goal of this investigation was to determine the utility of the automated CDL-based method for use in the stratification of U.S. land cover and potentially in ASF construction. This new method was designed to stratify the NASS area frames for all states. The experiment was conducted in the five selected states. The results indicated that this proposed new CDL-based method improved efficiency, objectivity, and accuracy as compared to the traditional stratification method. Consequently, the method is being implemented into the NASS operations for the entire U.S.

II. Background

A. NASS Area Sampling Frames

The NASS ASFs are based on a stratification of land cover in the U.S. by percent cultivated cropland and are the statistical foundations for providing estimates with complete coverage of U.S. agriculture. The area frame program is conducted in 49 states using approximately 11 000, 1 sq mi segments made up of approximately 41 000 individual farms. Selected farms are visited each year by enumerators, as part of the JAS, to identify the planting intentions for all agricultural land within the segments, including planted acreage and acreage intended for harvest. Acreage estimates for major commodities such as corn, soybeans, winter wheat, spring wheat, durum wheat, and cotton are generated from the JAS at state and national levels.

TABLE I
State Area Frame Implementation Year

State	Year	State	Year	State	Year
Alabama	1991	Maine	1989	Ohio	1996
Arizona	1984	Maryland	1997	Oklahoma	2010
Arkansas	1992	Massachusetts	1989	Oregon	2005
California	2011	Michigan	1990	Pennsylvania	2000
Colorado	1984	Minnesota	2009	Rhode Island	1989
Connecticut	1989	Mississippi	2005	South Carolina	1995
Delaware	1997	Missouri	2004	South Dakota	2009
Florida	2010	Montana	1986	Tennessee	2001
Georgia	1991	Nebraska	1983	Texas	1998
Idaho	1982	Nevada	1987	Utah	1988
Illinois	2006	New Hampshire	1989	Vermont	1989
Indiana	2005	New Jersey	1997	Virginia	2005
Iowa	1989	New Mexico	1985	Washington	2009
Kansas	1996	New York	1995	West Virginia	1989
Kentucky	2004	North Carolina	2000	Wisconsin	2001
Louisiana	2010	North Dakota	2011	Wyoming	1985

The primary use of the ASF within NASS is as the foundation of the JAS. The ASF is also used to measure the incompleteness of NASS list frame and for additional surveys such as NASS' objective yield survey and the Agricultural Coverage Evaluation Survey.

Within NASS, area frame construction is a lengthy process conducted one state at a time. Land in a state is divided into PSUs, which are defined by strata. This stratification process is conducted using ArcGIS software, aerial photography, satellite imagery, and ancillary agricultural information. PSUs are delineated by permanent boundaries such as roads, railroads, and streams and are approximately 3–4 sq mi for new frames. PSUs are randomly selected by strata and only selected PSUs are broken down using the previously described permanent boundaries into sampling units or segments. One sampling unit or segment from each randomly selected PSU is selected for the survey.

Frames are generally put in use for approximately 15–20 years with some in operation for as long as 30 or more years. Originally, when ASFs were created on paper, only two frames were built each year. In recent years, three to four frames were built each year due to technological improvements including the use of ESRI's ArcGIS software, aerial photography, satellite imagery, and ancillary agricultural information. Table I illustrates the implementation years for the NASS area frames. On average, five full-time employees working for a period of 4 months per state are required for new frame construction using NASS' traditional method [1]. Beginning in 2012, improved efficiencies were achieved by updating frames rather than building area frames from scratch, which reduced the time and cost of frame construction.

ASFs have been used in a variety of applications, such as evaluating the prevalence of brown stem rot in the north central

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TABLE II
TYPICAL LAND-USE STRATIFICATION CODES AND DEFINITIONS REPRESENTED IN THE NASS ASFs

Land -use strata codes	Codes strata definitions
11	General cropland, greater than 75% cultivated
12	General cropland, 51%–75% cultivated.
13	General cropland, greater than 50% cultivated
20	General cropland, 15%–50% cultivated
31	Ag-Urban, residential mixed with agriculture, more than 100 dwellings per square mile.
32	Residential/commercial, more than 100 dwellings per square mile, no cultivation
40	Less than 15% cultivated (e.g., rangeland/forest)
50	Non-agricultural (e.g., military bases, airports, national and state parks)
62	Water

United States [15], improving agricultural ground survey estimates as part of the MARS [16], and comparing the utility of frequently used estimators [17].

B. NASS ASF: Land Use Stratification

NASS' traditional land use stratification divides land area using permanent boundaries on the ground into broad land use categories and is known to improve efficiency for statistical sampling and estimation. In the construction of a NASS ASF, general cropland (based on percentage cultivation), agriculture/urban, residential/commercial, and nonagriculture are the commonly identified land covers. The agricultural stratum definitions vary between states depending on the type and intensity of agricultural production. Table II illustrates typical land-use stratification codes and definitions used in NASS. It should be noted that the states with strata 11 and 12 do not have a stratum 13. They are mutually exclusive. All strata are nonoverlapping. Once stratum definitions are assigned, all land is subdivided into PSUs. PSUs are designed to reduce labor cost in random sampling. Selected PSUs are further subdivided into segments or sample units, and a segment is randomly selected from each allocated PSU for enumeration [1]. A consequence of using PSUs is that all segments in the same PSU belong to the same stratum. Therefore, stratum homogeneity is critical for the performance of the NASS ASFs.

For the past 58 years, aerial photography and/or satellite imagery have been used to conduct land use stratification. Most recently, the Landsat Thematic Mapper (TM) satellite data were used to visually identify cultivated cropland and, when necessary, identify specific crop types. The National Agricultural Imagery Program (NAIP) data, which are 1 m, orthorectified, aerial photos acquired during the growing season are utilized as the base for digitizing PSU boundaries.

C. NASS Cropland Data Layer

The NASS CDLs are annually updated 30- to 56.0-m raster-formatted, georeferenced cropland classifications as shown in Fig. 1. Rulequest Research's See5 decision tree software is used to perform supervised classifications of all 48 conterminous states. Current CDL classification inputs include: Landsat 8 and Disaster Monitoring Constellation (DMC) satellite imagery;

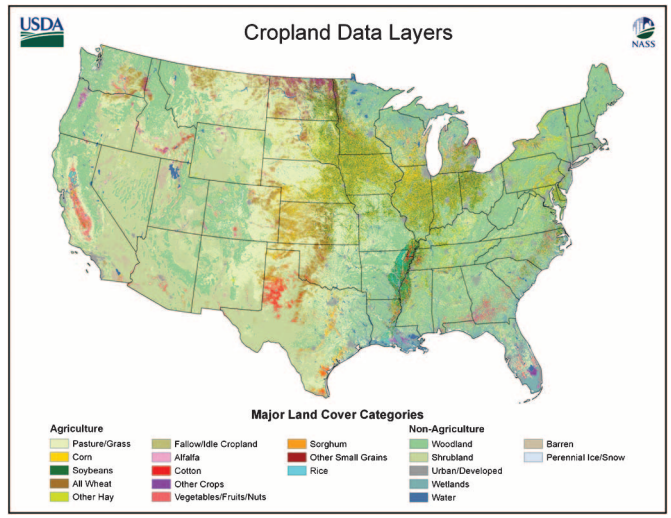

Fig. 1. NASS Cropland Data Layer products.

USGS digital elevation, percent canopy, and percent impervious raster datasets; and Farm Service Agency (FSA), Common Land Unit (CLU), and NLCD 2006, of which the last two datasets are used to select ground truth sample points [18].

Total crop-mapping accuracies for historic CDLs ranged from 85% to 95% for major crops [18]. These accuracy numbers are considered high for stratification purposes as errors between crop categories can be canceled when the categories are combined into cultivated and noncultivated for stratification. The 1997–2013 archive of CDL data is publically available on NASS' online geospatial application—CropScape [19].

The primary purpose of the CDLs at NASS is to provide independent acreage estimates to the NASS Agricultural Statistics Board and field offices. NASS' Remote Sensing Acreage Estimation Program, which began in 1997 with one state, has expanded to include all 48 U.S. conterminous states for 2008–2013. NASS does not use pixel counting for acreage estimation as pixel counting estimates often underestimate acreage as compared to NASS official estimates [20]. Consequently, NASS utilizes a linear model (1), which regresses the CDL pixel data to segment summary data collected from the NASS JAS as follows:

$$Y = a + bX \tag{1}$$

where dependent variable Y represents the estimated acres and independent variable X represents CDL-classified acres. The model coefficients a and b are estimated from JAS-reported acres and CDL-classified acres using a least square estimation procedure [18], [20].

Pixel counting of the CDL underestimates acreage for several reasons. First, roads tend to be over identified due to the CDL 30 m spatial resolution. Mixed (road/crop) pixels, the boundaries between the fields and roads on the ground, tend to be classified into roads because field edge pixels are excluded from the FSA CLU training data. The FSA CLU ground truth data for training and validation are buffered one pixel inward during preprocessing so that the mixed pixels at field edges are excluded from the sampled training points and from the independent validation dataset. The error caused by both training and validation ground

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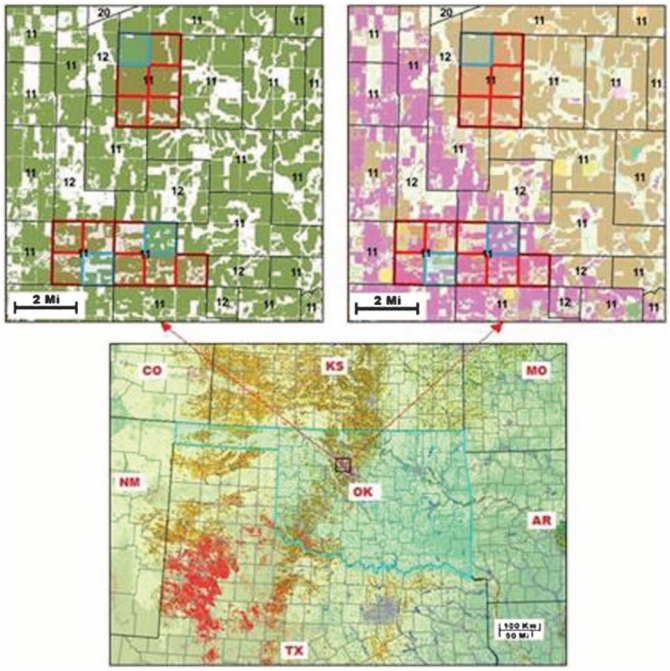

Fig. 2. (Top left) Zoom of the 2010 Oklahoma ASF with selected PSUs (red) and the selected segments (blue) overlaying a CDL-cultivated layer (green—cultivated, white—noncultivated); (top right): the same ASF overlaying a 2010 CDL image product (purple—rye, brown—winter wheat, green—soybeans, yellow—corn, pink—alfalfa). Bottom figure identifies the figure's location.

truth buffering is not accounted for in the CDL omission errors. A second source of crop acreage underestimation is from the misclassification of the CDL pixels inside crop fields because crop signatures are not always consistent across the entire field. This type of error is accounted for in the CDL omission error.

III. Methodology

A. Data and Preprocessing

The data files required for this investigation included: a state level ASF with stratum specific PSUs, a 2010 state level NASS CDL, and a 2010 JAS segment file with segment level percent cultivation calculated. The NASS traditional state level area frames were created using visual interpretation and used operationally to select the 2010 JAS sample. Although the NASS traditional area frames were built prior to 2010 as shown in Table I, they were all used operationally in 2010 and depended upon to accurately reflect land cover conditions based on percent cultivation. The 2010 CDLs included as many as 50 categories and a wide variety of crops. For the purpose of stratification, a cultivated dataset or "layer" was first generated by recoding CDL pixels of crop categories into "cultivated" and noncrop pixels into "noncultivated" [21]. To build the 2010 CDL-cultivated layers, crop and noncrop categories were recoded to "1" and "0," respectively. A typical cultivated layer is illustrated in Fig. 2 (top left) with green and white colors representing the cultivated and noncultivated areas, respectively. The cultivated layer is overlaid with an ASF with PSU boundaries. The exact crop types in each PSU are illustrated in Fig. 2 (top right) by overlaying the ASF over the CDL. The numbers on both graphs represent the PSU stratum definitions.

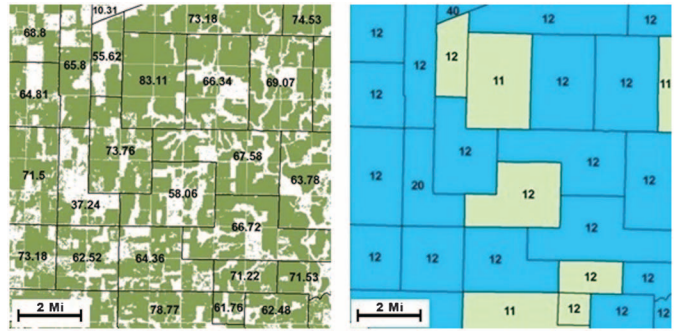

Fig. 3. (a) CDL-cultivated layer-based PSU percent cultivation. (b) The same ASF with CDL-derived strata definitions. PSUs that changed stratum definition using the automated method are highlighted in blue. The PSUs that did not change stratum definitions are highlighted in light green.

B. Stratification Method

NASS' traditional area frame stratification process involves visual interpretation of satellite imagery or aerial photography to subjectively determine PSU stratum definitions based on percent cultivated land in a PSU boundary. The automated stratification process replaces this traditional approach of visual interpretation with a procedure that automatically and objectively determines ASF PSU stratum definitions based on percent cultivated land within a PSU boundary using available geospatial land cover information. The detailed steps are given as follows:

1) Derive a state level cultivated layer from a current CDL by grouping all crop categories into one cultivated (crop) category and assigning the corresponding pixels with a value of "1," while grouping the remaining categories into one noncrop category and assigning the corresponding pixels with a value of "0."
2) Load an individual ASF PSU boundary.
3) Load a CDL-cultivated layer.
4) Overlay an ASF PSU boundary on the CDL-cultivated layer.
5) Compute percent cultivation of each ASF PSU by counting the total number of pixels with value "1" (cultivated) and the total number of all pixels within the PSU boundary. The percent cultivated is given by the number of "1" pixels divided by total number of pixels.
6) Determine the PSU stratum by checking the stratum definition look-up table to map the computed percent cultivation to a defined stratum, and label the PSU with a corresponding stratum number as a PSU boundary attribute.
7) Determine stratum definitions for all ASF PSUs in the state by repeating Steps 2) to 6) for every PSU.

Fig. 3 (left) illustrates PSU percent cultivation calculated from the CDL-based cultivated layer. With the calculated percent cultivation, each PSU could be labeled into a stratum category as shown in Fig. 3 (right) based on the state-specific stratum definitions as given by Table II. Fig. 3 (right) shows the resulting CDL-based stratification for the same frame. As a comparison, PSUs that changed stratum definitions when compared with the results from traditional method are colored in blue. PSUs that did not change stratum definition are in light green. This example indicates that the new method could yield

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TABLE III
FIVE STATE 2010 ASF ANALYSES: TRADITIONAL VERSUS CDL STRATIFICATION METHOD

2010 ASF Stratification method comparison								
		Traditional Stratification			CDL Stratification			*p* value
Stratum	% Cultivated	Segments	Correct	Accuracy (p_1)	Segments	Correct	Accuracy (p_2)	Ha: $p_1 \neq p_2$
Oklahoma 2010 ASF Analysis								
11	>75%	140	47	33.57%	43	27	62.79%	***0.001***
12	51%–75%	48	9	18.75%	77	30	38.96%	***0.024***
20	15%–50%	74	26	35.14%	98	42	42.86%	0.305
40	<15%	61	61	100.00%	105	96	91.43%	***0.027***
Total		323			323			
Ohio 2010 ASF Analysis								
11	>75%	110	84	76.36%	85	76	89.41%	***0.019***
12	51%–75%	35	15	42.86%	42	23	54.76%	0.055
20	15%–50%	42	28	66.67%	48	37	77.08%	0.271
40	<15%	53	47	88.68%	65	57	87.69%	0.869
Total		240			240			
Georgia 2010 ASF Analysis								
13	>50%	91	38	41.76%	28	22	78.57%	***0.001***
20	15%–50%	132	65	49.24%	165	100	60.61%	0.050
40	<15%	90	85	94.44%	120	106	88.33%	0.150
Total		313			313			
Virginia 2010 ASF Analysis								
13	>50%	15	8	53.33%	4	2	50.00%	1.000
20	15%–50%	100	50	50.00%	61	31	50.82%	0.920
40	<15%	64	60	93.75%	114	87	76.32%	0.003
Total		179			179			
Arizona 2010 ASF Analysis								
13	>50%	65	44	67.69%	59	45	76.27%	0.289
20	15%–50%	23	8	34.78%	15	9	60.00%	0.127
40	<15%	54	52	96.30%	68	61	89.71%	0.296
Total		142			142			
Five state 2010 Strata summary								
11	>75%	250	131	52.40%	128	103	80.47%	***0.000***
12	51%–75%	83	24	28.92%	119	53	44.54%	***0.025***
13	>50%	171	90	52.63%	91	69	75.82%	***0.000***
20	15%–50%	371	177	47.71%	387	219	56.59%	***0.000***
40	<15%	322	305	94.72%	472	407	86.23%	***0.000***
Total		1197	727	60.74%	1197	851	71.09%	***0.000***

significantly different results. It is observed that this proposed new CDL-based process greatly improves stratification efficiency and objectivity.

C. Stratification Results Evaluation

To evaluate the effectiveness of the CDL-based stratification method, the results were compared with those of the traditional stratification method based on 2010 JAS segment ground truth data. Stratification performance or "accuracy" was assessed based on the percent of the sampled and enumerated JAS segments that matched the definition of the PSUs within which they were selected. During the JAS, enumerators recorded crop and noncrop acreage for all selected segments. JAS segment stratum definitions (percent cultivation) were calculated directly from the reported segment data. Only selected JAS segments were enumerated. Remaining segments in the selected PSUs were not enumerated in the JAS due to cost limitations. Due to the fact that not all segments in the selected PSUs were enumerated, the validation was conducted based on the enumerated segment data, which was the only available ground truth. It was a goal of PSU segmentation that a high percentage of sample segments match the stratum definitions of the PSUs from which they were selected. Therefore, it was assumed that enumerated segments reflected the originating PSU stratum definitions. Both the traditional and CDL stratification methods were evaluated in the same manner.

An assessment of the resulting accuracies indicated that the CDL stratification method generally resulted in higher accuracies as shown in Table III, but these results did not indicate whether the differences in these two methods were statistically significant. The ultimate goal of this evaluation was to determine whether the proposed CDL stratification method achieved equivalent or improved accuracies when compared with the traditional (visual interpretation) area frame stratification method. Therefore, two-tailed proportion tests, a chi-square test or a Fisher's exact test, for sample sizes less than five were conducted for each state and each stratum. In these tests, it is assumed that p_1 and p_2 represent the accuracy results from the traditional stratification method and from the proposed CDL-based stratification method, respectively. The hypotheses of the significance tests were H_0: $p_1 = p_2$ and H_a: $p_1 \neq p_2$. The null hypothesis stated that there was no difference in the accuracies of the two stratification methods, while the alternative hypothesis stated that the accuracies of the two stratification methods were significantly different. The tests were performed for each

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state and each stratum with a confidence level of 95% or significance level of 0.05 in this paper. The null hypothesis was accepted if the p value exceeded 0.05.

IV. Experimental Results and Discussion

A. Comparison of Traditional and CDL Stratification Results

A comparison was made between the stratification results achieved by the traditional and CDL stratification methods using JAS reported data as in situ validation. It should be noted that for this analysis, strata 31, 32, 50, and 62 were merged into stratum 40 for the purpose of method comparison experiments. All stratifications were PSU based.

Table III presents the accuracy results for both the traditional and the CDL-derived stratification of the 2010 ASF PSUs for Oklahoma, Ohio, Georgia, Virginia, and Arizona and as a five state strata summary. In Table III, the accuracy results of the traditional stratification method and the CDL stratification method are presented side by side. The column at the far right identifies the p values of the chi-square or Fisher's exact tests.

As shown in Table III, for the Oklahoma 2010 traditional stratification, of the 323 total segments in the state, 140 were in PSUs defined as stratum 11 using visual interpretation based on stratum definition. Of the 140 segments, JAS reported that 47 were stratum 11, an accuracy of 34%. For the CDL stratification results, of the 323 segments, 43 were labeled in stratum 11 PSUs. Of the 43 segments, the JAS reported 27 were stratum 11, an accuracy of 63%.

Similarly, in Oklahoma stratum 20, 74 segments were in PSUs identified by the traditional stratification as stratum 20. Among these 74 segments, the JAS reported that 26 were stratum 20, which represented an accuracy of 35%. Of the 323 segments, 98 were located in PSUs identified by the CDL-based stratification as stratum 20. Of these 98 stratum 20 segments, the JAS reported that 42 were stratum 20, an accuracy of 43%.

As shown in Table III, the accuracies were calculated and summarized in the same manner for all strata. The p values were highlighted in bold italics if the differences were considered statistically significant at the 95% confidence level. At the individual state level, stratum 20 was the only stratum that showed no statistically significant difference between the two stratification methods at the confidence level of 95%. Table III also illustrates the individual state level analyses across five strata for the Ohio, Georgia, Virginia, and Arizona analyses. In Ohio, accuracy differences in stratum 11 were statistically significant at the 95% confidence level. In Georgia, accuracy differences in stratum 13 were statistically significant. The results for Virginia and Arizona are not as compelling as Oklahoma, Ohio, and Georgia. There were no significant differences in accuracy in these two states except in Virginia stratum 40 in which the traditional method achieved a higher accuracy than the CDL stratification method. This result is not surprising, since the CDL accuracy in low or nonagricultural areas is relatively low. The low accuracy in stratum 40 stratification is inherited from low accuracies of the CDLs.

In summary, land cover in the five states stratified with the automated CDL method generally had a higher rate of accuracy than the traditional method for all strata, except stratum 40, using the JAS reported data as validation. As shown in Table III, the CDL method achieved higher accuracy in the highly cultivated strata (11 and 13). CDLs' high total crop accuracies for major crops in intensively cropped areas enable the new CDL stratification method to achieve higher accuracies in highly cultivated strata such as strata 11, 12, and 13.

The number of segments in specific strata changed significantly when comparing the traditional versus the CDL stratification method of the five state frames. Table III shows that the number of segments included in stratum 11 across the five states decreased from 250 (traditional) to 128 (CDL) segments. Furthermore, the number of segments included in stratum 40 across the five states increased from 322 (traditional) to 472 (CDL) segments. The traditional method resulted in an over identification of cultivated segments in high agricultural areas while the CDL method over identified less cultivated segments.

Although the CDL method achieved higher accuracies than the traditional method in all high to medium intensity cultivated strata, the accuracies for both methods in strata 12 and 20 were lower than those of stratum 11. The primary reason for reduced accuracy in these strata was due to the heterogeneity of the land cover. It is difficult to define a stratum 12 or 20 PSU that is homogeneous, unless it is small. The cropland generally is clustered in one portion of the PSU and the remainder of the PSU has small amounts of agriculture. When the PSUs are selected in these strata and the segments are broken down, it is common that the selected segments not represent their PSU stratum definitions. One recommendation, to improve PSU homogeneity would be to reduce the size of PSUs during new ASF construction. This would improve ASF performance in strata 12 and 20.

The summary of the analysis results for five strata across all five states were shown in the bottom section of Table III. As shown in Table III, the CDL-based method achieved higher accuracies than the traditional method statistically in four of the five strata (11, 12, 13, and 20) when all five states were aggregated into one large population. The traditional method achieved higher accuracy in stratum 40 (low agriculture). This indicated that superiority of the CDL-based method to the traditional method was statistically sound.

B. Stratum Definition Sensitivity Analysis

To evaluate the impact of stratum definition change to stratification accuracy, a sensitivity analysis was conducted on the Oklahoma 2010 ASF. The goal of this analysis was to determine the impact of hard thresholds, in stratum definitions (Table II), on the accuracy results for both methods. The 2010, JAS data collected for all Oklahoma segments were used in evaluating the impact of small changes in stratum definitions on stratification accuracy. Table IV summarizes the results of the sensitivity analysis of the stratum definition range changes. As shown in Table IV, all strata were defined by a range of percent cultivation. To analyze the sensitivity of stratification accuracies to the changes in stratum definition, the official range of stratum percent cultivation was increased or decreased about 5% to 10%. The corresponding stratification accuracy was measured

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TABLE IV
OKLAHOMA 2010 ASF ANALYSIS: TRADITIONAL VERSUS CDL STRATIFICATION METHOD: SENSITIVITY ANALYSIS. (THE STRATUM DEFINITION NUMBERS WITH (*) ARE NASS OFFICIAL STRATUM RANGE OF PERCENT CULTIVATION)

Stratum definition			Traditional stratification				CDL stratification				p value
Stratum	% Cultivated	Change	Segments	Correct	Accuracy (P_1)	Sensitivity	Segments	Correct	Accuracy (P_2)	Sensitivity	Ha: $P_1 \neq P_2$
11	> 80%	5%	140	40	28.57%	1.000	43	24	55.81%	1.395	***0.001***
	>75%*	0%	140	47	33.57%	N/A	43	27	62.79%	N/A	***0.001***
	>70%	5%	140	61	43.57%	2.000	43	32	74.42%	2.326	***0.004***
12	55%–70%	9%	48	4	8.33%	1.157	77	20	25.97%	1.443	***0.019***
	51%–75%*	0%	48	9	18.75%	N/A	77	30	38.96%	N/A	***0.018***
	45%–80%	11%	48	13	27.08%	0.758	77	42	54.55%	1.417	***0.003***
20	20%–45%	10%	74	18	24.32%	1.081	98	28	28.57%	1.429	0.533
	15%–50%*	0%	74	26	35.14%	N/A	98	42	42.86%	N/A	0.305
	10%–55%	10%	74	30	40.54%	0.541	98	51	52.04%	0.918	0.135
40	<10%	5%	61	57	93.44%	1.311	105	86	81.90%	1.905	0.060
	<15%*	0%	61	61	100.00%	N/A	105	96	91.43%	N/A	***0.027***
	<20%	5%	61	61	100.00%	0.000	105	96	91.43%	0.000	***0.027***
Total			323				323				

accordingly. Stratum sensitivity was defined by the ratio of change in stratification accuracy to a change in the range of percent cultivation for each stratum as follows:

$$\text{Stratum definition sensitivity} = \Delta(\text{stratification accuracy})/\Delta(\text{percent cultivation}). \tag{2}$$

As shown in Table IV, stratification accuracies changed as the stratum definition (percent cultivation) ranges changed. The sensitivity of the stratification accuracies vary for different stratification methods, strata, and range changes. However, it is observed that the patterns of change for both stratification methods are the same. As shown in Table IV, stratification accuracies for stratum definition 11 for both the traditional and CDL methods are more robust when the range of percent cultivation is reduced and more sensitive when the range of percent cultivation is increased. This result is expected because reduced range means increased homogeneity for high agricultural PSUs. For the strata definitions 12, 20, and 40, the accuracies for both methods are significantly more sensitive when the range of percent cultivation is reduced than when it is increased. For stratum definition 12, the change in sensitivity for the new CDL method caused by expanding or reducing the range of percent cultivation are insignificant. For stratum definition 40, the stratification accuracy is insensitive to increasing the range of percent cultivation (5%) though it is sensitive to a decrease in the range of percent cultivation. It is observed that increasing the range of percent cultivation of the stratum definitions improves the stratification accuracy and vice versa. This finding indicates that a large definition range means that the strata are more inclusive and thus yields improved accuracy especially for the traditional method. However, how to find an optimal range for each stratum is out of scope of this paper. Overall, as shown in Table IV, changes in the range of percent cultivation of the stratum definitions do not change the difference between the stratification accuracies of the traditional and the CDL methods statistically for all Oklahoma strata except stratum 40. For stratum 40, originally, the stratification accuracy difference between both methods is statistically significant. However, when the definition range is reduced by 5%, the p value becomes 0.060, which is slightly higher than the confidence level of 0.05. This indicates that the accuracy difference between both methods is no longer statistically significant. Having a significant change in accuracy does not necessarily mean that a reduction in the range for stratum 40 is more sensitive, since a reduction from 5% to 15% is a large change in definition range. Therefore, it is concluded that changing the range of percent cultivation of the stratum definitions did not change the difference between the stratification accuracies of the traditional and the CDL methods statistically for strata of high or medium agricultural intensity (strata 11, 12, and 20).

C. Impact of Hay on Stratification

Additional stratification errors might be brought about by high error rates in the identification of the "other hay/non-alfalfa" category in the CDL classifications, especially in Ohio. Hay is spectrally difficult to separate from the grass and pasture classes. In many cases, the term hay refers to a land use rather than land cover as grasses can be grown for hay production. Therefore, it was important to determine whether including the hay class in cultivation had a significant impact on stratification accuracy, and if so, what mitigation procedure should be adopted in stratification operational procedures. Consequently, the impact of hay inclusion/exclusion on accuracies on both stratification methods was examined based on the JAS data. Similar statistical tests were performed to determine whether the differences in accuracy were statistically significant. The accuracies were compared for all states at the stratum level and as a five-state stratum summary based on 2010 CDL data.

In Table V, the stratification results derived by including or excluding the other hay/non-alfalfa category in the CDL-based cultivated layer and the JAS-calculated validation data were listed in two separated groups, respectively. As shown in Table V, the accuracy differences for most strata in states were insignificant. However, the accuracy differences were statistically significant for stratum 12 in Ohio and stratum 40 in Virginia. With hay excluded, the accuracies decreased from 54.76% to 32.43% for stratum 12 in Ohio and increased from 76.32% to 90.51% for stratum 40 in Virginia. Overall, the five state stratum summary shows that total accuracy increased from 71.09% to 74.69% with

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TABLE V
CDL STRATIFICATION ACCURACY COMPARISON WITH RESPECT TO HAY (FIVE STATES 2010 STRATA SUMMARY)

		Hay included			Hay excluded			*p* value
Stratum	State	Segments	Correct	Accuracy (p_1)	Segments	Correct	Accuracy (p_2)	Ha: $p_1 \neq p_2$
11	Oklahoma	43	27	62.79%	27	18	66.67%	0.742
	Ohio	85	76	89.41%	76	66	86.84%	0.614
	Total	128	103	80.47%	103	84	81.55%	0.835
12	Oklahoma	77	30	38.96%	73	35	47.95%	0.267
	Ohio	42	23	54.76%	37	12	32.43%	***0.046***
	Total	119	53	44.54%	110	47	42.73%	0.783
13	Georgia	28	22	78.57%	24	20	83.33%	0.736
	Virginia	4	2	50.00%	3	1	33.33%	1.000
	Arizona	59	45	76.27%	58	43	74.14%	0.789
	Total	91	69	75.82%	85	64	75.29%	0.935
20	Oklahoma	98	42	42.86%	65	30	46.15%	0.678
	Ohio	48	37	77.08%	46	34	73.91%	0.721
	Georgia	165	100	60.61%	158	92	58.23%	0.664
	Virginia	61	31	50.82%	39	21	53.85%	0.768
	Arizona	15	9	60.00%	16	9	56.25%	0.833
	Total	387	219	56.59%	324	186	57.41%	0.826
40	Oklahoma	105	96	91.43%	158	142	89.87%	0.674
	Ohio	65	57	87.69%	81	66	81.48%	0.306
	Georgia	120	106	88.33%	131	120	91.60%	0.388
	Virginia	114	87	76.32%	137	124	90.51%	***0.002***
	Arizona	68	61	89.71%	68	61	89.71%	1.000
	Total	472	407	86.23%	575	513	89.71%	0.141
Total		1197	851	71.09%	1197	894	74.69%	***0.048***

hay excluded and a p value of 0.048 indicates that this difference is statistically significant at a 95% confidence level though it is marginal. These results indicate that excluding the CDLs other hay/non-alfalfa category from the cultivated data layer may have significant impact on state level stratification results for some state in some strata.

These results can be explained by the fact that classification accuracies related to the other hay/non-alfalfa category and the geodistribution of other hay/non-alfalfa are different in different states. For example, the producer and user accuracies for other hay/non-alfalfa in the 2010 Ohio CDL were 14.20% and 55.20%, respectively, which are poor for these categories [22]. The major classification errors came from eastern Ohio, where small farms are prevalent. In eastern Ohio, the FSA CLU data are limited with reduced numbers of farmers signing up with FSA. Furthermore, the spatial resolution of the satellite imagery is too coarse at 30 m to identify and classify the fields accurately. Many of the PSUs in this area of eastern Ohio belong to stratum 12. Merging the other hay/non-alfalfa category into the cultivated category greatly cancels the classification errors from other hay/non-alfalfa. Therefore, excluding other hay/non-alfalfa will reduce the cultivated layer accuracy in the area. Another example is stratum 40 in Virginia. The producer and user accuracies for other hay/non-alfalfa in Virginia in the 2010 CDL were 48.54% and 58.66%, respectively [22]. Excluding other hay/non-alfalfa from the cultivated category and merging it into noncultivated category will cancel some errors in the noncultivated category, which constitutes a major portion of stratum 40. Thus, it may increase the stratum 40 stratification accuracy as most land in Virginia is low-intensity agriculture.

D. Single Versus Multiple Year CDL Data

Utilizing the multiyear CDL data might improve the cultivated layer accuracies. Therefore, additional testing was conducted to determine whether stratification accuracies could be improved using multiyear CDL data for the automated stratification process. State level stratifications using different multiyear CDL (2007–2010) cultivated data layers were first conducted [21]. The multiyear CDL data-based stratification accuracies were then compared with the stratification accuracies obtained from the single year (2010) CDL-cultivated layer of the five test states.

The single year CDL-cultivated data layer included pixels categorized to cultivated crop in the 2010 CDL only. The multiyear cultivated layers were derived using different CDL data composition rules which determined the pixels to be categorized in the output data layer as cultivated. In this experiment, four consecutive years of CDL data (2007–2010) were used. Two sets of cultivated data were derived with two composite rules: a pixel was categorized to cultivated in the multiyear cultivated layer 1) if it was classified as a cultivated crop at least two times in the original CDL inputs and 2) if a pixel was categorized to a cultivated crop in the 2010 CDL as well as categorized to a cultivated crop at least two times in the original CDL inputs. The multiyear cultivated layers composited with rule 1) and rule 2) were called multiyear composite 1 and 2 in Table VI, respectively. Stratification accuracies achieved using these two datasets were listed along with accuracies using the single year data for all states and strata in Table VI. As shown in Table VI, the minimum p value was 0.211, which is much larger

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TABLE VI
CDL STRATIFICATION ACCURACY COMPARISON USING SINGLE YEAR VERSUS MULTIYEAR CDL DATA (FIVE STATES 2010 STRATUM SUMMARY)

	Single year (2010)			Multi-year composite 1			Multi-year composite 2			*p* value	*p* value
Stratum	Segments	Correct	Accuracy (p_1)	Segments	Correct	Accuracy (p_2)	Segments	Correct	Accuracy (p_3)	Ha: $p_1 \neq p_2$	Ha: $p_1 \neq p_3$
11	103	84	81.55%	93	78	83.87%	134	101	75.37%	0.669	0.254
12	110	47	42.23%	114	54	47.37%	83	43	51.81%	0.485	0.211
13	85	64	75.29%	77	60	77.92%	102	71	69.61%	0.693	0.388
20	324	186	57.41%	286	172	60.14%	319	184	57.68%	0.494	0.944
40	575	513	89.71%	627	545	86.92%	559	505	90.34%	0.221	0.533
Total	1197	894	74.69%	1197	909	75.94%	1197	904	75.52%	0.477	0.637

than 0.05 the level of significance. This result indicated that the differences in stratification accuracies between using the single year data and either of the two multiyear CDL composite data for any of individual stratum in five test states were not statistically significant. The test p values of 0.477 and 0.637 also indicated that the differences in accuracies using single year CDL data versus using multiyear composite 1 and 2 for all states across all strata were not statistical significant.

Overall, the differences in stratification accuracies were very small when using either single year or multiyear CDL composite data because the CDL input data were consistent over time. However, it is important to note that at the local level these differences may be significant.

E. Applications in NASS Operation

Based on these research results, NASS has begun implementing the CDL automated stratification method into NASS area frame operations in two major applications.

First, the automated method is being used as the primary stratification method for building state area frames. However, the operational stratification process remains a hybrid approach, a combination of automated and manual stratification. The new CDL automated stratification method is applied on existing state frames to highlight PSUs with matching or nonmatching stratum definitions. PSUs with matching stratum definitions are assumed correct and no changes are made. PSUs with nonmatching stratum definitions are manually inspected using satellite data, aerial photography, and FSA CLU data to determine the stratum definitions. When new frames were built in the past, all analyses were conducted from scratch with 100% of the PSUs requiring digitization and all stratum definitions determined using visual interpretation [1]. To improve efficiency and reduce the cost of construction, old area frames are currently being reused with the automated stratification process highlighting PSUs that have potentially changed stratum definitions. Only nonmatching PSUs, which constitute just an average of 20% of all PSUs, are targeted for manual inspection. This is a significant improvement in efficiency. To improve stratum homogeneity, many of the manually inspected PSUs are broken down into smaller units. New state frames have been created for Arizona, Georgia, New Mexico, Oklahoma, and South Dakota, using the CDL automated stratification method.

A second application of automated stratification within NASS operations is using the proposed automated stratification method as an additional tool to determine the order of revision for state frames. Currently, four state frames are being built each year, with the recent implementation of the CDL automated method. To determine which frames should be revised next, a careful calculation has to be made. In the past, frame age, coefficients of variation (CVs), percent of frame segments meeting stratum definition (frame performance) and contribution of the state to U.S. agriculture were the primary criteria used to determine the order of state frame revisions. Currently, NASS Area Frame staff members have added the automated stratification procedure as an additional tool to objectively measure the degree of improvement in frame performance that can be expected by using the CDL data. This new Area Frame procedure relies on analysis of PSU stratum definitions. The analysis is performed using the CDL automated method and the JAS data as validation. By comparing CDL-based stratification results to the current year's JAS reported data, the "potential" improvement expected from building a new frame using the CDL data can be computed. Based on this analysis, state frames are ranked from a low to high potential for improvement. This method helps NASS objectively determine the optimal order to conduct Area Frame updates.

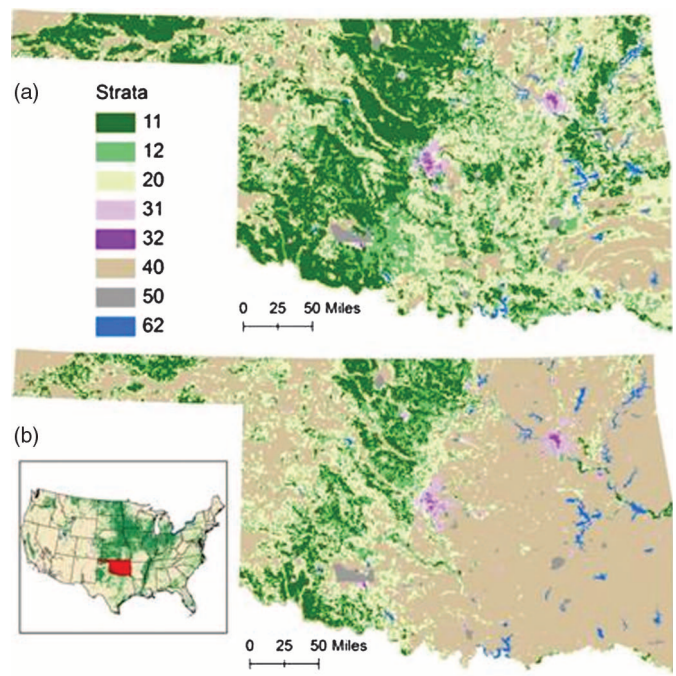

Fig. 4. Oklahoma ASFs (a) 2010 and (b) 2013. Stratum 11 (greater than 75% cultivated) was overestimated in the 2010 ASF, which was created using the traditional method and updated to more accurately reflect conditions in the 2013 ASF using the CDL-based automated stratification method.

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Overall, with the implementation of the CDL automated method in NASS area frame operations, new state frames are being built at reduced cost with improved objectivity, efficiency, and accuracy. For example, the 2010 Oklahoma area frame was constructed in 4552 employee hours using the NASS traditional method as compared with the 2013 Oklahoma frame which was constructed in 1980 employee hours using the CDL-based stratification method. This time calculation includes additional editing of PSUs that have changed stratum definitions and editing to improve stratum homogeneity, all useful for improving frame quality and performance. Furthermore, analysis of the 2010 Oklahoma frame indicated an accuracy of only 34% of segments meeting stratum definition when compared with the 2012 JAS segment data. After rebuilding the 2013 Oklahoma frame, an accuracy of 79% was achieved using the 2013 JAS segment data as *in situ* validation. Fig. 4 illustrates official NASS products of the traditional 2010(a) and the CDL based 2013(b) NASS Oklahoma ASFs. As shown in Fig. 4, stratum 11 (dark green) was overestimated in the 2010(a) Oklahoma ASF when compared with the 2013(b) Oklahoma ASF using the 2012 JAS survey data as *in situ* ground truth.

V. Conclusion

This paper proposed a new automated CDL-based method for deriving percent cultivation and subsequently stratifying U.S. land cover. The goal of this research was to determine the utility of the automated CDL-based method for use in the stratification of U.S. land cover and potentially in ASF construction. The CDL-based stratification of NASS ASF PSUs was successfully conducted for Oklahoma, Ohio, Virginia, Georgia, and Arizona as an experiment. The stratification accuracies of the traditional and new CDL stratification methods were compared based on *in situ* validation data collected by enumerators during the 2010 JAS.

Results of the five-state analyses indicated that the new automated CDL method was more accurate in determining U.S. percent cultivation in intensively cropped areas and weaker in low agricultural areas. The CDL-based stratification achieved higher accuracies in strata 11, 12, 13, and 20, while the traditional method achieved higher accuracies in stratum 40. The differences in the accuracies were statistically significant at a 95% confidence level. Using multiyear composite cultivated layers did not improve stratification accuracies as compared with results of single year data. The differences in stratification accuracy which resulted from including or excluding hay in cultivation were overall marginally significant at a 95% confidence level. However, the accuracy differences are significant for some states such as Ohio and Virginia in certain strata, which were related to the original CDL accuracy. To evaluate the impact of the stratum definition change to the stratification accuracy, a sensitivity analysis was conducted on the Oklahoma 2010 ASF results. It was found that changes in the range of the stratum definitions did not change the difference in stratification accuracies between the traditional and the CDL methods statistically for strata of high or medium agricultural intensity (strata 11, 12, and 20).

The novelty of the proposed method was using geospatial CDL data to objectively and automatically compute percent cultivation of the ASF PSUs as compared to the traditional method that subjectively determines percent cultivation using visual interpretation of satellite data. This proposed new CDL-based process improved efficiency, objectiveness, and accuracy as compared to the traditional stratification method. It was concluded that adoption of the automated CDL stratification method in ASF construction helped NASS achieve the goals of improving efficiency, reducing cost, and improving the precision of JAS estimates by updating the NASS ASFs with greater frequency and stratification accuracy.

Future research will involve assessing the stratification improvement derived with the CDL automated method by comparing the variances of estimators using the CDL stratification as a form of poststratification compared with the variance from the original stratification. Also, it is necessary to further develop and test a technique to more efficiently and objectively identify ASF PSUs for potential subdivision, which have large variances, so that a lower variance can be achieved.

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Claire G. Boryan received the Bachelor's degree in foreign affairs from the University of Virginia, Charlottesville, VA, USA, in 1984, and the Master's degree in geographic and cartographic science from George Mason University, Fairfax, VA, USA, in 2002, where she is currently pursuing the Ph.D. degree in earth systems and geoinformation sciences.

She is a Geographer and Head of the Geospatial Science and Survey Section, Research and Development Division, National Agricultural Statistics Service (NASS), Washington, DC, USA. Her research interests include remote sensing methods, geographic information science, and applied research using geospatial data to improve agricultural statistics.

Ms. Boryan is a member of the American Society of Photogrammetry and Remote Sensing. She is a recipient of the USDA Secretary's Honor Award for Excellence in 2011 and the NASS Administrators Award for Excellence in 2012.

Zhengwei Yang (M'02) received the Bachelor's degree in electrical engineering from Shanghai Science and Technology University, Xuhui, Shanghai, China, in 1982, the Master degree in systems engineering from Shanghai Jiaotong University, Xuhui, Shanghai, China, in 1985, and the Ph.D. degree in electrical engineering from Drexel University, Philadelphia, PA, USA, in 1997.

Currently, he is an IT Specialist with Research and Development Division, USDA National Agricultural Statistics Service (NASS), Washington, DC, USA, and an Affiliate Faculty with the Center for Spatial Information Science and Systems, George Mason University, Fairfax, VA, USA. His research interests include remote sensing methods and GIS technology and their application in agriculture. His work spans conceptual, theoretical, and application research as well as system development.

Dr. Yang is a member of American Geophyscial Union and American Society of Photogrammetry and Remote Sensing. He was a recipient of the 2011 USDA Secretary's Honor Award for Excellence.

Liping Di (M'01–SM'05) received the B.Sc. degree in remote sensing from Zhejiang University, Hangzhou, Zhejiang, China, in 1982, the M.S. degree in remote sensing/computer applications from the Chinese Academy of Science, Beijing, China, in 1985, and the Ph.D. degree in geography from University of Nebraska–Lincoln, Lincoln, NE, USA, in 1991.

He was a Research Scientist with the Chinese Academy of Science from 1985 to 1986 and NOAA National Geophysical Data Center, Boulder, CO, USA, from 1991 to 1994. He served as a Principal Scientist from 1994 to 1997 and a Chief Scientist from 1997 to 2000 with Raytheon ITSS, Waltham, MA, USA. Currently, he is a Professor of Geographic Information Science and the Director of the Center for Spatial Information Science and Systems, George Mason University, Fairfax, VA, USA. His research interests include remote sensing, geographic information science and standards, spatial data infrastructure, global climate and environment changes, and advanced Earth observation technology. He is the Chair of ISO 19130: Imagery Sensor Models for Geopositioning. He has been the Chair of the Data Archiving and Distribution Technical Committee of IEEE Geoscience and Remote Sensing Society since 2005.

Dr. Di is a member of American Geophyscial Union, American Association of Geographers, and American Society of Photogrammetry and Remote Sensing.

Kevin Hunt received the Bachelor's and Master's degrees in geography from the University of Missouri, Columbia, MO, USA, in 2007 and 2009, respectively.

He is a Cartographic Technician with Research and Development Division, National Agricultural Statistics Service (NASS), Fairfax, VA, USA. His research interests include land use stratification methods using geospatial sciences and GIS technology and their application to improve agricultural statistics.

Mr. Hunt is a recipient of the NASS Administrator Unit Award for Excellence in 2013.

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