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Evaluation of a New Data Collection Approach on the June Area Survey

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Abstract
Every year the United States Department of Agriculture's National Agricultural Statistics Service (NASS) conducts the June Area Survey (JAS). The JAS is based on an area frame, which provides complete coverage of the contiguous U.S. The data collected from the JAS are used to supply direct estimates of acreage and measures of sampling coverage for NASS's list frame, which consists of all known farms in the U.S. The JAS is NASS's largest annual survey, and, prior to the COVID-19 pandemic, had always been conducted via personal interviews. Due to the pandemic, the JAS was not carried out in 2020. In 2021 it was conducted by mail and telephone, and in 2022 limited personal interviews were allowed. Moreover, a new mobile survey instrument was made available as of 2021, granting field interviewers the ability to collect data via web-enabled tablets as an alternative to the traditional paper questionnaire. These shifts in data collection mode impacted the ability of field interviewers to use familiar methods during interviews. In conjunction with these changes, NASS developed new data analysis tools that integrated administrative, remotely sensed, and other data sources to aid in imputing the nonresponse records. This paper examines JAS data quality under evolving data collection and imputation paradigms by characterizing survey response across 2019, 2021, and 2022. Additionally, JAS record-level corn and soybean acreages are compared with corresponding, gold-standard administrative data for the same years. Response rates decreased substantially when the primary data collection mode was changed from in-person interviews to telephone interviews. Across all study years, data quality was minimally affected, particularly for records for which full survey responses were received. In 2022, the use of a mobile instrument during personal interviews was associated with significantly lower data quality than other modes.

Key words: nonresponse, area frame, survey mode, data quality, data collection, administrative data, CATI, multiple data sources, imputed data, in-person interviews

1. Introduction and Background

In recent years, many United States (U.S.) federal statistical agencies have been facing declining response rates across surveys (Czajka and Beyler 2016, Johansson et al. 2017) as well as relatively flat budgets (Citro et al. 2024). This has necessitated an increased investment in resources to achieve similar data quality. The onset of the COVID-19 pandemic brought even more need for new and creative survey methodologies to focus, as data collection modes were limited to only those conducted from a distance. Research has shown that overall personal interviews provide better quality data (Heerwegh et al. 2008, Blumberg et al. 2021). Thus, the changes to survey methodologies observed during the height of the pandemic caused questions to arise regarding the quality of survey data collected during that time.

The U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) had conducted the June Area Survey (JAS) via in-person interviews annually since 1954. When the pandemic struck, NASS had to pivot away from in-person interviews, raising concerns about the resulting quality of the collected data. In this paper, the data quality measures JAS data collected pre-pandemic (2019), during the pandemic (2021), and post-pandemic (2022) are compared.

The JAS is one of NASS's largest and most costly programs aside from the quinquennial Census of Agriculture. The nature of the JAS is tripartite as it relates to the Agency's mission (Cotter et al. 2010). First, it provides an annual measure for the number of farms and land in farms in the U.S. Second, the JAS produces direct estimates of large crop commodities such as corn, soybeans, and wheat, among others. Finally, the JAS is used to measure the incompleteness of the NASS list frame.

The JAS is based upon an area frame, which ensures complete coverage of all land within the 48 contiguous U.S. For each state, land within the area frame is divided into homogeneous strata based on percent cultivated land and further into substrata based on similarity of agriculture. The land within each substratum is divided into primary sampling units (PSUs). PSUs are sampled from each substratum with replacement using stratified simple random sampling to target major agricultural commodities. Then smaller, similar-sized segments of land (about one square mile or 640 acres) are delineated within each selected PSU. One segment is randomly sampled from each selected PSU to be fully enumerated during the JAS (see Figure 1).

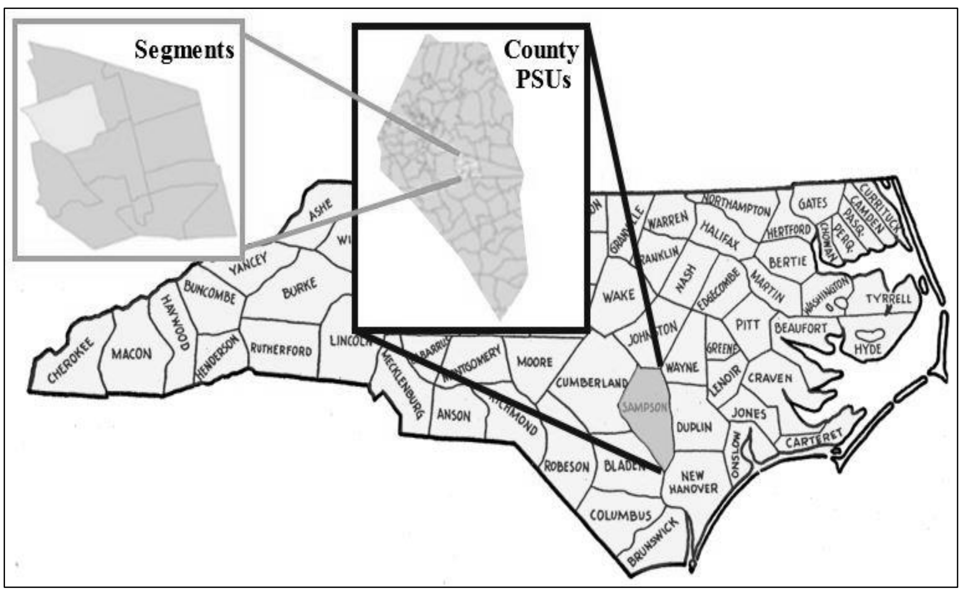

Figure 1. NASS area sampling frame for North Carolina.

The JAS has a rotating panel design where approximately twenty percent of the sample is replaced with new segments annually, and segments that have been in the sample for five years are rotated out.

In March 2020, during the initial phases of the pandemic, NASS did not have time to evolve its data collection processes for the 2020 JAS. Thus, the difficult decision was made to not conduct the 2020 JAS. Due to the continuing nature of the pandemic, in October 2020, NASS leadership made the decision to conduct the 2021 JAS without any in-person interviews. This decision led to numerous changes in the data collection process, which are described in Section 2. For the 2022 JAS, many of the 2021 data collection changes were operationalized, and a limited number of in-person interviews were conducted.

When shifting to a different mode of data collection for the JAS, the primary question was how this would affect the overall quality of the JAS data. This paper focuses on the impact on unit-level reports of planted corn and soybean acreage. Using administrative data, the JAS data quality was assessed and compared for 2019 (pre-pandemic data), 2021 (in-pandemic data), and 2022 (post-pandemic data) as described in Section 3. The results of this data quality assessment are provided in Section 4. In the final section, the strengths and weaknesses of the revised processes as well as the future of the JAS data collection are discussed.

Section 2. JAS data collection

Section 2.1. Pre-pandemic data collection

The newly rotated-in segments (new segments) are prescreened in May, prior to the June data collection period, to identify segment boundaries (outlined in white in Figure 3), agricultural and non-agricultural areas within the segment, and the name and address (N&A) information of possible owners and operators. Field interviewers are provided N&A information from the Farm Service Agency (FSA), plat maps, county segment maps, and other resources to help with the prescreening (Figure 2). They are also instructed to conduct internet searches in their attempt to determine who operates the land. For previously enumerated segments (old segments) the names and addresses are available from the previous year. Yet many of the older segments still need improvements on the N&A information.

Figure 2. JAS Survey Materials.

Field interviewers are provided a paper aerial photograph showing the sampled segment area (Figures 2 and 3). Interviewers must account for all land inside the segment boundary. They divide each segment into tracts of land (outlined in black in Figure 3). Obvious non-agricultural areas, such as roads, rivers, etc., are assigned a tract letter and automatically classified as a non-agricultural tract. Each of the remaining tracts of land is assigned a tract letter that represents a unique land operating arrangement. These tracts are then screened for agricultural activity and classified as either an agricultural tract or a non-agricultural tract.

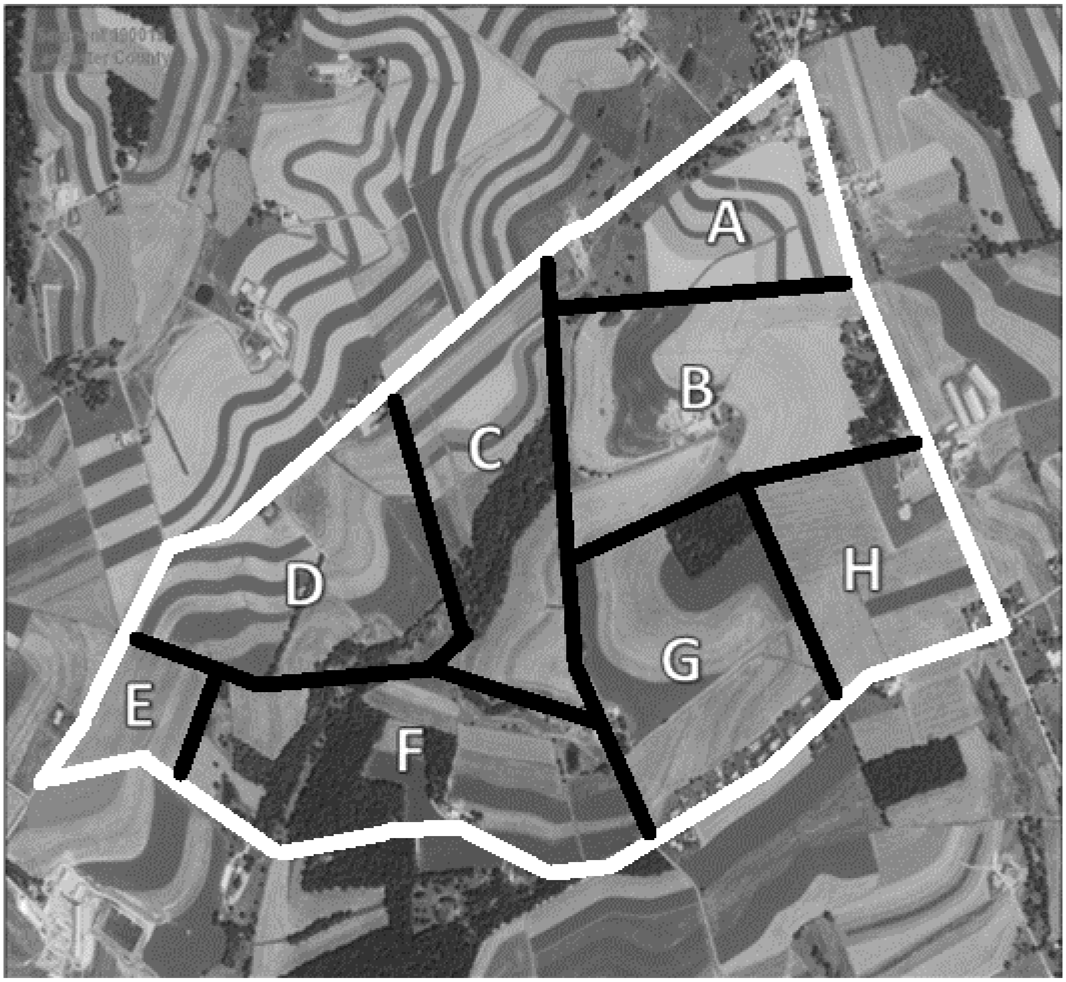

Figure 3. The area outlined in white is the segment. Tracts are outlined in black and labeled with white letters.

JAS data collection is conducted during the first two weeks of June when field interviewers return to interview only the agricultural tract farm operators. Because the primary purpose of the JAS is to provide crop and livestock acreages, field interviewers spend most of their prescreening time on improving the information on the agricultural tracts for new segments.

2.2. Pandemic Data Collection

For the 2021 JAS, all data were collected via computer-assisted telephone interviews (CATI). To enable CATI to be feasible, numerous changes were made in the JAS pre-survey and survey processes, requiring the survey timeline to be adjusted (Figure 4).

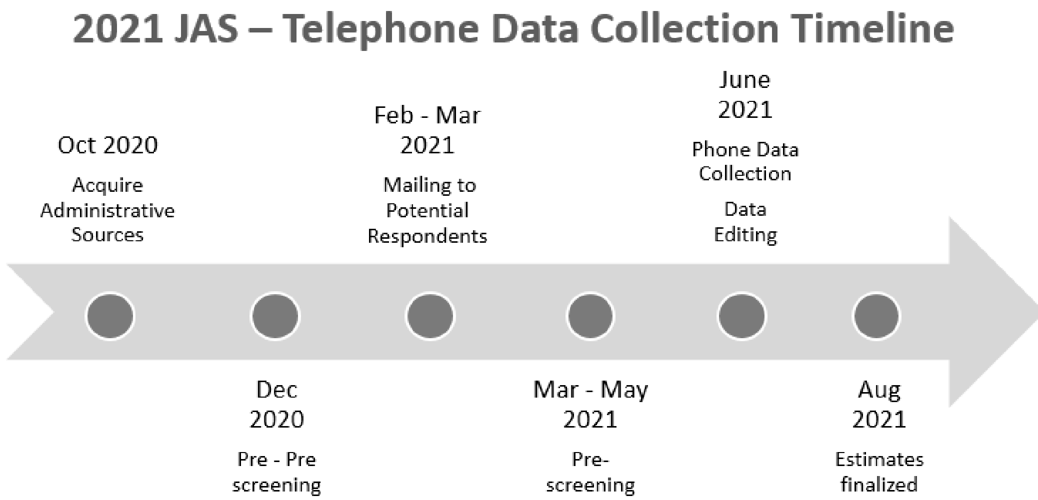

Figure 4. 2021 JAS Data Collection Timeline.

During the JAS's prescreening period, information for older segments is normally not reviewed. For 2021, this information was retained, reviewed, and utilized to build a master mail list. Because interviewers could not prescreen the land to identify who owned and operated it, an interactive tool, called the pre-prescreening tool, was built to identify potential operators of the land (Figure 5). This tool allowed field office staff to view the land spatially. Each new segment was spatially screened, and name, address, and telephone information were linked to it to build the mail list. A listing with names and addresses of potential producers was prepared for all tracts in old as well as new segments. The producers were then mailed a sample packet, with segment maps and copies of the questionnaire, before starting prescreening in March 2021. An example mailed segment map is shown in Figure 6. These were mailed to inform respondents they would be contacted via phone during the data collection period, and to ensure that respondents and interviewers were referring to the correct geospatial areas during the interview. Similar processes were followed for the 2022 JAS.

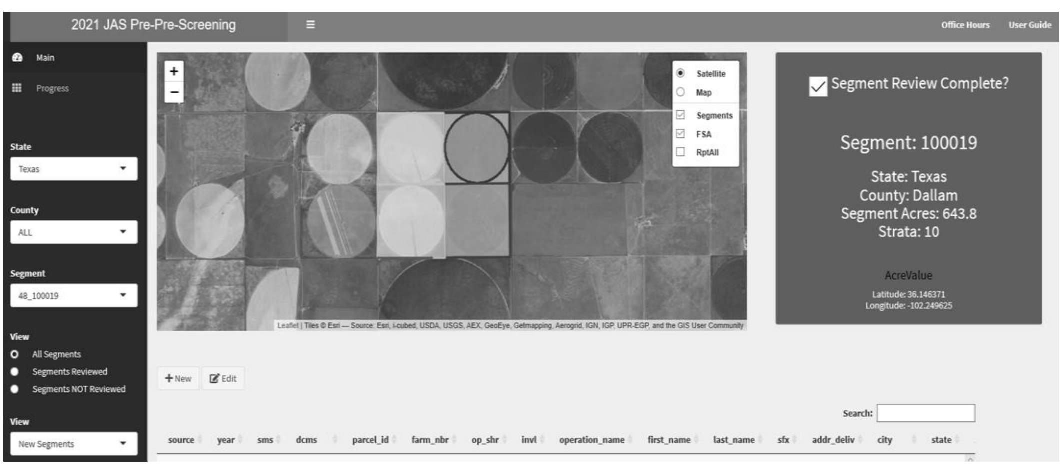

Figure 5. Screenshot of the Pre-Prescreening Tool.

Figure 6. Example of a segment map that was mailed.

A mobile instrument was developed for collecting responses. This survey instrument enabled interviewers to enter JAS data collected via a web application installed on iPads, which they were using to collect data for other surveys. This mobile instrument was presented as an optional alternative to the traditional paper questionnaire and was available to interviewers conducting personal (pre- and post-pandemic) or telephone (pandemic and post-pandemic) interviews.

Some respondents refused to participate or were inaccessible. As a result, tract-level information had to be hand imputed. This manual imputation is standard for the JAS; however, the amount of imputation during normal survey conditions is less than what was anticipated in 2021. To prepare for this, the June Area Land Tool was released. This tool uses historical crop-type mapping via the Cropland Data Layer (CDL) (Boryan et al. 2011), in-season predictions, and FSA administrative data, which will be more fully described in Section 3, to impute JAS tracts whenever the information is available (Figure 7).

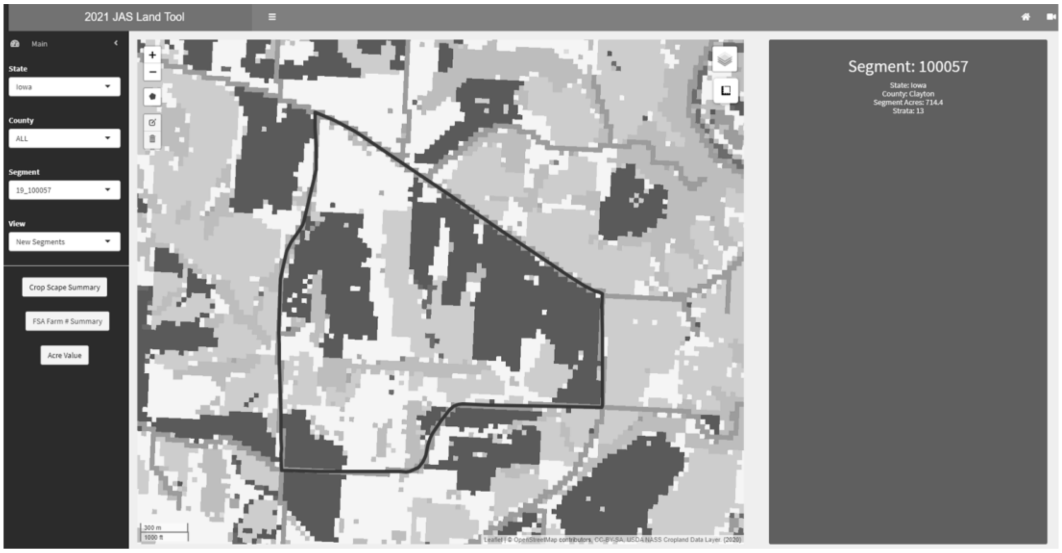

Figure 7. Screenshot of June Area Land Tool.

Historically, maps are stored after the end of each JAS survey cycle at their respective regional field office. In 2021, the Agency allocated resources to a new JAS tract digitization effort. For this effort, all tracts in the 2021 JAS sample were digitized, and all new segments rotating into the sample in subsequent years were digitized immediately following the data collection period. Tract-level information, such as boundary lines and tract IDs corresponding to tabulated tract-level data, are updated on the JAS photo enlargements of sampled segments during the survey period. NASS staff use the photo enlargements as reference to draw digital tract boundaries using GIS software. These newly digitized records are uploaded to a centralized database where they can be utilized for analysis.

3. Assessing Quality

The 2021 JAS data collection was conducted using telephone interviews, a complete change in mode from the 2019 and earlier JAS in-person data collection. Numerous changes were made in the JAS process to accommodate this shift in mode. They could improve the survey process for in-person interviews as well. And, they could have an impact on data quality for either data collection mode. Because the mode of data collection is completely confounded with the other changes, any change in data quality cannot be directly attributable to the change in mode but reflects the overall effect of changes in mode and survey processes on data quality. This will be discussed more fully in Section 5.

When available, data from the FSA are the gold standard for determining what crop was grown in a specific agricultural field. Farmers participating in USDA programs or purchasing crop insurance report their crop plantings each year on the FSA-578 form. Data from these reports are linked to parcels of land via FSA Common Land Unit (CLU) polygons (USDA 2017). FSA CLUs are digital, geospatially referenced polygons that correspond with crop field boundaries (Figure 8).

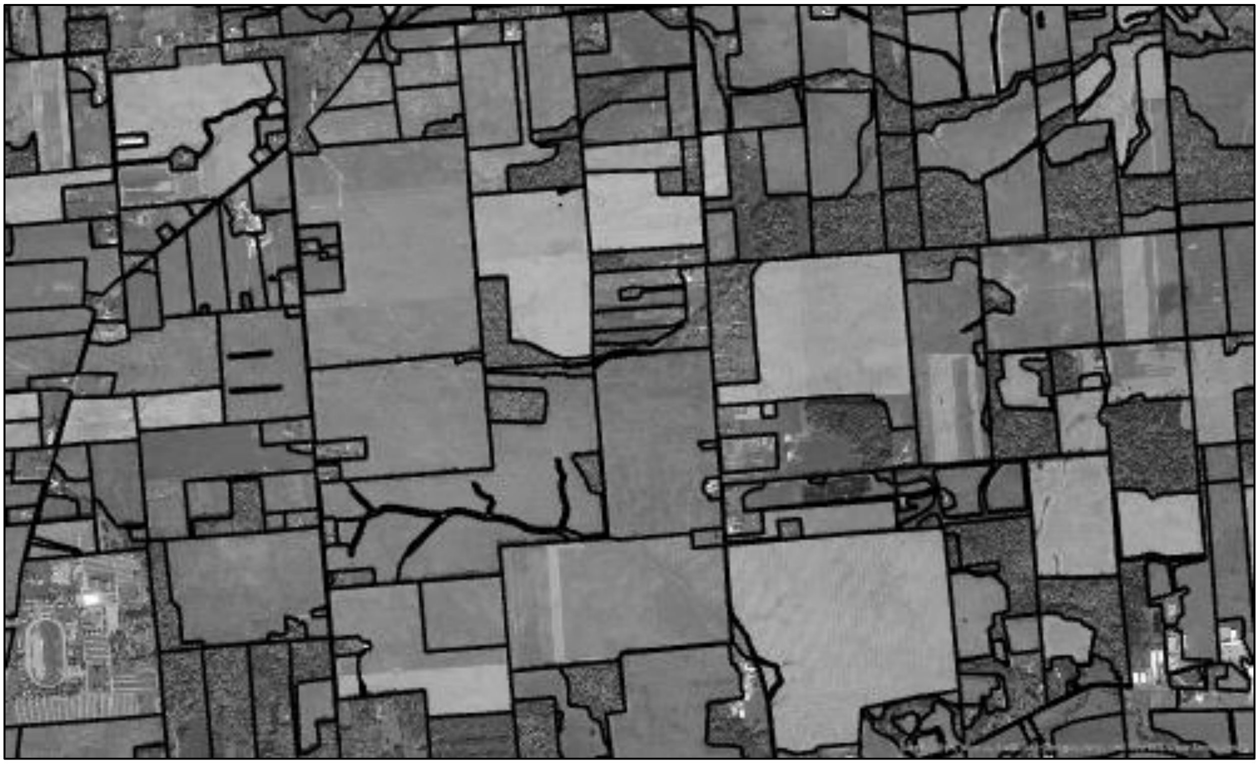

Figure 8. An example of FSA CLUs, outlined in black. Each polygon represents an agricultural field, excluding non-agricultural areas such as farmsteads.

The deadline for submitting the FSA-578 form varies with crop and region, but is generally July 15th in the major corn-producing areas of the U.S. Further, the producer can update FSA-578 data during the growing season. For this study, final FSA-578 data available at the end of the 2019, 2021, and 2022 growing seasons were used as ground-reference for the corresponding years of JAS data. JAS digitized tract boundaries were used to link survey data with the FSA administrative data by performing a spatial join between the digitized tract boundaries and FSA CLUs. The spatial join was performed under the condition that the FSA CLU centroid must be contained within a JAS digitized tract to be linked to that tract. By this process, all reported 578 data could be spatially linked to a digitized tract via the CLUs. Some FSA data were lost due to mismatches between IDs in the 578 reports and the CLU files. Additionally, it is technically possible that the spatial join method results in a loss of FSA data. For example, if a large field overlaps a JAS digitized tract but the centroid is outside of the tract, it would be excluded from the join. However, agreement between crop fields delineated by digitized tracts and FSA CLUs was good, since similar rules were observed for their creation, primarily avoiding cutting across homogenous fields. For 2019 data, the 2021 digitized tracts had to be used, resulting in a loss of about 20% of the 2019 segments that were rotated out of the sample and replaced with new segments in 2021. It was assumed that tract boundaries changed minimally between the two years.

Additionally, digitized tract acreages and JAS tract acreages did not always agree. This resulted either from errors in the digitization process, errors in survey reporting/imputing, or both. Tracts where high levels of disagreement in terms of absolute error (AE) between JAS acreage and digitized acreage occurred were not used in the analysis. AE is defined as,

$$AE = |Reported\ or\ Imputed\ \ JAS\ \ Acreage\ - Digitized\ tract\ acreage|.$$

Tracts with high disagreement were identified as outliers by the interquartile range (IQR) approach. By this rule,

$$Lower\ Limit\ of\ Acceptable\ range = \ Q1_{AE}\ -\ 1.5(Q3_{AE} - Q1_{AE}\ )$$
$$Upper\ Limit\ of\ Acceptable\ range = \ Q3_{AE}\ +\ 1.5(Q3_{AE} - Q1_{AE}\ )$$

$Q1_{AE} = lower\ quartile\ of\ AE\ values$
$Q3_{AE} = upper\ quartile\ of\ AE\ values$

This resulted in an approximately 11% loss of agricultural tracts each year, with 1,821 tracts being removed from analysis for 2019, 2,317 tracts being removed for 2021, and 2,432 tracts being removed for 2022. As a result of all linking activities and outlier removal, 13,957 agricultural tracts were available for analysis in 2019, 18,829 in 2021, and 19,269 in 2022.

3.1. Measures of Data Quality

Three measures of data quality are considered: response rate, misclassification rate, and mean error of acres planted to corn (soybeans) for all available tracts.

Response rate was derived by combining information from two questionnaire items: the questionnaire-level response code and the tract information source indicator. The questionnaire-level response code indicated whether there was (1) a full response, (2) some or all the questionnaire items were refused by the respondent, or (3) the target respondent was inaccessible by the field interviewer assigned to that tract. The tract information source indicator specified whether the tract-level data largely originated from an interview with the respondent, observation by the field interviewer, or auxiliary data sources such as previously reported data or geospatial data contained in the June Area Land Tool. The complex combinations of questionnaire-level response coding and tract information source indication made it difficult to state with confidence the exact source of imputed information. JAS tract crop acreages may be based on a combination of information from interviews, observations, and auxiliary information. Additionally, questionnaire response behaviors are not mutually exclusive in the JAS (e.g., partial questionnaire refusals). For this reason, only those tracts where the questionnaire-level response code indicated a response and the tract information source indicator indicated an interview were categorized as responded. All other combinations of response codes for these two variables were fully or partially imputed in some way, and those tracts were considered to be imputed.

Although CLUs were originally designed to have a single crop, a small minority of them have multiple crops. JAS tracts can also have multiple crops. Thus, a JAS tract is said to have been correctly classified with respect to corn (soybeans) if (1) the corresponding CLU had the reported crop ***and*** (2) the number of acres reported or imputed as corn (soybeans) was within 10% of the FSA reported data for the corresponding CLU. For this assessment, the Absolute Percent Error (APE) is defined as

$$APE_{crop} = 100\left|1 - \frac{JAS\ crop\ acreage_i}{FSA\ crop\ acreage_i} \mid FSA\ crop_i > 0\right|$$

where $FSA\ crop\ acreage_i$ is a positive number of acres planted to corn or soybeans in FSA tract i. If $APE_{crop} <\ 10\%$, the JAS tract is said to have been correctly classified with respect to that crop:

$$correct\ classification_{crop} = \begin{cases} 1, if\ APE_{crop} <\ 10\% \\ 0, if\ APE_{crop} > 10\% \end{cases}$$

The acres planted to corn (soybeans) is an important component in forecasting corn (soybean) production. To assess field-level error in reporting corn (soybean) acreage, two components are considered: (1) whether the correct crop is reported and (2) whether the reported acreage is correct. Given the FSA-578 fields that have corn (soybeans), the mean error (ME) is defined to be the average difference in the FSA and JAS reported crop acreage across all FSA-reported corn (soybean) fields.

$$ME = \frac{\sum_i (FSA\ crop\ acreage_i - JAS\ crop\ acreage_i)}{n}$$

where $i =\ tracts$ and $n =\ number\ of\ tracts$.

3.2. Analysis of Speculative Region

Within the U.S., the crop forecasts for corn and soybeans are defined by law as speculative because these crops, among others, are traded on the commodity market. For each speculative crop, NASS identifies a speculative region composed of the top producing states. For this report, the assessment focused on the ten corn speculative region states and the eleven soybean speculative region states in the U.S. (see Figure 9). The corn and soybean speculative regions include Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Minnesota (MN), Missouri (MO), Nebraska (NE), Ohio (OH), and South Dakota (SD). The corn speculative region additionally includes Wisconsin (WI), and the soybean speculative region includes Arkansas (AR) and North Dakota (ND). For each analysis, this paper breaks down the review at the speculative region, non-speculative region, and all U.S. states.

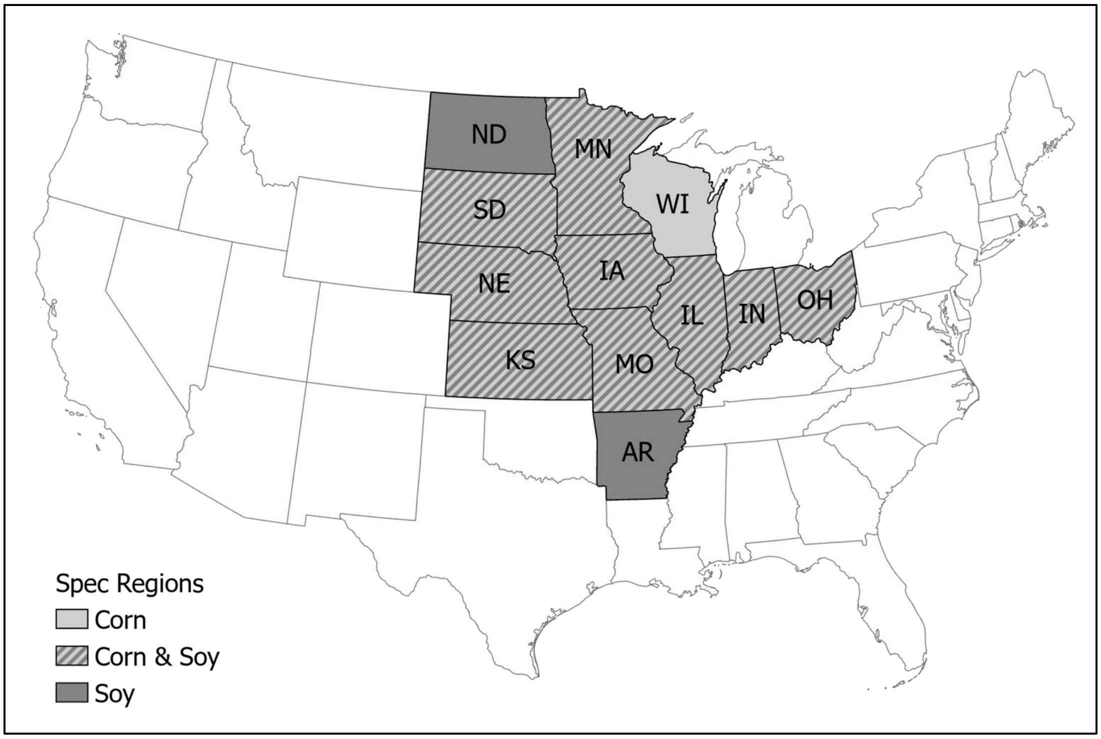

Figure 9. Top producing corn and soybean states in the U.S. – speculative region states.

3.3. Analysis of Data Quality

The data collection mode was entirely Paper Assisted Personal Interview (PAPI) in 2019, as had been the norm for over 50 years. In 2021, the data collection mode was entirely conducted by telephone, and interviewers either used Paper Assisted Telephone Interview (PATI) or Computer Assisted Telephone Interview on mobile device (mCATI) via a newly developed instrument. In 2022, interviewers were encouraged to use telephone interviews but were once again allowed to conduct personal interviews via PAPI or the new Computer Assisted Personal Interview on a mobile device (mCAPI).

Although primary interest here lies in the effects of data collection mode on response quality, the numerous changes made to the JAS survey process could have also affected the JAS data quality. The non-mode changes were introduced for the 2021 JAS and continued for the 2022 JAS. For comparisons of data quality between 2019 and 2021 or between 2019 and 2022, mode effects are confounded with other process changes implemented as well as any year effect. Comparisons between 2021 and 2022 also have a year effect, if any, but are not subject to confounding due to changes in the survey process. Additionally, 2021 and 2022 allow for comparisons of data quality between cases where paper questionnaires were used by interviewers and where computerized questionnaires on mobile device were used. The modes used over the three study years are summarized in Table 1.

Table 1. Breakdown of Survey Mode Used for Each Year

Mode\Year	2019	2021	2022
PAPI	100%		16%
PATI		78%	58%
mCAPI			5%
mCATI		22%	21%

As noted above, all unit and item nonresponse for tract-level data were imputed. Because reported data should be better than imputed data, it is important to assess how the change in modes and survey processes impacted the response rate. A logistic regression was fit using SAS's GLIMMIX procedure to assess whether the response rate differed significantly among the years or between the speculative (spec) and non-speculative (non-spec) regions, as well as the potential interaction between years and regions. All in-scope data were considered for this model. Given the heavy overlap of the two areas, the corn spec region and soybean spec region were combined into a single "combined spec region" for this model.

Additionally, two separate logistic regression models were fit to assess whether classification accuracy rates of corn or of soybeans differed significantly among years, between the respective spec and non-spec regions, or between reported data and imputed data, as well as the potential two-way interactions among these three covariates. The response variable indicated whether each JAS tract identified as having corn (soybeans) was planted to corn (soybeans) according to the corresponding FSA data.

3.4. Mode Impact on Crop Acreage Classification Accuracy

Two separate logistic regression models were fit to investigate the impact of survey response, survey mode, and tract characteristics on a JAS tract being correctly classified as corn or soybeans. The covariates considered in the corn and the soybean models are the same. Only the 2022 survey is considered here because this was the only year all four modes of data collection were available to the survey interviewers. The response variable is an indicator variable for correct classification. The main-effect covariates are as follows:

- *TractAcres* is the total number of acres of the JAS tract.
- *Stratum* is a categorical variable indicating expected degree of cultivation within a tract. Lower strata (e.g., strata 10 and 20) indicate higher levels of cultivation. Stratum 30 is reserved for areas with high urbanicity compared to undeveloped or agricultural lands. Stratum 40 represents areas of little to no cultivation.
- *SpecRegion* is an indicator variable of whether the tract resides in the crop speculative region.
- *Response* is an indicator variable of whether the tract data resulted from a full response.
- *Mode* is a categorical variable indicating the primary data collection mode used for the tract.

In addition, all two-way interactions were included. As before, the GLIMMIX function in SAS was used to estimate the coefficients for the above model.

4. Results

For the analysis of response rates, the interaction between year and region was not significant, indicating that the difference in spec and non-spec regions did not differ significantly with year. Compared to the 2019 pre-pandemic response rates, the response rates were significantly lower in 2021 ($p < 0.0001$) and 2022 ($p < 0.0001$) when, respectively, no and limited in-person interviews were conducted. However, the change in response rate was marginally significant between 2021 and 2022 ($p = 0.0827$). Further, the response rate was consistently significantly lower in the combined spec region than the rest of the country (see Figure 10). For this and other models, interpretation of model coefficients is under the assumption that all other variables are held constant. Additionally, the inverse-link transformation was applied to transform log odds to outcome probabilities for the purpose of easier interpretation.

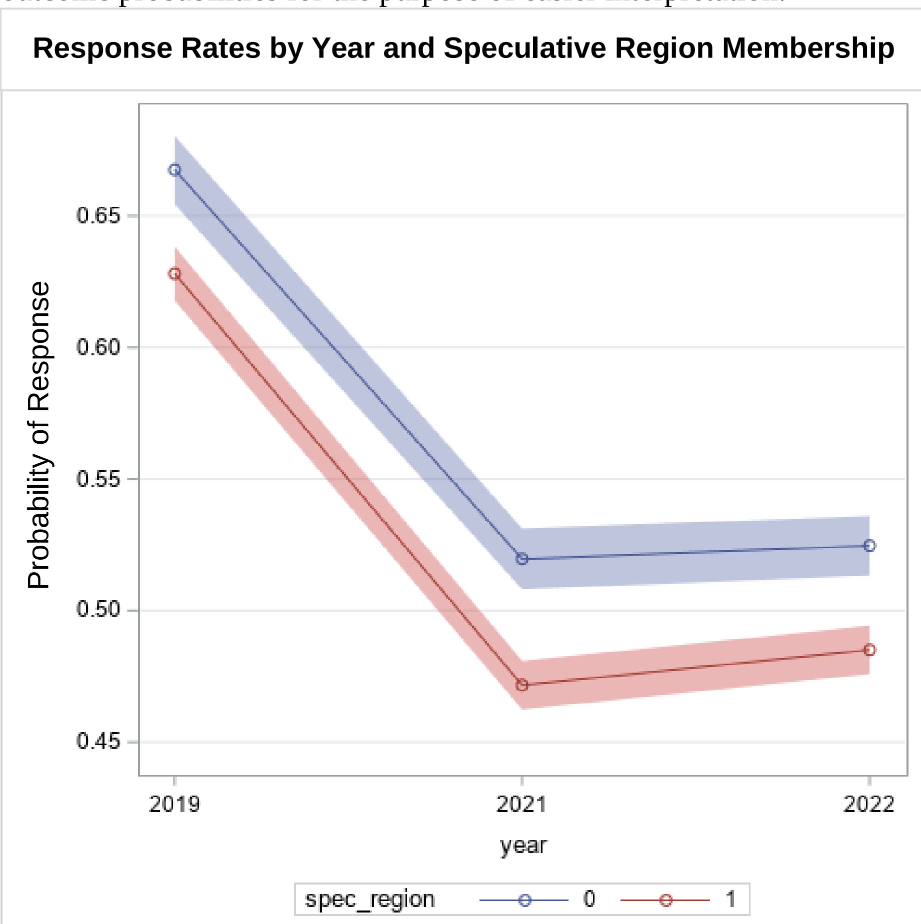

Figure 10. Estimated probability of response for the combined spec region (1) versus the non-spec region (0) for 2019, 2021, and 2022 with 95% confidence bands.

When assessing differences in classification accuracies across years, the results differed for corn and soybeans (see Figure 11). For corn, the interactions between year and response, year and region, and region and response were all significant. For soybeans, only the region and response interaction was significant. For corn, 2021 had a classification accuracy of 91.95%, which was significantly higher than either 2019 or 2022, though 2019 and 2022 were not significantly different from one another. However, all classification accuracies differed by less than 2%. For soybeans, only 2022 had significantly lower classification accuracy at 90.84%, and as was the case for corn, all years differed in accuracy by less than 2%. A broad summary of classification accuracies is provided in Table 2.

The significant interaction between year and corn spec region demonstrated that in 2019, records in the spec region had significantly lower corn classification accuracy than records in the non-spec states; however, 2021 and 2022 showed no significant difference in classification accuracy by spec region membership. While the interaction between soybean spec region and year was not significant for soybean classification accuracy, records in the soybean spec region consistently had significantly lower soybean classification accuracies for each year. The soybean classification accuracy across years among records in spec states was 89.82%, versus 92.5% for records in non-spec states.

For both corn and for soybeans, year over year, classification accuracy among response cases was significantly higher than for imputed cases.

For soybeans, among the response cases, the classification accuracies did not differ significantly between years, with the exception of 2019, which was significantly higher than 2022 ($p = 0.0485$). For corn classification accuracy, there was more variability by year and the interaction between response and years was significant. Still, no coherent pattern was apparent beyond the significantly higher classification accuracy for response cases.

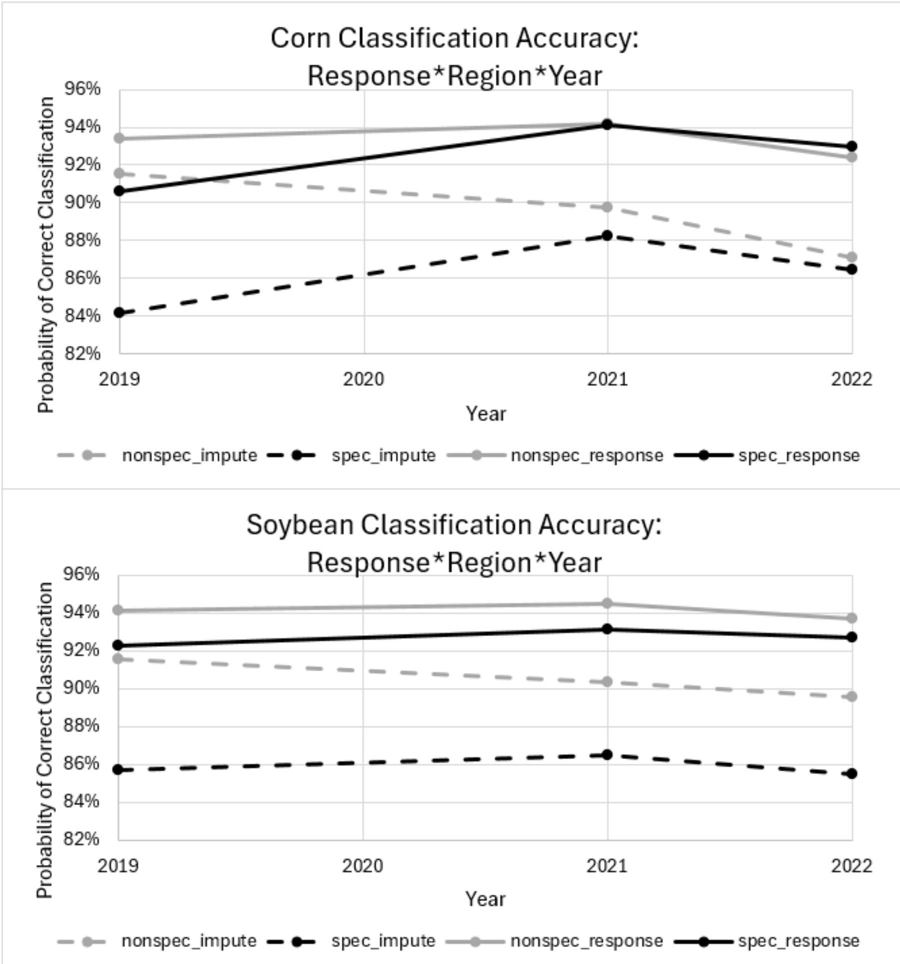

Figure 11. Corn (top) and soybean (bottom) classification accuracies for combinations of spec/non-spec regions and response/imputed across years.

For both corn and soybeans, there was a significant interaction between spec region membership and response. For both crops, imputed cases had lower accuracies than response cases, as expected; however, this difference was more pronounced among cases in the spec region than in non-spec states (Figure 12).

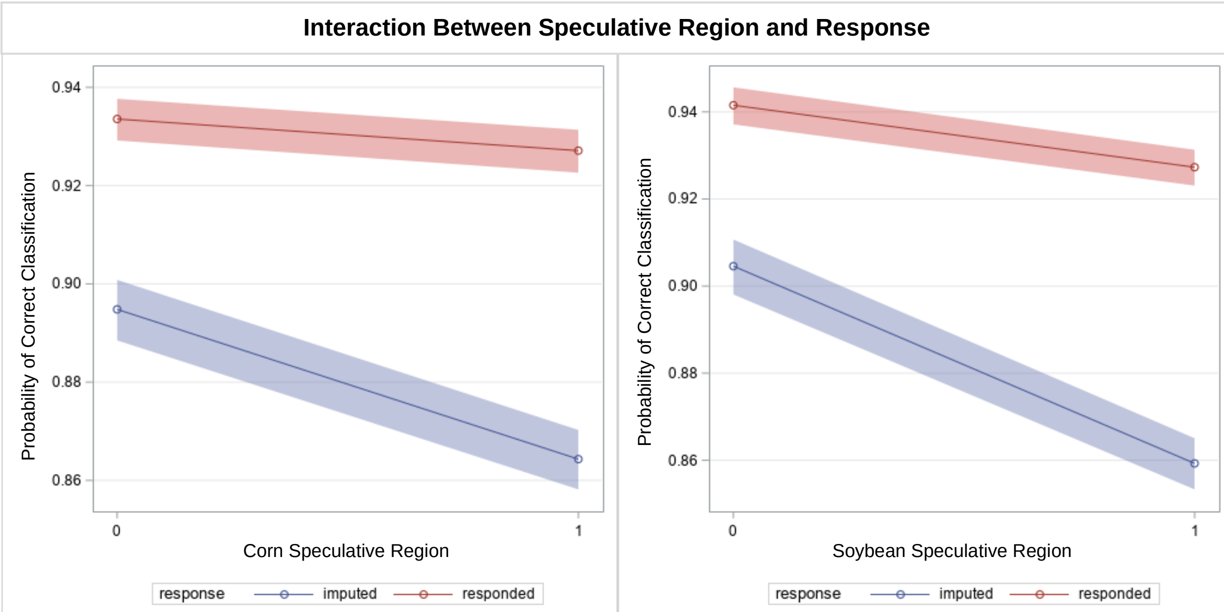

Figure 12. The probability of correct classification based on response/imputation by spec (1) and non-spec (0) region for corn (left) and soybeans (right).

Table 2. Classification Accuracy and Mean Error by Response for Corn and Soybean Planted Acres at the Tract Level

		Classification Accuracy				**Mean error (Acres)**			
		Corn		**Soybeans**		**Corn**		**Soybeans**	
	Region	Responded	Imputed	Responded	Imputed	Responded	Imputed	Responded	Imputed
2019	Spec States	90.5%	84.2%	92.2%	85.7%	4.16	7.63	2.31	5.20
	Non-spec States	93.4%	91.5%	94.3%	91.4%	1.59	1.42	0.52	0.51
	USA	91.9%	87.3%	93.0%	87.8%	2.93	4.99	1.57	3.47
2021	Spec States	94.1%	88.2%	93.1%	86.5%	-1.86	-0.88	0.34	0.98
	Non-spec States	94.2%	89.6%	94.5%	90.2%	-0.84	0.43	0.02	1.28
	USA	94.2%	88.9%	93.7%	87.9%	-1.36	-0.29	0.20	1.10
2022	Spec States	93.0%	86.4%	92.8%	85.4%	-1.30	-0.85	-0.60	3.09
	Non-spec States	92.4%	87.0%	93.6%	89.4%	-0.28	1.20	-0.67	2.06
	USA	92.7%	86.7%	93.1%	87.0%	-0.79	0.08	-0.63	2.68

Table 3. Classification Accuracy of Tract Planted Acreage by Mode

		Corn				Soybeans			
Year	**Region**	PAPI	PATI	mCAPI	mCATI	PAPI	PATI	mCAPI	mCATI
2019	Spec States	88.1%				89.7%			
	Non-spec States	92.8%				93.4%			
	USA	90.2%				91.2%			
2021	Spec States		91.7%		88.2%		90.3%		86.6%
	Non-spec States		92.4%		91.0%		93.2%		91.1%
	USA		92.0%		89.9%		91.4%		88.8%
2022	Spec States	90.6%	89.7%	84.6%	89.0%	90.4%	89.5%	83.0%	87.0%
	Non-spec States	89.6%	90.7%	86.4%	88.1%	90.9%	92.9%	88.8%	88.7%
	USA	90.4%	90.2%	85.3%	88.5%	90.5%	91.1%	84.9%	87.9%

Highlighted cells represent most used mode in that survey year and region.

A breakdown of classification accuracy by data collection mode and year, as well as by speculative region membership, is provided in Table 3. The highlighted cells indicate which data collection modes were most prevalent in the JAS datasets, with PAPI being most common in 2019 and PATI being most common for both 2021 and 2022. The final set of models (one for corn and the other for soybeans) explores the impact of *Mode* on classification accuracy in 2022; the potential effects of *TractAcres, Stratum, Response,* and *SpecRegion* and the interaction of *Mode* with these covariates are also evaluated. The full set of regression model parameters and interaction effects for both the corn and soybean models are shown in Tables 4 and 5, respectively.

Table 4. Logistic Regression Model Parameters (Corn Acreage)

Type III Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
TractAcres	3	18791	5.19	**0.0014**
Stratum	2	18791	5.08	**0.0062**
SpecRegion	1	18791	0.45	0.504
Response	1	18791	160.32	**<.0001**
Mode	3	18791	3.58	**0.0132**
TractAcres*Stratum	6	18791	2.87	**0.0085**
Stratum*Mode	6	18791	3.2	**0.0038**

Table 5. Logistic Regression Model Parameters (Soybean Acreage)

Type III Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
TractAcres	3	19218	8.11	**<.0001**
Stratum	2	19218	15.18	**<.0001**
SpecRegion	1	19218	14.34	**0.0002**
Response	1	19218	163.49	**<.0001**
Mode	3	19218	8.71	**<.0001**
TractAcres*Stratum	6	19218	4.23	**0.0003**
TractAcres*SpecRegion	3	19218	8.96	**<.0001**
Stratum*SpecRegion	2	19218	4.54	**0.0107**

For both the corn and soybean models, most main effects (*TractAcres*, *Stratum*, *Response*, and *Mode*) were highly significant (see Tables 4 and 5). For the soybean model, *SpecRegion* was also statistically significant. Reports resulting from the 2022 JAS survey responses were associated with significantly higher classification accuracies than reports resulting from some form of imputation. Tracts where data resulted from survey responses had an estimated 4.96% higher probability of correct corn acreage recorded than tracts with data resulting from some form of imputation, and 4.25% higher probability of correct soybeans acreage recorded than tracts with data resulting from some form of imputation. When comparing data collection modes, mobile-based modes had lower probabilities of correct crop acreage classification than paper-based modes. PAPI had 6.27% higher probability of correct corn acreage classification and 2.37% higher probability of correct soybean acreage than mCAPI. PATI had 5.52% higher probability of correct corn acreage classification and 2.5% higher the odds of correct soybean acreage than mCAPI. For soybean acreage, both PAPI and PATI had, respectively, 1.35% and 1.48% higher probabilities of correct classification than mCATI. Meanwhile, classification accuracy did not differ significantly between tract data collected using the traditional PAPI or PATI. For both crop types, as tract sizes increased, classification accuracies increased. Similarly, stratum 40, which represents land with little to no cultivation, had higher classification accuracies than the ag strata (10, 20), which have land with higher levels of cultivation, for both crops.

For the model investigating corn acreage classification accuracy, the interaction between stratum and tract acreage was significant. Although classification accuracies increased as tract sizes increased, this occurred more profoundly for stratum 40. The interaction between mode and stratum was also significant. Although accuracies across modes for both the ag strata (10, 20) were consistent, stratum 40 was reactive to different modes, showing the lowest accuracies for mCAPI and relatively higher accuracies for all other modes (see Figure 13).

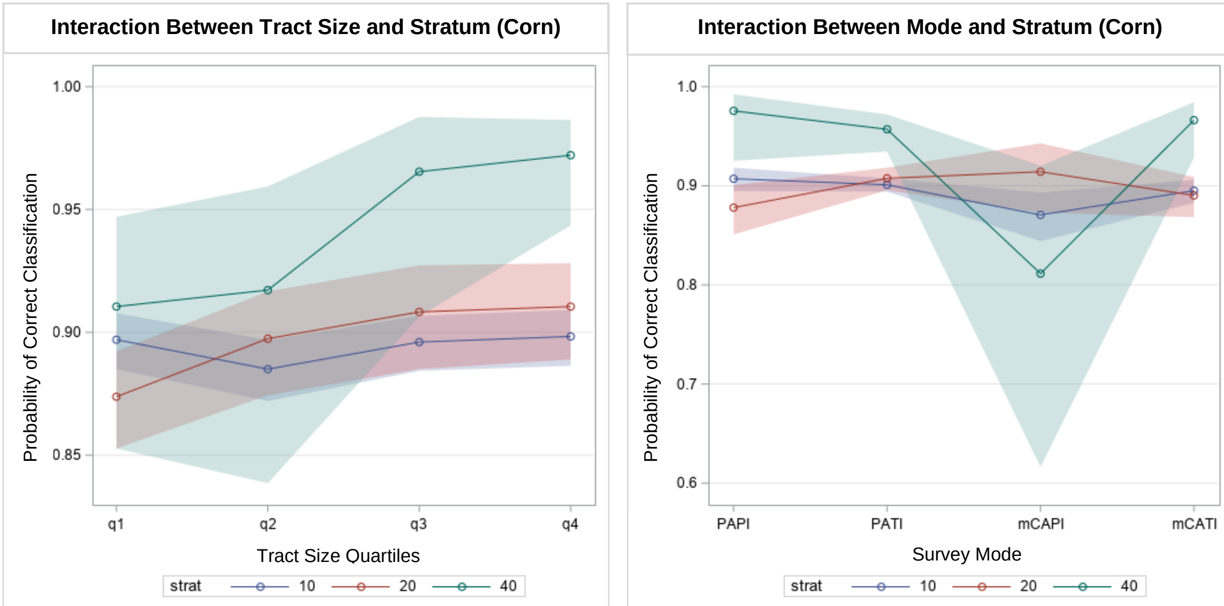

Figure 13. The probability of correct classification of tract-level corn acres based on stratum and tract size (left) and survey mode (right).

For the model investigating soybean acreage classification accuracy, the interaction between stratum and tract acreage was significant (see Figure 14). Although classification accuracies increased as tract sizes increased, this occurred more profoundly for stratum 40. Stratum 40 tracts also showed higher accuracies for low acreage tracts. The interactions between region and tract acreage, as well as between region and stratum were also significant (see Figure 15). In both cases, the non-spec region had higher accuracies, particularly as the acreage increased, as well as strata became less cultivated. This is again explained by the prevalence of tracts with no crop acreage in the larger, stratum 40 areas.

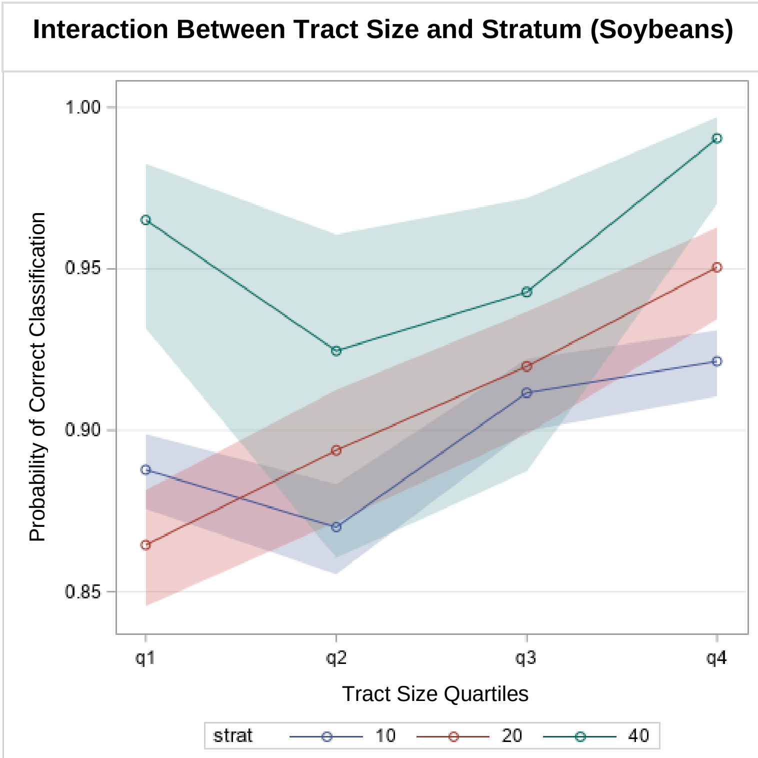

Figure 14. The probability of correct classification of tract-level soybean acres based on stratum and tract size.

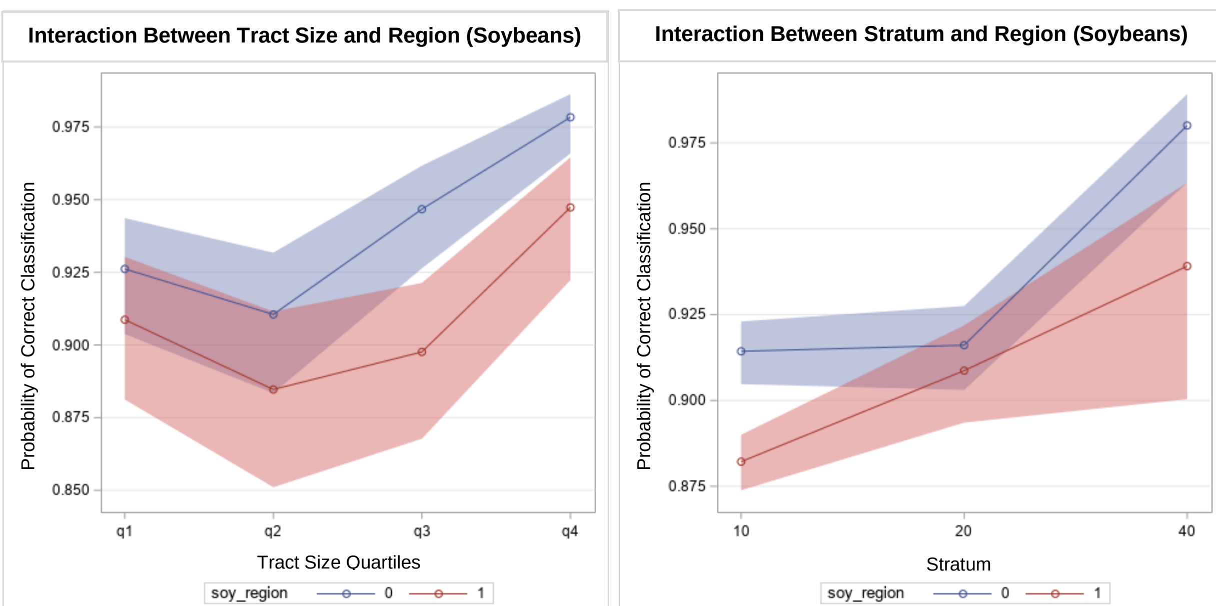

Figure 15. The probability of correct classification of tract-level soybean acres by spec (1) and non-spec (0) region and tract size (left) and stratum (right).

5. Conclusions and Discussion

Despite the limitations set forth by the COVID-19 pandemic, NASS successfully completed the JAS via telephone and mail in 2021 and subsequent years. The evaluation of the JAS shows data quality does not always suffer when shifting away from personal interviews in data collection; however, more nonresponse was observed. Nonresponse has been increasing for most of NASS surveys, and it is not evident how much of the change in the response rates was due to the changes in mode or how much is associated with a continuing downward trend.

Due to the shift in data collection modes, the cost of the JAS decreased substantially. Compared to 2019, the data collection costs of the JAS were roughly 61.5% in 2021 and 65.8% in 2022. Interviewers received substantial increases in their hourly wages in both 2021 and 2022; otherwise, the cost savings would have been greater. However, the proportion of imputed records was greater for 2021 and 2022 compared with 2019.

The use of non-survey data sources and innovative technological mechanisms led to the deployment of several analysis tools that helped improve the accuracy rates of the imputed values as compared to reported values. The effects of these new tools and the changes in data collection modes are confounded when comparing results across years. In discussing the effect of data collection modes, it is important to remember that the changes observed from 2019 to either 2021 or 2022 are at least partially affected by these new tools. Considering different cross sections of the data, the non-speculative regions for corn and soybeans are performing particularly well compared to the speculative regions. This can be attributed to the large occurrence of tracts in the non-speculative regions that simply have no planted corn or soybean acres, which is well reflected in both the survey data and the corresponding FSA data.

Some expected relationships, such as higher data quality in high-agricultural strata and among full survey responses, were observed for both corn and soybean models. Overall, the models indicated that telephone interviews performed well. Compared to the traditional PAPI, PATI was found to have similar classification quality, especially in the speculative states. The standout mode in terms of error was mCAPI, which was significantly associated with lower quality crop acreage recording. Even though mCAPI is in-person, the mobile instrument was new and may have caused more challenges for field interviewers than gains in streamlining the data collection process. Although all modes were available to the interviewers for data collection in 2022, the mCAPI option was elected the least often.

This study has shed light on the difficulty of fully capturing error resulting from the encoding of survey mode and survey response status. This is compounded by the plentiful partial-response cases. This was less of an issue in the era of JAS data collection before 2020 when the survey relied on a single data collection mode and imputation was more reliant on observation and previously reported survey data. Since then, proper reporting of data collection mode requires greater effort from interviewers and there are insufficient options on the JAS questionnaire to represent all imputation activities utilized. The new multi-modal paradigm for a survey increasingly relying on imputation warrants greater attention to measuring these characteristics of data collection to continue support of high-quality survey estimates and error reporting.

Like many organizations, NASS identifies the importance of balancing saving time and resources with the requirement to maintain overall quality of collected data, which is required to achieve the goal of publishing sound and reliable official estimates. The learning curve experienced during the COVID-19 pandemic led to the development of innovative tools, creative data collections methods, and intentional acquisition of high-quality administrative data that have managed to maintain survey data quality, particularly in major growing regions of large commodities.

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