## Appendix A.

## **Census of Agriculture Methodology**

The purpose of a census is to enumerate all objects with a defined characteristic. For the census of agriculture, that goal is to account for "any place from which \$1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year." To do this, NASS creates a Census Mail List (CML) of agricultural operations that potentially meet the farm definition, collects agricultural information from those operations, reviews the data, corrects or completes the requested information, and combines the data to provide information on the characteristics of farm operations and farm producers at the national, State, and county levels. In this appendix, these census processes are described.

#### THE CENSUS POPULATION

#### The Census Mail List

The National Agricultural Statistics Service (NASS) maintains a list of farmers and ranchers from which the CML is compiled. The goal is to build as complete a list as possible of agricultural places that meet the farm definition. The CML compilation begins with the list used to define sampling populations for NASS surveys conducted for the agricultural estimates program. Each record on the list includes name, address, telephone number, and email plus additional information that is used to efficiently administer the census of agriculture and agricultural estimates programs.

NASS builds and improves the list on an ongoing basis by obtaining outside source lists. Sources include State and federal government lists, producer association lists, seed grower lists, pesticide applicator lists, veterinarian lists, marketing association lists, and a variety of other agriculture-related lists. NASS also obtains special commodity lists to address specific list deficiencies. These outside source lists are matched to the NASS list using record linkage programs. Most names on newly acquired sources are already on the NASS list. Records not on the NASS list are treated as potential farms until NASS can confirm their existence as a qualifying farm. Staff in NASS regional and field offices routinely contact these potential farms to determine whether they meet the farm definition. For the 2022 Census of Agriculture, NASS made a concerted effort to work with community-based organizations not only to improve list coverage for

minorities but also to increase census awareness and participation.

List building activities for developing the 2022 CML started in 2019 by updating list information from respondents to the 2017 Census of Agriculture. Between 2017 and 2022, NASS conducted a series of National Agricultural Classification Surveys (NACS) on over 2.1 million records, which included nonrespondents from the 2017 census and newly added records from outside list sources. The NACS report forms collected information that was used to determine whether an operation met the farm definition. If the definition was met, the operation was added to the NASS list and subsequently to the CML. Addressees that were nonrespondents to a NACS were also added to the CML and identified with a special status code.

Measures were taken to improve name and address quality. Additional record linkage programs were run to detect and remove duplicate records both within each State and across States. List addresses were processed through software programs that utilize the United States Postal Service's National Change of Address System and the Locatable Address Conversion System to improve mail delivery. Records on the list with missing or invalid phone numbers were matched against a nationally available telephone database to obtain as many phone numbers as possible. To reduce costs, operations with characteristics that indicated they were unlikely to be farms, according to the farm definition, were removed from the list.

The official CML for the 2022 Census of Agriculture was established on September 3, 2022. The list contained 2,879,343 records. Of these, 2,079,333 records were thought to meet the NASS farm definition and 800,010 were potential farm records, which included NACS nonrespondents, other records added to the CML by the NASS regional field offices after the record linkage process, and late adds to the CML that were not included in any previous NACS or State screening survey.

#### Not on the Mail List (NML)

Extensive efforts are directed toward developing a CML that includes all farms in the U.S. However, some farms are not on the list, and some agricultural operations on the list are not farms. NASS uses its June Area Survey (JAS) to

quantify the number and types of farms not on the CML. The records in the JAS that are not on the CML are said to be in the Not-on-the-Mail List (NML) domain. If a JAS record in the NML domain is determined to be a farm during the census, it is an NML farm. The NML farms are used to measure coverage associated with the grown crops, farm numbers, and inventories of cattle. Sampled segments in the JAS are personally enumerated. Each operation identified within a segment boundary is known as a tract.

The 2022 JAS sample was increased to improve the farm counts for operations that produced specialty commodities or had socially disadvantaged or minority producers. The total JAS sample consisted of 14,015 segments of which 4,933 were additional ACES segments. This set of additional segments is referred to as the Agricultural Coverage Evaluation Survey (ACES) segments. The ACES segments were selected using a multivariate sampling design that targeted specific items at the U.S. level. The 2022 JAS consisted of sample segments from all States, with the exception of Alaska where NASS does not maintain an area frame.

During the JAS/ACES enumeration process, each tract is identified as either agricultural or non-agricultural. Each JAS/ACES agricultural tract is identified as a farm or nonfarm in June based on the farm definition of \$1,000 of sales or potential sales of agricultural products. Non-agricultural tracts are further classified into categories: with farm potential, with unknown farm potential, or with no farm potential. The names and addresses collected in the 2022 JAS/ACES were matched to the CML. Those from the 2022 JAS/ACES that did not match were determined to be in the NML domain and sent a yellow census report form so that they could be differentiated from the green report form sent to those addressees on the CML. Instructions on the census report form directed any respondent who received duplicate forms to complete the CML form and to mail all duplicate forms back together. Those who returned a CML and an NML form had been misclassified as NML and were removed from the NML domain.

The initial NML mailout consisted of 41,273 records. A total of 40,775 NML records were analyzed, of which 1,913 records were confirmed to be NML and in-scope.

The farm/nonfarm status of each NML domain operation was determined based on the reported data in the census form. An operation in the NML domain that was determined to be a farm is referred to as an NML farm. Characteristics of NML farms and their producers provided a measure of the undercoverage of farms present in the CML.

The percentage of farms not represented on the CML

varied by State. In general, NML farms tended to be small in acreage, production, and sales of agricultural products. Farm operations were missing from the CML for various reasons, including the possibility that the operation started after development of the CML, the operation was so small that it did not appear in any agriculture-related source list, or the operation was misclassified as a nonfarm prior to census mailout. The CML was used with the NML in a capture-recapture framework to represent all farming operations across all States in the JAS sample.

## DATA COLLECTION OUTREACH AND PROMOTIONAL EFFORTS

NASS planned and executed a multi-phase strategic communications campaign for the 2022 Census of Agriculture, to increase the level of awareness and response among all U.S. agricultural producers.

- Phase 1 ran from April 2021 June 2022. It raised awareness about the census and list building, encouraged producers to sign up in response to NASS mailings and at community, association, and other stakeholder meetings where NASS partners reached out.
- Phase 2 ran from July 2022 October 2022. It notified farm producers and agricultural organizations that the census would be mailed in November and encouraged communications regarding the census.
- Phase 3 ran from November 2022 May 2023. It focused on census data collection with messaging urging response to remind producers that it was not too late to respond.
- Phase 4 ran from August 2023 February 2024. It thanked producers for their participation and NASS partners for their support and informed everyone of the February 2024 data release plan.

The communications campaign focused on these primary areas: partnership building, local-level outreach, public relations, media relations, paid media, social media and some paid advertising. Some external support was provided by a private communications agency (i.e. primarily assisted with design and paid advertising).

The unifying force behind the 2022 communications campaign was the theme "Your Voice. Your Future. Your Opportunity." This was accompanied by supporting messages and artwork that created a consistent look and feel for all census communications. All messages and materials served the purpose of inspiring action: Sign Up to Be Counted - Show the Value of Your Work - *Grow Your* 

Farm Future - Shape Farm Policy/Programs - Respond to the Census of Agriculture - Be counted - The Census of Agriculture is Your Voice, Your Future, Your Opportunity.

#### Partnership and Local-Level Outreach

At the national level, NASS officials met with leaders from dozens of agricultural organizations, State Departments of Agriculture, and other USDA agencies to successfully secure their support in promoting the census among their constituencies. Stakeholders partnered with NASS to promote the 2022 Census of Agriculture through publications (e.g. newsletters), special mailings, speeches, social media, websites, and other communications. In addition, through grassroots-level outreach and efforts, NASS partnered with a number of community-based organizations to reach minority and limited-resource farmers and ranchers. National-level outreach was encouraged and mirrored at the regional, State, and local levels. Among the highlights of these partnership efforts was the production of multiple television and radio public service announcements featuring the U.S. Secretary of secretaries, Agriculture, State directors, and commissioners of agriculture and leaders from community-based organizations.

## **Coverage of American Indian and Alaska Native Farm Producers**

To maximize coverage of American Indian and Alaska Native agricultural producers, special procedures were followed in the census. A concerted effort was made to get individual reports from every American Indian and Alaska Native farm or ranch producer in the country. If this was not possible within some reservations, a single reservationlevel census report was obtained from knowledgeable reservation officials. These reports covered agricultural activity on the entire reservation. NASS staff reviewed these data and removed duplication with any data reported by American Indian or Alaska Native producers who responded on an individual census report form. Additionally, NASS obtained, from knowledgeable reservation officials, the count of American Indian and Alaska Native producers (on reservations) who were not counted through individual census report forms, but whose agricultural activity was included in the reservation-level report form.

Table D, American Indian and Alaska Native Producers: 2022 provides the number of producers (1) reported as American Indian or Alaska Native in the race category, either as a single race or in combination with other races, on the individual census report forms (for up to four per farm) and (2) identified as American Indian or Alaska Native producers farming on reservations by

reservation officials. The count from the individual report forms is summarized in the "Individually reported" column. It includes up to four producers on or off reservations. The "Other" column provides counts of producers on reservations as reported by a reservation or tribal official. The "Total" column is simply a sum of the "Individually reported" and the "Other" columns. Tables in other parts of the publication count the reservation-level reports as single farms.

#### **Public Relations**

In the public relations arena, NASS worked with internal and external, national, regional, and local stakeholders to equip them with communications tools and resources to deliver the census communications message to their audiences. NASS utilized its Intranet, the Partner Tools section on the census webpage, and a regularly scheduled, newsletter-type email update to deliver materials to staff across its 12 regions, other USDA agencies and external stakeholders. The materials included but were not limited to: customizable news releases, public announcement scripts, and a PowerPoint template; Secretary of Agriculture video public service announcements, and drop-in advertisements; informational, instructional, and testimonial videos; website buttons and banners; brochures in multiple languages; social media posts; flyers; posters; FAQ sheets, talking points, and more. In addition, at the national level, NASS issued six news releases during data collection (three more were produced before data collection to inform and prepare producers) citing department and agency spokespeople, published half a dozen timely and relevant pieces to the USDA blog highlighting the census, and conducted three social media campaigns. These public relations efforts at the national and local-levels helped ensure that NASS' message about the census was continually in the media, including print and online publications, a variety of social media, radio, and some television programs. Media outlets included both those specializing in agriculture and more general outlets.

#### Paid Media

With a very limited budget, NASS was able to apply a small portion of funds toward paid advertising. For the 2022 Census of Agriculture, NASS strategically advertised in regional print publications, online, and with national agriculture news services (i.e., TV, radio) to bolster reach both in general and within geographically specific, previously under-represented populations and lower response areas.

#### **DATA COLLECTION**

#### **Method of Enumeration**

Data collection was accomplished primarily by mail, Computer-Assisted Self Interview (CASI) on the Internet, and personal enumeration for special classes of records in operations. Personal the census enumeration (interviewing) involved the use of both Computer-Assisted Telephone Interview (CATI) and Computer-Assisted Personal Interview (CAPI) data collection instruments. Enumerators at the five NASS Data Collection Centers conducted CATI data collection. In addition, enumerators under contract with NASS through the National Association of State Departments of Agriculture (NASDA) conducted phone and personal interviews with respondents. For the 2022 Census of Agriculture, NASS implemented a pre-notification strategy to increase awareness, improve overall responses, and encourage respondents to report early to avoid continued correspondence. All records with an e-mail address received an e-mail message marketing the improved web form and announcing the census mail packets were coming.

### **Report Forms**

Four versions of report forms were used for the 2022 Census of Agriculture:

- General form (22 A100)
- Hawaii form (22 A101)
- American Indian form (22 A300)
- Farm Status form (22 A400)

The general form facilitated reporting crops and livestock most commonly grown and raised in the U.S. The short form expedited reporting specific crops or livestock for pre-identified farms and ranches in the U.S. The Hawaii form targeted crops and livestock specifically grown or raised on farms and ranches in Hawaii. The American Indian form focused on crops and livestock for farms and ranches on reservations in Arizona, New Mexico, and Utah. All report forms allowed respondents to write in specific commodities that were not prelisted on their report form.

## **Report Form Mailings**

Census data collection began on November 22, 2022. Nearly all producers on the CML received a letter inviting them to report online. They received a unique survey code and instructions for completing their census online. The letter encouraged producers to report online early to avoid receiving mail and phone follow-up. Approximately 3

million mail packets were mailed in December 2022. Each packet contained a cover letter, instruction sheet, a labeled report form, and a return envelope. The Census Bureau's National Processing Center (NPC) in Jeffersonville, IN was contracted to perform mail packet preparation, initial mailout, and two follow-up mailings to nonrespondents.

The initial mailout was followed by a thank-you reminder correspondence in January 2023. This pressure-sealed envelope reminded respondents of the approaching deadline and that they could report online. First follow-up mail packets were mailed in mid-February 2023 to approximately 1.5 million nonrespondents. Second follow-up mail packets were mailed in mid-March 2023 to approximately 1 million nonrespondents. A final mailing went to approximately 800,000 non-respondents. This mailing included a drastically reduced four-page questionnaire designed to primarily determine if the operation was a farm or not in business.

#### Nonresponse Follow-up

Operating concurrently with NPC's mail data collection efforts, NASS Data Collection Centers targeted selected groups of census nonrespondents for telephone enumeration. NASS regional field offices targeted selected groups of census nonrespondents for in-person enumeration. These efforts were referred to as:

- Must Case Follow-up
- American Indian Producer Follow-up
- National Nonresponse Follow-up
- Not on Mail List (NML) Follow-up

Must Case Follow-up. Must cases are known large or unique operations, the absence of which could have significantly affected the accuracy of census results. For the 2022 Census of Agriculture, 125,697 records were categorized as Must cases. Each active Must operation was accounted for by mail receipt, phone interview, or personal enumeration; if an operation was no longer in business, its nonfarm status was documented. Call centers conducted CATI calling of nonrespondent Must cases from March 2023 through May 2023, after the initial and first follow-up mailings. Following the CATI calling, the remaining nonresponse Must cases were assigned to regional field offices for personal enumeration. Because of the potential importance of Must cases, they were all accounted for and therefore not eligible for nonresponse weighting adjustment.

American Indian Producer Follow-up. The American Indian report form (22-A300) was mailed to all operations in Arizona, New Mexico and Utah thought to have an American Indian producer. It was included in the initial

mailout, but due to poor mail response, a personal enumeration data collection strategy was utilized with no additional mail follow-up. A concerted effort was made to get individual reports from every American Indian farm producer in the country. If this was not possible within a reservation, a single reservation-level census report was obtained from knowledgeable reservation officials. These reports covered agricultural activity on the entire reservation. NASS staff reviewed these data and removed any duplicate data reported by American Indian producers from that reservation who responded on an individual census report form. Additionally, NASS obtained, from knowledgeable reservation officials, the count of American Indian farm producers (on the reservations) who were not counted through individual census report forms, but whose agricultural activity was included in the reservation-level report form.

National Nonresponse Follow-up (Excludes Must Records). In April 2023, a group of records that were not part of other nonresponse data collection efforts were identified for additional phone contacts. In total, 82,237 records with specified demographics and/or eligibility for Census Special Studies (follow-ons) were made available for nonresponse Computer-Assisted Telephone Interviews (CATI).

Not-on-the-Mail List (NML) Follow-up. To account for farming operations not on the CML, NASS used its 2022 JAS sample from the NASS area frame, augmented with the ACES segments. Because the NASS area frame covers all land in the U.S. with the exception of Alaska, it includes all farms. As previously described, NASS conducted a record linkage operation between the CML records and the records from the 2022 JAS/ACES. Those 2022 JAS records that did not match records on the CML were designated as "Not-on-the-Mail List" (NML) records. These records were mailed a yellow census form so that it could be differentiated from the green forms mailed to CML records. The NML records were mailed at the same time as the census mailing and received the same follow-up procedures as the census mailing through the first followup in mid-February 2023. Beginning in March 2023, CATI was used for nonresponse follow-up for NML nonrespondents.

#### REPORT FORM PROCESSING

#### **Data Capture**

The Census Bureau's National Processing Center (NPC) in Jeffersonville, IN was contracted to process returned mail packets. NASS staff on site at the NPC provided technical guidance and monitored NPC processing activities. All report forms returned to the NPC were immediately

checked in, using bar codes printed on the mailing label, and removed from follow-up report form mailings. All forms with any data were scanned and an image was made of each page of a report form. Optical Mark Recognition (OMR) was used to capture categorical responses and to identify the other answer zones in which some type of mark was present.

Data entry operators keyed data from the scanned images using OMR results that highlighted the areas of the report forms with respondent entries. The keyer evaluated the contents and captured pertinent responses. Ten percent of the captured data were keyed a second time for quality control. If differences existed between the first keyed value and the second, an adjudicator handled resolution. The decision of the adjudicator was used to grade the performance of the keyers, who were required to maintain a certain accuracy level.

The images and the captured data were transferred to NASS's centralized network and became available to NASS analysts on a flow basis. The images were available for use in all stages of review.

## **Editing Data**

Captured data were processed through a computer formatting program that verified that records were valid – that the record ID number was on the list of census records, that the reported counties of operation and production were valid, and other related criteria. Rejected records were referred to analysts for correction. Accepted records were sent to a complex computer batch edit process. Each execution of the computer edit in batch mode consisted of records from only one State and flowed as the data were received from NPC, the NASS Computer-Assisted Self Interview (CASI), or the Computer-Assisted Telephone Interview (CATI) applications.

The computer edit determined whether a reporting operation met the qualifying criteria to be counted as a farm (in-scope). The edit examined each in-scope record for reasonableness and completeness and determined whether to accept the recorded value for each data item or take corrective action. Such corrective actions included removing erroneously reported values, replacing an unreasonable value with one consistent with other reported data, or providing a value for an item omitted by the respondent. To the extent possible, the computer edit determined a replacement value. Strategies determining replacement values are discussed in the next section. Operations failing to meet the qualifying criteria for being classified as a farm were categorized as out-ofscope for the census. Records that NASS had reason to believe might have been erroneously classified as out-ofscope (indications of recent and/or significant agricultural activity reported on NASS surveys, for example) were referred to analysts for verification.

The edit systematically checked reported data section-by-section with the overall objective of achieving an internally consistent and complete report. NASS subject-matter experts had previously defined the criteria for acceptable data. Problems that could not be resolved within the edit were referred to an analyst for intervention. Prior to the census mail-out, NASS established a group of analysts in a Census Editing Unit in the National Operations Center in St. Louis, MO who examined the scanned images, consulted additional sources of information, and determined an appropriate action. Regional field office analysts also participated using an interactive version of the edit program to submit corrected data and immediately re-edit the record to ensure a satisfactory solution.

## **Farm Status Form Editing**

From the CML, 883,732 records were selected to receive a Farm Status form as a final follow-up form; this form was derived from the full census report form by selecting a subset of the questions on the full form. Since these questions were also asked on the general form, the edit was able to treat the Farm Status form responses as though they were incomplete general forms, as described in the previous paragraphs.

## **Imputing Data**

The edit determined the best value to impute for reported responses that were deemed unreasonable and for required responses that were absent. If an item could not be calculated directly from other current responses, the edit determined whether acreage, production, or inventory items had been reported for that farm on a recent NASS crop or livestock survey. For producers who had not changed in five years, demographics such as race and gender were taken from the previous census. Administrative data from the Farm Service Agency were used for a few items, such as Conservation Reserve Program acreage. When deterministic edit logic and previously-reported data sources were unable to provide a current value, data from a reporting farm of similar type, size, and location were considered. In cases where automated imputation was unable to provide a consistent report, the record was referred to an analyst for resolution.

Separate system processes were established to efficiently provide data from a similar farm to the edit when donor imputation was required. The farm characteristics used to define similarity between a recipient record and its donor record were determined dynamically by the edit logic. Euclidean distance was used for similarity computations, with each contributing similarity characteristic scaled appropriately. The most similar farm based on this criterion (the "nearest neighbor") was identified and returned to the edit for use as a donor. The calculated distance between the centroids of the principal counties of production of the donor and recipient was always included as one of the measures of similarity.

To provide donors to the automated edit, a pool of successfully edited records was maintained for each section of the report form. These donor pools began with 2017 census data, reconfigured to emulate 2022 data and then edited using 2022 logic. Data from the 2020 Census Content Test were similarly remapped and edited before being added to the original donor pools. As 2022 records were successfully processed, they were added to the donor pools, which maintained the most recent data for each farm. Donor pools were updated approximately every other week, as determined by edit processing schedules. After several updates, all initial data records were dropped, leaving only 2022 records in the donor pools. After each update, donor pool records were grouped into strata containing farms in the same State of similar type and size, using a data-driven algorithm to define strata. Certain American Indian farms were treated as a separate group, effectively having their own donor pool.

In response to each donor request issued by the edit, a dedicated system process would search the appropriate stratum and respond with the most similar donor, while giving preference to more recent donors. In relatively rare instances where it was unable to provide a donor, the donor selection process issued an appropriate failure message to the edit. Imputation failures occurred for several different reasons. The requirement that an imputed value be positive could have ruled out all available donors, as could have the necessity for the donor record to satisfy a particular constraint - say, that the donor record has cattle, but no milk cows. In general, an imputation failure occurred if there were no satisfactory donors in the same profile as the report being edited. Records with imputation failures were either held until more records were available in the donor pool or referred to an analyst. In addition, when such a failure occurred in finding a donor for expenditure data, donor pool averages were provided in lieu of an individual donor, wherever possible. This "failover" utility was first introduced for the 2012 census imputation process, and significantly reduced the number of imputation failures among the expenditure and labor variables. During the early stages of editing, records requiring imputation for production (and hence yields) of field crops or hay, land values, or certain expenditure variables, were set aside or "parked." These records were edited when the donor pools contained only 2022 records, ensuring that 2022 data were used in the imputations for the variables.

After receiving a donor's data, the edit substituted the values into the edited record. In many cases, the donor record's data value was scaled using another data field specified in the edit logic. In such cases, the size of the auxiliary field's value in the edited record, relative to its value in the donor record, was used to appropriately scale the donor record's value for the field to be imputed. The imputed data were then validated by the same edit logic to which reported data were subject. Since imputation was conducted independently for each occurrence, reports requiring multiple imputations may have drawn from multiple donors.

As was done for the 2017 Census, for records reporting three or more persons as producers, a different imputation process was used for certain items (specifically the items in question 3) in the Personal Characteristics Section. Records with one or two persons reported as producers had these data edited and imputed using the decision logic table edit and donor pool imputation process. Records with three or more persons reported as producers, and for which it was determined that these data were inconsistent or missing, had these data imputed using a fully conditional specification method. During the edit for records reporting three or more producers, the items needing imputation were marked, and the record was flagged. At the end of the data collection period, the data for these records (both the items needing to be imputed and the other variables needed by the model) were pulled and run through the imputation program. The resulting imputed values were loaded back to the records, and the records were made available for review.

#### **Data Analysis**

The complex edit ensured the full internal consistency of the record. Successfully completing the edit did not provide insight as to whether the report was reasonable compared to other reports in the county. Analysts were provided an additional set of tools, in the form of listings and graphs, to review record-level data across farms. These examinations revealed extreme outliers, large and small, or unique data distribution patterns that were possibly a result of reporting, recording, or handling errors. Potential problems were investigated and, when necessary, corrections were made, and the record interactively edited again.

When NASS summarizes data from the census of agriculture, each individual report is typically assigned to a single "principal" county. The principal county is the county in which the majority of an operation's agricultural

products are produced, as reported by the producer. For large operations that have significant production in multiple counties, their reports may be broken up into multiple source counties to more accurately summarize the data. Similarly, for large farms operating in more than one State, separate report forms are completed by State in order to assign the proper portion of the farm's total agricultural production to each State in which the farm operates.

## ACCOUNTING FOR UNDERCOVERAGE, NONRESPONSE, AND MISCLASSIFICATION

Although much effort has been expended making the CML as complete and accurate as possible, it does not include all U.S. farm operations, resulting in list undercoverage. Additionally, some farm operations on the CML did not respond to the census, despite numerous contact attempts. Finally, although each operation was classified as a farm or a nonfarm based on their census responses, some were misclassified; that is, some nonfarms were classified as farms and some farms were classified as nonfarms. NASS's goal is to produce agricultural census totals for publication at the county level that are fully adjusted for these factors: list undercoverage, nonresponse, and misclassification.

In 2017, NASS used a series of models based on a subset of the responding census and all the JAS records in a captureframework separately adjust recapture to undercoverage, nonresponse, and misclassification. For the 2022 Census of Agriculture, the capture-recapture methodology was extended to model the probability of capture with a single model, thereby allowing the utilization of all census responses and JAS records in the adjustments. To implement capture-recapture methods, two independent samples are required. The 2022 Census of Agriculture (based on the CML) and the 2022 JAS (based on the area frame) were those two samples. Historically, NASS has been careful to maintain the independence of the CML and the area frame. Thus, the Census of Agriculture and the JAS were assumed to be independent after accounting for heterogeneity in the capture probabilities based on characteristics of records.

For a farm to be identified as a farm, and thus captured by the census, it must be on the CML, respond to the census report form, and be classified as a farm on the form. Thus, the capture probability  $\pi_C$  is of interest:

 $\pi_{\rm C} = \pi({\rm CML, Responded, Farm on Census|Farm})$ 

Two types of classification error can occur. First, a farm can be misclassified as a nonfarm. This type of misclassification is accounted for in determining the probability of capture  $\pi_C$ . The second type of classification error results when a response to the census is classified as a farm operation when it does not meet the definition of a farm. That is, some farms on the CML may be misclassified from their census report response and may be nonfarms. To account for the misclassification of nonfarms as farms, the probability of a farm on the census being classified correctly must be estimated; that is,

 $\pi_{CCFC} = \pi(Farm \mid Farm \text{ on Census})$ 

where *CCFC* represents Correct Census Farm Classification. To adjust for undercoverage, nonresponse, and misclassification, each CML record classified as a farm based on its response to the census report form was given a weight of the ratio of the estimated probability of correct classification of a farm on the census and the estimated probability of capture  $(\hat{\pi}_{CCFC}/\hat{\pi}_{C})$  where the hat symbol (^) denotes an estimate). To estimate the number of farms with a given set of characteristics, the weights of CML records responding as farms on the census and having that set of characteristics were summed.

This estimator is referred to as the capture-recapture estimator (CR):

$$CR = \sum_{i \in F} \frac{\hat{\pi}_{CCFC,i}}{\hat{\pi}_{C.i}}$$

where F is the set of all CML records classified as farms based on their responses to the census report form.

To estimate these probabilities  $(\hat{\pi}_c \text{ and } \hat{\pi}_{cCFC})$ , the records in the 2022 JAS sample were matched to the 2022 CML using probabilistic record linkage allowing the records only on the CML, JAS, and on both the CML and JAS to be identified. All CML records and JAS tracts were used to estimate the capture-recapture probabilities jointly.

## **Resolving Farm Status**

The farm status based on census responses to either the CML or NML census data collection and the response on the JAS agreed in most cases; these records are referred to as having resolved farm status. However, in other cases, a record was identified as a farm (nonfarm) on the JAS and as a nonfarm (farm) on the CML or the NML. Such records are said to have conflicting or unresolved farm status. An operation identified as a farm is referred to as in-scope; an operation identified as a nonfarm is referred to as out-of-scope. From the set of matched records, two groups with conflicting farm status were identified: 1) in-scope JAS records that were out-of-scope on the census and 2) census in-scope and JAS out-of-scope records. The records with conflicting farm status were sent to NASS regional field offices for review. In each case, efforts were made to

determine whether (1) the status had changed between June and December when the census was conducted, (2) the JAS farm status was correct, (3) the census farm status was correct, (4) the records were incorrectly matched, or (5) the farm status could not be resolved.

The probability that an operation is a farm was estimated for census and JAS by using a conditional logistic model. Only those records identified as a farm based on either their JAS response or their Census response were used to develop the model for estimating the probability a record is associated with a farm. Operations with matching farm status were considered as certain if the farm status agreed between the JAS and the CML. If the status between the JAS and CML was conflicting, then the operation was treated as uncertain during the modeling stages. Characteristics of the operations were considered as potential covariates in the model. Variable selection was conducted using a stepwise algorithm to maximize the conditional likelihood. The probability of being a farm is estimated for each record classified as a farm based on their JAS or census response. The estimated probability is used as a weight in all subsequent modeling.

## **Capture Probabilities**

Recall that, for a farm to be identified as a farm, and thus captured, by the census, it must be on the CML, respond to either the census or JAS report form and, based on that response, be classified as a farm. Therefore, the probability of capture  $\pi_C$  may be written as

 $\pi_C = \pi(\text{CML}, \text{Responded}, \text{Farm on Census}|\text{Farm})$ =  $\pi(\text{CML}|\text{Farm})\pi(\text{Responded}|\text{CML}, \text{Farm})\pi(\text{Farm on Census}|\text{CML}, \text{Responded}, \text{Farm})$ 

Terms in the probability of capturing a farm depend on characteristics of the farm. These terms, as well as the corresponding terms associated with a farm being captured by the JAS, were jointly estimated from a single model. Using all Census and JAS data, model variables were selected by applying a stepwise variable selection algorithm and expert opinion. Estimation was based on a conditional weighted likelihood. The events of a farm being included in the CML, the JAS or both were included in the likelihood. The event of a farm not being included in either the JAS or the CML was excluded from the likelihood but was accounted for through the model's capture-recapture properties. Although the probability of capture is estimated for both CML and JAS records, only CML records with a census response are given a census weight; records with only a JAS response are not given a census weight or used further to produce census estimates.

Because Alaska is not included in the JAS and thus has no area frame, the Alaskan agricultural operations were not

included in the capture-recapture process. No adjustments were made for undercoverage or misclassification. To account for nonresponse, the CML records were divided into three groups: (1) the Must records, (2) the Criteria Records, and (3) the remaining CML records. The must records received a weight of one, thereby receiving no adjustment for nonresponse. The probability of response for each of the other two groups was the proportion of responders within the group. Each record within the group was then given a weight equal to the reciprocal of the probability of response.

### **Misclassification**

An operation is misclassified if: (1) it meets the definition of a farm but is classified as a nonfarm on the census or (2) it does not meet the definition of a farm but is classified as a farm on the census. The first type of misclassification is accounted for when modeling the probability of capture. An adjustment is still needed for the misclassification of nonfarms as farms. As with farm status and capture, the probability of this misclassification depends on an operation's characteristics. Thus, a conditional logistic model was developed. Given that a farm on the CML was classified as a farm in the census, the probability of its being a farm was modeled based on its characteristics.

#### **CALIBRATION**

Each operation identified as being in-scope on the CML was given a weight equal to the probability of misclassifying a nonfarm as a farm on the census divided by the probability of capture. This weight accounted for undercoverage, nonresponse, and both types of misclassification.

The record weighting processes were initially applied at the State level to produce adjusted estimates of farm numbers, land in farms, and for 64 different categories of characteristics of the farm operation or the farm producer-value of agricultural sales (10); age (2); female; race (3); Hispanic origin; 4 sales categories for each of 10 major commodities (40); and farm type groups (7). The Statelevel number of farms and land in farms were two additional adjusted estimates, resulting in 66 categories. To reduce the intercensal variation at the State level, the State targets were smoothed by averaging the 2022 estimates from capture-recapture and the published 2017 State estimates.

These State estimates were general purpose in that they did not provide any control over expected levels of commodity production of the individual farm operation. As a result of this limitation, the procedures could have over-adjusted or under-adjusted for commodity production. To address this, a second set of variables, known as commodity targets, was added to the calibration algorithm. These targets were commodity totals from administrative sources or from NASS surveys of nonfarm populations (e.g., USDA Farm Service Agency program data, Agricultural Marketing Service market orders, livestock slaughter data, cotton ginning data). The introduction of these commodity coverage targets strengthened the overall adjustment procedure by ensuring that major commodity totals remained within reasonable bounds of established benchmarks.

Each State was calibrated separately. The calibration algorithm addressed commodity coverage. The algorithm was controlled by the 65 State farm operation coverage targets and the State commodity coverage targets. Because calibration targets are estimates subject to uncertainty, NASS allowed some tolerance in the determination of the adjusted weights. Rather than forcing the total for each calibration variable computed using the adjusted weights to equal a specific amount, NASS allowed the estimated total to fall within a tolerance range.

To ensure that all subdomains for which NASS publishes summed to their grand total, integer weights were produced by a discrete calibration algorithm. This eliminated the need for rounding individual cell values and ensured that marginal totals always added correctly to the grand total. If a weight was initially not in the interval [1,6], it was trimmed so that it was in that interval. That is, adjusted weights less than 1 were set to 1, and those greater than 6 were set to 6. The remaining non-integer weights were then rounded sequentially to reduce the distance of the estimated totals from the targets.

Calibration adjustments began with the computation of a priority index for each record. The priority index was the absolute value of the gradient of the relative error associated with increasing or decreasing a record's weight by one. The record with the highest priority index was then selected as a candidate to increase or decrease its weight by one to reduce the cumulative distance from the targets as measured by the relative error. If the new value produced an improvement and satisfied the range restrictions, the weight was updated and new priorities were assigned; otherwise, the record with the next highest priority index was processed. This process was iteratively performed until convergence was attained. Because census data collection was assumed to be complete for very large and unique farms, their weights were set to 1 during the calibration adjustment process. For all other farms, the final census record weights were forced to be an integer number in the interval [1, 6]. The calibration process considered all targets simultaneously through the priority index. Although calibration was seldom able to adjust weights so that all State targets were met, all targets were brought collectively as close to the targets as possible.

The proportions of selected census data items that were due to coverage, response, and classification adjustments are displayed in Tables A and C.

#### **DISCLOSURE REVIEW**

After tabulation and review of the aggregates, a comprehensive disclosure review was conducted. NASS is obligated to withhold, under Title 7, U.S. Code, any total that would reveal an individual's information or allow it to be closely estimated by the public. Farm counts are not considered sensitive and are not subject to disclosure controls. Cell suppression was used to protect the cells that were determined to be sensitive to a disclosure of information.

Based on agency standards, data cells were determined to be sensitive to a disclosure of information if they failed either of two rules. The threshold rule failed if the data cell contained less than three operations. For example, if only one farmer produced turkeys in a county, NASS could not publish the county total for turkey inventory without disclosing that individual's information. The dominance rule failed if the distribution of the data within the cell allowed a data user to estimate any respondent's data too closely. For example, if there are many farmers producing turkeys in a county and some of them were large enough to dominate the cell total, NASS could not publish the county total for turkey inventory without risking disclosing an individual respondent's data. In both ofthese situations, the data were suppressed and a "(D)" was placed in the cell in the census publication table. These data cells are referred to as primary suppressions.

Since most items were summed to marginal totals, primary suppressions within these summation relationships were protected by ensuring that there were additional suppressions within the linear relationship that provided adequate protection for the primary. A detailed computer routine selected additional data cells for suppression to ensure all primary suppressions were properly protected. These data cells are referred to as complementary suppressions. These cells are not themselves sensitive to a disclosure of information but were suppressed to protect other primary suppressions. A "(D)" was also placed in the cell of the census publication table to indicate a complementary suppression. A data user cannot determine whether a cell with a (D) represents a primary or a complementary suppression.

Regional field office analysts reviewed all complementary suppressions to ensure no cells had been withheld that were vital to the data users. In instances where complementary suppressions were deemed critically important to a State or county, analysts requested an override, and a different complementary cell was chosen.

#### **CENSUS QUALITY**

The purpose of the census of agriculture is to account for "any place from which \$1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year." To accomplish this, NASS develops a CML that contains identifying information for operations that have an indication of meeting the census definition, develops procedures to collect agricultural information from those records, establishes criteria for analyst review of the data, creates computer routines to correct or complete the requested information, and provides census estimates of the characteristics of farms and farm producers with associated measures of uncertainty.

It is not likely that either the CML includes all operations that meet the definition of a farm or that all those that do meet the definition of a farm respond to the census inquiry. The goal is to publish data with a high level of quality. The quality of a census may be measured in many ways. One of the first indicators used is a measure of the response to the census data collection as it has generally been thought that a high response rate indicates more complete coverage of the population of interest. This is a valid assumption if the enumeration list, the CML here, has complete coverage of the population of interest. In the case of the census of agriculture, the definition requiring advance knowledge of sales makes achieving a high level of coverage difficult. To ensure that the census of agriculture is as complete as possible, records are included that might not meet the census definition of a farm – in fact, almost 50 percent more records than the anticipated number of qualifying farm operations were included in the 2022 CML. A second indicator of quality then is the coverage of the farm population by the CML. Other indicators of quality relate to the accuracy and completeness of the data, and the validity of the procedures used in processing the data.

In some cases, NASS was able to produce measures of quality – such as the response rate to the data collection, the coverage of the census mail list, and the variability of the final adjusted estimates. In other cases, measures were not produced but descriptions of procedures that NASS used to reduce errors from the procedures were subsequently provided.

#### **Census Response Rate**

The response rate is one indicator of the quality of a data

collection. It is generally assumed that if a response rate is close to a full participation level of 100 percent, the potential for nonresponse bias is small, although this has been questioned in the literature. The response rate for the 2022 Census of Agriculture CML was 61.0 percent, as compared with the 2017 Census of Agriculture's response rate of 71.8 percent and 74.6 percent for the 2012 Census of Agriculture.

The 2022 Census of Agriculture's response rate used the fourth response rate formula (RR4) from the American Association of Public Opinion Research's Response Rate Standard Definitions manual:

$$RR4 = \frac{C_{adj}}{C_{adj} + R + NC + O + Replicated + e(U)} (100)$$

where

 $C_{adj}$  = number of fully and partially completed records, excluding replicated records

R = number of explicit refusals

NC = number of non-contacted operations known to be eligible

O = number of other types of nonrespondents *Replicated* = number of replicated records U = number of operations of unknown eligibility e(U) = estimated number of operations of unknown eligibility assumed to be eligible

Records were classified into the above variables based on the combination of their active status (AS) codes, in-scope status, and replication status. Active status refers to the eligibility status of records for selection on the CML. All replicated records were considered a form of nonresponse and were classified into other nonrespondents; in-scope status was considered immaterial.

Certain active status classifications indicated records of unknown agricultural status. These classifications included records to be removed from the CML but had data from outside sources indicating agricultural activity, new records from outside data sources, nonrespondents and refusals to the NACS, records for regional office handling only, and records with Farm Service Agency or Conservation Reserve Program data on operations that are not owned by the principal producer. These records were stratified (grouped) based on their probabilities of being inscope had they responded. The estimated number of inscope nonrespondents was calculated for the hth stratum (group) by the following formula:

$$e(U_h) = \left(\frac{C_{in-scope,h}}{C_h}\right) U_h$$

where

 $e(U_h)$  = estimated number of operations of unknown eligibility assumed to be eligible in the hth group  $C_{in\text{-}scope,h}$  = the number of completed and in-scope census records in the hth group

 $C_h$  = the number of completed census records in the hth group

 $U_h$  = number of operations of unknown eligibility in the hth group

## **Census Coverage**

As a side-product of the statistical adjustment used to account for undercoverage, nonresponse of farms on the CML, and misclassification of responses to the census, the proportion of the adjustments due to each of those factors can be derived. The percentage of final census estimates due to adjustments for undercoverage, nonresponse, and misclassification as well as the total percent adjustment for selected items are displayed in Tables A and C.

#### MEASURED ERRORS IN THE CENSUS PROCESS

NASS uses statistical procedures in compiling the CML, in its data collection procedures, in data editing and processing, and in compiling the final data. Additionally, it uses statistical procedures to both measure errors in the various processes when adjusting for those errors in the final data. One example is the statistical process used to account for undercoverage, nonresponse of farms on the CML, and misclassification of responses to the census. The basis of the undercoverage adjustment is the capturerecapture procedure that uses the area sample enumeration from the JAS. The largest contributors to error in the census estimates are due to the adjustments for undercoverage, misclassification, nonresponse, integer calibration.

## Variability in Census Estimates due to Statistical **Adjustment**

In conducting the 2022 Census of Agriculture, efforts were initiated to measure error associated with the adjustments for farm operations that were not on the CML; for farm operations that were on the CML but did not respond to the census report form; for farms and nonfarms that were misclassified as nonfarms and farms, respectively; and for integer calibration. These error measurements were developed from the standard error of the estimates at the national, State, and county levels and were expressed as coefficients of variation (CVs) at the national and State levels and as generalized coefficients of variation (GCVs) at the county levels.

The standard error of an estimate is an estimate of the

standard deviation of the sampling distribution of the estimator. In each case, standard errors were computed using an approach based on a delete-a-group jackknife methodology. To conduct the jackknifing, k = 10 mutually exclusive and exhaustive groups of records were formed. The groups were selected using a stratified random design so that each group reflected capture status by the CML and the JAS. Based on estimated weights for records in each group, a delete-a-group jackknife estimator of the variance would account for the uncertainty associated with modeling the capture-recapture probabilities and the uncertainty due to integer calibration. Therefore, the weights within each jackknife group were computed using the group-specific models and calibrated to match groupspecific targets. For a given data item *i*, such as the number of farms, the estimate was computed at the specified geographical level, such as nation, State, or county, using the weights obtained for group *j*. Estimates of the variance and standard error associated with the estimator  $T_i$  are then, respectively.

$$\sigma_i^2 = \frac{k-1}{k} \sum_{j=1}^k \left( T_i^{(j)} - \sum_{l=1}^k \frac{T_i^{(l)}}{k} \right)^2; \quad SE(T_i) = \sqrt{\sigma_i^2}$$

Ten (10) calibration-adjusted jackknife groups were used to provide standard errors for 2022 State and national estimates (i.e., k=10). For the estimate of the number of farms with a given set of characteristics, only the CML records with those characteristics were used to obtain the overall estimate as well as the estimates from each calibrated jackknife group.

Note that the calibrated jackknife groups were only constructed once, and different subsets of the records were used to compute estimates and standard errors for the data items.

The CV is a measure of the relative amount of error associated with the sample estimate:

$$CV_i = \frac{SE(T_i)}{T_i} 100\%$$

where  $SE(T_i)$  is the standard error of the capture-recapture estimate for data item i. This relative measure allows the reliability of a range of estimates to be compared. For example, the standard error is often larger for large population estimates than for small population estimates, but the large population estimates may have a smaller CV, indicating a more reliable estimate. For county-level estimates, a generalized coefficient of variation (GCV) was determined for each estimate within a State. A generalized variance function relates a function of the variance of an estimator to a function of the estimator.

Within a State, the standard error of an estimate for a data item was often found to be linearly related to the estimate of that item with an intercept of zero. Based on this modeled relationship, the GCV is the slope of the line relating the standard error to the estimate, multiplied times 100 to represent the GCV as a percentage.

The standard error is the product of the CV (or GCV for county estimates) and the estimate divided by 100. As an example, if the GCV for a State is 25 percent and a county's estimate is 4, then the standard error is 25(4)/100 = 1. The standard error of an estimated data item from the census provides a measure of the uncertainty associated with that estimated data item due to the possible outcomes of the census collection, including incompleteness of the CML, nonresponse to the census, misclassification either as a farm or as a nonfarm, and the integer calibration. With 95 percent confidence, an estimate is within two standard errors of the true value being estimated. For this example, with 95 percent confidence, the estimate of 4 is within 2(1) = 2 of the true county value.

Note: The standard errors and consequently, the CVs tend to be substantially smaller than those reported for the 2017 Census of Agriculture. For 2017, the model of the probability of capture incorporated information from the approximately 40,000 respondents to the 2017 JAS and the census records matching a JAS record. In contrast, the models for the 2022 Census of Agriculture relied on information from the approximately 1 million responding CML records and the 2022 JAS, some of which were on both the CML and the JAS. The large increase in the number of records used in the modeling process led to a major decrease in the measures of uncertainty (standard errors and CVs).

Table B presents the fully adjusted estimates with the coefficient of variation for selected items.

# NONMEASURED ERRORS IN THE CENSUS PROCESS

As noted in the previous section, errors can be introduced from adjustments for coverage, nonresponse, and misclassification and from integer calibration. These errors are measurable. However, nonsampling errors are imbedded in the census process that cannot be directly measured as part of the design of the census but must be contained to ensure an accurate count. Extensive efforts were made to compile a complete and accurate mail list for the census, to elicit response to the census, to design an understandable report form with clear instructions, to minimize processing errors through the use of quality control measures, to reduce matching error associated with the capture-recapture estimation process, and to minimize

error associated with identification of a respondent as a farm operation (referred to as classification error). The weight adjustment and tabulation processes recognize the presence of nonsampling errors; however, it is assumed that these errors are small and that, in total, the net effect is zero. In other words, the positive errors cancel the negative errors.

## **Respondent and Enumerator Error**

Incorrect or incomplete responses to the census report form or to the questions posed by an enumerator can introduce error into the census data. Steps were taken in the design and execution of the Census of Agriculture to reduce errors from respondent reporting. Poor instructions and ambiguous definitions lead to misreporting. Respondents may not remember accurately, may estimate responses, or may record an item in the wrong cell. To reduce reporting and recording errors, the report form was tested prior to the census using industry-accepted cognitive testing procedures. Detailed instructions for completing the report form were provided to each respondent. Questions were phrased as clearly as possible based on previous tests of the report form. Computer-assisted telephone interviewing software included immediate integrity checks of recorded responses so suspect data could be verified or corrected. In addition, each respondent's answers were checked for completeness and consistency by the complex edit and imputation system.

## **Processing Error**

Processing of each census report form was another potential source of nonsampling error. All mail returns that included multiple reports, respondent remarks, or that were marked out of business and report forms with no reported data were sent to an analyst for verification and appropriate action. Integrity checks were performed by the imaging system and data transfer functions. Standard quality control procedures were in place that required that randomly selected batches of data keyed from image be reentered by a different operator to verify the work and evaluate key entry operators. All systems and programs were thoroughly tested before going on-line and were monitored throughout the processing period.

Developing accurate processing methods is complicated by the complex structure of agriculture. Among the complexities are the many places to be included, the variety of arrangements under which farms are operated, the continuing changes in the relationship of producers to the farm operated, the expiration of leases and the initiation or renewal of leases, the problem of obtaining a complete list of agriculture operations, the difficulty of contacting and identifying some types of contractor/contractee relationships, the producer's absence from the farm during the data collection period, and the producer's opinion that part or all of the operation does not qualify and should not be included in the census. During data collection and processing of the census, all operations underwent a number of quality control checks to ensure results were as accurate as possible.

## **Item Nonresponse**

All item nonresponse actions provide another opportunity to introduce measurement errors. Regardless of whether previously reported data, administrative data, the nearest neighbor algorithm, the fully conditional specification method, or manual imputation is used to complete a nonresponse item, some risk exists that the imputed value does not equal the actual value. Previously reported and administrative data were used only when they related to the census reference period. A new nearest neighbor was randomly selected for each incident to eliminate the chance of a consistent bias.

## **Record Matching Error**

The process of building and expanding the CML involves finding new list sources and checking for names not on the list. An automated processing system compared each new name to the existing CML names and "linked" like records for the purpose of preventing duplication. New names with strong links to a CML name were discarded and those with no links were added as potential farms. Names with weak links, possible matches, were reviewed by staff to determine whether the new name should be added. Despite this thorough review, some new names may have been erroneously added or deleted. Additions could contribute to duplication (overcoverage) whereas deletions could contribute to undercoverage. As a result, some names received more than one report form, and some farm producers did not receive a report form. Respondents were instructed to complete one form and return all forms so the duplication could be removed.

Another chance for error came when comparing June Area Survey tract producer names to the CML. Area producers whose names were not found on the CML were part of the measure of list incompleteness, or NML. Mistakes in determining overlap status resulted in overcounts (including a tract whose producer was on the CML) or undercounts (excluding a tract whose producer was not on the CML). All tracts determined to not be on the list were triple checked to eliminate, or at least minimize, any error. NML tract producers were mailed a report form printed in a different color. To identify duplication, all respondents who received multiple report forms were instructed to complete the CML version and return all forms so

duplication could be removed.

Records in the 2022 JAS were matched to the 2022 census using probabilistic record linkage. The records of operations with differing farm status were sent out to be reviewed by NASS regional field offices. If farm status could not be resolved, the probability of an operation being a farm was imputed using a missing data model. The uncertainty associated with this estimate apart from model uncertainty was accounted for, but errors not found through this process were not.

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2022 [For meaning of abbreviations and symbols, see introductory text.]

Item	Total	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Farmsnumber Land in farmsacres	53,599	993	40.9	17.4	14.7	8.9
	14,602,240	336,018	27.0	2.9	8.2	15.9
Farms by size: 1 to 9 acresfarms	6,418	305	E6 1	37.0	17.6	1.5
10 to 49 acres farms	33,182 18,772	1,499 525	56.1 55.3 48.0	37.4 27.4	16.3 15.9	1.5 1.6 4.7
10 to 49 acres acres 50 to 69 acres farms	465,096	12,410	45.8	22.4	17.7	5.7
	4,146	144	40.5	12.5	16.9	11.1
70 to 99 acres farms	241,828	8,249	40.4	12.4	16.9	11.1
acres	4,716	198	36.1	10.5	15.1	10.4
	386,952	16,043	36.0	10.4	15.1	10.5
100 to 139 acres	3,907	59	34.1	7.8	12.4	13.9
	454,893	7,942	34.0	7.7	12.2	14.1
140 to 179 acres	2,293	65	34.2	7.2	15.0	12.1
	359,621	10,401	34.2	7.2	15.1	12.0
180 to 219 acres	1,586	69	31.0	5.1	10.9	15.0
	313,171	13,238	31.0	5.1	11.1	14.8
220 to 259 acres	1,244	61	33.4	4.9	14.6	13.8
	295,900	14,483	33.3	4.9	14.7	13.7
260 to 499 acres	3,857	147	31.8	3.1	16.6	12.2
	1,386,524	53,646	31.7	3.0	16.6	12.1
500 to 999 acres	2,919	93	26.3	1.6	14.2	10.5
	2,061,737	70,407	26.1	1.6	13.9	10.6
1,000 to 1,999 acres	2,043	190	24.1	0.9	6.2	17.0
	2,826,727	264,144	23.9	0.8	6.0	17.2
2,000 acres or more	1,698	87	26.0	0.9	3.0	22.1
	5,776,609	249,368	23.3	1.0	2.8	19.5
Irrigated land use: Harvested cropland	2,950	116	26.1	12.7	12.5	10.9
Pastureland and other land farms	605,934	25,958	36.1 22.8 44.4	0.7	2.4 16.4	19.6
Pastureland and other land	124 4,736	17 1,947	58.3	15.9 4.4	16.7	12.1 37.3
Market value of agricultural products sold\$1,000	18,029,033	397	23.3	4.5	8.0	10.7
Farms by value of sales: Less than \$1,000	11,913	563	52.4	31.0	17.2	4.1
\$1,000 to \$2,499 farms	1,328	(Z)	62.6	46.0	15.2	1.4
	3,956	262	50.4	31.1	17.0	2.3
\$1,000	6,485	(Z)	50.1	30.8	17.0	2.3
\$2,500 to \$4,999 farms	4,033	150	46.7	27.6	16.0	3.1
\$1,000	14,684	1	46.7	27.5	16.0	3.2
\$5,000 to \$9,999 farms	4,648	182	43.8	25.3	14.3	4.3
\$1,000	33,121	1	43.6	25.2	14.2	4.2
\$10,000 to \$19,999 farms	4,513	253	36.5	16.5	13.6	6.3
\$1,000	64,307	3	36.4	16.3	13.7	6.4
\$20,000 to \$24,999 farms	1,534	87	38.0	15.5	12.9	9.6
\$1,000	34,246	2	38.0	15.4	12.9	9.6
\$25,000 to \$39,999	2,696	98	37.3	13.4	13.5	10.4
\$1,000	84,461	3	37.1	13.2	13.4	10.4
\$40,000 to \$49,999 farms	1.417	92	39.1	10.1	13.1	16.0
\$1,000	63,124	4	39.0	10.0	13.0	16.0
\$50,000 to \$99,999 farms	3,982	170	36.6	8.4	12.7	15.5
\$1,000	283,565	12	36.2	8.3	12.6	15.3
\$100,000 to \$249,999 farms	4,687	127	35.1	5.9	12.0	17.2
\$1,000	760,768	21	35.0	5.8	12.2	17.0
\$250,000 to \$499,999 farms	3,286	58	33.5	4.2	20.8	8.5
\$1,000	1,182,066	22	33.6	4.2	20.8	8.6
\$500,000 to \$999,999 farms	2,662	79	28.4	6.3	16.8	5.4
\$1,000	1,922,804	70	29.1	6.3	17.3	5.5
\$1,000,000 or more	4,272	129	24.2	3.8	6.6	13.9
\$1,000	13,578,074	353	20.3	3.9	6.0	10.4
Farms by legal status for tax purposes: Family or individualfarms	45,401	969	41.5	19.3	14.4	7.9
acres Partnershipfarms	8,956,083	296,376	27.9	4.0	9.7	14.2
	3,177	144	39.6	7.4	14.7	17.5
Corporation:	2,369,872	72,738	22.1	0.8	3.2	18.1
Family held	3,605	105	34.3	10.0	16.2	8.1
	2,919,012	99,192	27.0	3.0	15.0	9.0
Other than family held farms acres	471	28	45.9	8.5	28.2	9.1
	162,535	25,718	32.7	3.8	17.8	11.2
Other - estate or trust, prison farm, grazing association, American Indian Reservation, etc	945	35	40.7	13.3	13.3	14.1
	194,738	8,316	40.0	2.8	7.2	30.0
Tenure:	194,730	0,310	40.0	2.0	7.2	30.0
Full owners	37,552	889	45.1	23.3	15.8	6.1
	3,162,791	71,344	35.2	9.5	13.3	12.4
Part owners farms acres	13,753	286	29.7	3.1	12.2	14.4
	10,491,854	327,664	24.6	1.1	7.3	16.3
Tenants farms acres	2,294	76	39.2	6.3	12.8	20.1
	947,595	67,885	25.4	1.7	4.7	19.0
Producers characteristics by- ¹ (see text) Sex of operator: Male	51,113	896	41.5	17.1	15.2	9.1
wale lams acres Female farms	14,301,769 28,229	323,835 604	41.5 27.1 41.3	2.8 19.3	8.3 14.9	16.0 7.1
remaie larms acres	5,724,456	119,566	41.3 22.7	3.6	9.0	10.2
Primary occupation: Farming	37,198	661	36.5	11.3	13.8	11.3
Otherfarms	57,084	1,128	46.1	18.7	18.2	9.2

See footnote(s) at end of table. --continued

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2022 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

[For meaning of abbreviations and symbols, see introductory text.]	Total	Standard error	Adjustment as percent	Percent of total adjustment	Percent of total adjustment from	Percent of total adjustment from
Producers characteristics by- ¹ (see text) - Con.			of total	from coverage	nonresponse	misclassification
Hispanic, Latino, or	570	0.7	47.5	04.5	40.0	0.0
Spanish originfarms acres	570 116,971	27 20,333	47.5 24.0	21.5 6.5	19.2 11.7	6.8 5.9
Race: American Indian or						
Alaska Native	124 24,216	11 2,551	41.1 25.1	18.8 4.2	6.3 4.0	16.0 17.0
Asian farms acres	103 13,033	12 2,631	38.8 30.6	18.5 7.7	13.7 17.1	6.6 5.9
Black or African American	80 11,960	6 241	12.5 3.3	6.9 1.1	3.8 1.7	1.7 0.6
Native Hawaiian or Other Pacific Islander	15	3	26.7	17.8	8.2	0.7
White farms	2,769 53,405	(H) 986	45.8 41.0	10.7 17.4	34.5 14.7	0.7 8.9
acres More than one race reported	14,570,752 249 37,593	336,890 12 5,124	27.0 42.6 27.2	2.8 18.3	8.2 16.2	15.9 8.1 5.4
	37,593	5,124	21.2	4.6	17.2	5.4
Military service:  Never served or only on active duty for training in the Reserves or National Guard (see text)	87,661 6,621	1,336 156	42.3 42.1	15.9 14.6	16.6 15.0	9.8 12.5
All producers by age group <sup>1</sup> : Under 25 yearsfarms	1,962	189	58.3	19.4	29.5	9.4
25 to 34 years	9,096 14,627	455 265	59.6 50.1	25.8 16.9	21.8 22.2	12.0 11.0
45 to 54 years farms 55 to 64 years farms	15,336 21,083	304 389	42.6 38.4	14.9 15.2	17.2 13.3	10.6 9.9
65 to 74 years farms 75 years and over farms	20,434 11,744	374 218	35.6 34.6	13.4 13.0	13.2 12.2	9.0 9.3
Net cash farm income of operations:	,					
Farms with gains of- <sup>2</sup> Less than \$1,000farms	1,275	39	42.7	22.4	15.6	4.7
\$1,000 to \$4,999 farms	608 3,714	(Z) 87	42.1 40.4	21.8 18.7	15.1 13.2	5.1 8.5
\$1,000 \$5,000 to \$9,999farms	10,334 2,770	(Z) 76	39.7 37.4	18.1 14.2	13.0 12.4	8.7 10.8
\$1,000 \$10,000 to \$24,999farms	20,262 4,573	1 117	37.4 36.3	14.0 11.5	12.3 13.7	11.1 11.1
\$1,000 \$25,000 to \$49,999farms	76,049 3,974	2 169	36.0 35.4	11.4 8.9	13.4 12.0	11.2 14.5
\$1,000 \$50,000 or morefarms	143,853 13,094	6 286	35.5 30.1	8.8 5.5	12.3 12.5	14.4 12.0
\$1,000 Farms with losses of-	6,521,012	170	23.5	4.4	7.3	11.9
Less than \$1,000	1,421 737	51 (Z)	45.5 46.9	26.6 27.4	15.0 15.2	3.9 4.3
\$1,000 to \$4,999 \$1,000 \$1,000	6,025 17,590	432	49.2 49.6	28.7 29.5	16.0 15.8	4.4 4.3
\$5,000 to \$9,999	5,432 39,704	150 1	51.5 51.5	30.7 31.0	16.8 16.6	4.0 4.0
\$10,000 to \$24,999	6,722 106,401	239 4	51.0 50.7	28.7 28.4	16.5 16.6	5.7 5.7
\$25,000 to \$49,999 farms \$1,000	2,603 90,525	56 2	47.6 47.6	22.7 22.5	17.9 17.8	7.0 7.3
\$50,000 or more	1,996 379,193	87 34	39.1 30.4	11.9 7.3	18.4 16.9	8.8 6.1
Livestock and poultry: Cattle and calves inventoryfarms	13,984	515	35.2	25.0	7.1	3.1
number Beef cows inventory farms	770,048 9,990	30,952 668	19.3 32.7	6.2 22.7	7.8 6.6	5.2 3.4
number Milk cows inventory farms	177,730 1,521	2,505 26	22.3 35.5	11.8 25.1	5.7 8.6	4.8 1.8 2.4
number Hog and pigs inventory farms	183,176	20,335 79	7.4 42.9	0.9 20.8	4.1 19.5	2.4 2.6
number Layers inventory farms	2,150 4,372,121 6,009	282,762 311	33.9 50.0	10.6 29.5	19.5 17.8	2.6 3.8 2.7
number Broilers soldfarms	35,924,482 715	681,918 30	4.0 42.2	1.8 23.4	1.7 17.0	0.5 1.9
number Aquaculture soldfarms	51,943,087 60	1,654,125 10	12.6 43.3	6.2 21.5	5.8 16.4	0.6 5.4
\$1,000	11,832	5	30.0	5.6	19.4	4.9
Selected crops harvested: Corn for grain	19,082	427	34.2	5.1	11.1	18.1
Durum wheat for grainfarms	5,376,022	207,689	25.3	0.9	4.7	19.6
Other spring wheat for grainfarms	-	-	-	-	-	-
Winter wheat for grain acres	3,008	56 7.748	29.4	4.8	17.2	7.4
Sorghum for grain acres	262,177 39	7,748 9	27.9 28.2	3.1 4.2	16.5 19.7	8.4 4.3 3.6
Soybeans for beans	4,366 18,671	1,083 350	26.2 27.4	4.0 5.4	18.5 21.9	3.6 0.2 0.8
Ricefarms	5,687,521 -	139,090	24.9	3.3	20.9	0.8
Cotton acres acres	- - -	- - -		- -		

See footnote(s) at end of table. --continued

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2022 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

Item	Total	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Selected crops harvested: - Con.						
Peanuts farms		-	-	-	-	-
Barley farms	39	10	38.5	15.6	21.4	1.6
Oats acres ares ares ares	133	169 18 347	22.1 30.8 19.5	5.8 15.2 6.8	15.3 13.0 8.2	1.0 2.6 4.4
Forage - land used for all hay and haylage,	40.007	204	07.4	07.4		
grass silage, and greenchopfarms		634 16.125	37.4 26.7	27.1 15.9	9.9 10.0	0.4 0.7
Land in vegetables (see text)	1,456	78 3.164	38.3 14.1	21.6 1.0	14.6 0.7	2.1 12.4
Potatoes farms	271	34	36.9	22.3	9.8	4.8
acres Tomatoes in the openfarms	572	2,319 58	19.8 36.2	0.3 21.3	(Z) 14.0	19.5 0.9
Sweet corn (see text) farms	449	1,515 46	21.4 33.9	11.0 19.5	9.4 13.3	1.0 1.0
acres Lettucefarms	184	255 13	8.6 38.0	4.0 23.4	4.0 13.5	0.5 1.1
Land in orchards (see text)	855	3 56	29.3 48.9	17.5 20.9	10.9 24.5	0.9 3.5
Applesfarms	397	256 34	26.8 45.6	9.1 17.4	13.3 24.4	4.5 3.8
acres Grapes (including muscadine) (see text)farms	264	140 18	20.2 50.0	5.6 21.0	10.3 25.8	4.3 3.2
acres Orangesfarms	-	50	31.6	11.9	16.6	3.0
Almondsfarms	7	3	57.1	35.0	20.6	1.6
acres Land in berries	587	(Z) 40 43	53.3 45.1 24.8	37.0 19.8 9.3	15.2 21.5 12.7	1.2 3.8 2.8

<sup>&</sup>lt;sup>1</sup> Data were collected for a maximum of four producers per farm.
<sup>2</sup> Farms with total production expenses equal to market value of agricultural products sold, government payments, and farm-related income are included as farms with gains of less than \$1,000.

# Table B. **Reliability Estimates of State Totals: 2022** [For meaning of abbreviations and symbols, see introductory text.]

Item	.,,	Total	Coefficient of variation (percent)	Item	Total	Coefficient of variation (percent)
Farms		53,599 14,602,240	1.9 2.3	Producers characteristics by- 1 (see text) - Con.		
Farms by size:	40.00	. 1,002,210	2.0	Hispanic, Latino, or Spanish originfarms	570	4.8
1 to 9 acres		6,418	4.7	acres	116,971	17.4
10 to 49 acres		33,182 18,772	4.5 2.8	Race:		
50 to 69 acres	acres farms	465,096 4,146	2.7 3.5	American Indian or Alaska Nativefarms	124	8.5
70 to 99 acres	acres	241,828 4,716	3.4 4.2	acres Asianfarms	24,216 103	10.5 11.4
100 to 139 acres	acres	386,952 3.907	4.1 1.5	acres	13,033 80	20.2
	acres	454,893	1.7	acres	11,960	7.3 2.0
140 to 179 acres	acres	2,293 359,621	2.8 2.9	Native Hawaiian or Other Pacific Islanderfarms	_15	20.0
180 to 219 acres	acres	1,586 313,171	4.3 4.2	acres Whitefarms	2,769 53,405	(H) 1.8
220 to 259 acres	farms	1,244 295,900	4.9 4.9	acres More than one race reportedfarms	14,570,752 249	2.3 5.0
260 to 499 acres		3,857 1,386,524	3.8 3.9	acres	37,593	13.6
500 to 999 acres		2,919 2,061,737	3.2 3.4	Military service: Never served or only on active duty for training		
1,000 to 1,999 acres	farms	2,043	9.3	in the Reserves or National Guard (see text) producers	87,661	1.5
2,000 acres or more		2,826,727 1,698	9.3 5.1	Active duty now or in the past (see text) producers	6,621	2.4
	acres	5,776,609	4.3	All producers by age group <sup>1</sup> : Under 25 yearsfarms	1,962	9.6
Irrigated land use: Harvested cropland	farms	2,950	3.9	25 to 34 years	9,096 14,627	5.0 1.8
Pastureland and other land	acres	605,934 124	4.3 13.4	45 to 54 years farms 55 to 64 years farms	15,336 21,083	2.0 1.8
rasturcianu and otnerianu	acres	4,736	41.1	65 to 74 yearsfarms	20,434	1.8
Market value of agricultural products sold	\$1,000	18,029,033	2.2	75 years and overfarms	11,744	1.9
Farms by value of sales:				Net cash farm income of operations: Farms with gains of- <sup>2</sup>		
Less than \$1,000	\$1,000	11,913 1,328	4.7 13.5	Less than \$1,000	1,275 608	3.0 5.0
\$1,000 to \$2,499	farms \$1,000	3,956 6,485	6.6 7.3	\$1,000 to \$4,999	3,714 10,334	2.3 2.9
\$2,500 to \$4,999	farms	4,033	3.7	\$5,000 to \$9,999farms	2,770	2.7 2.6
\$5,000 to \$9,999	\$1,000 farms	14,684 4,648	3.7 3.9	\$1,000 \$10,000 to \$24,999farms	20,262 4,573	2.6
\$10,000 to \$19,999	\$1,000 farms	33,121 4,513	4.2 5.6	\$1,000 \$25,000 to \$49,999farms	76,049 3,974	3.2 4.3
\$20,000 to \$24,999	\$1,000 farms	64,307 1,534	5.2 5.6	\$1,000 \$50,000 or more farms	143,853 13,094	4.5 2.2
\$25,000 to \$39,999	\$1.000	34,246 2,696	5.6 3.6	\$1,000	6,521,012	2.6
\$40,000 to \$49,999	\$1,000	84,461	3.9	Farms with losses of- Less than \$1,000farms	1 404	2.6
	\$1,000	1,417 63,124	6.5 6.6	\$1,000	1,421 737	3.6 4.8
\$50,000 to \$99,999	\$1.000	3,982 283,565	4.3 4.1	\$1,000 to \$4,999farms \$1,000	6,025 17,590	7.2 6.3
\$100,000 to \$249,999	\$1.000	4,687 760,768	2.7 2.7	\$5,000 to \$9,999farms \$1,000	5,432 39,704	2.8 2.9
\$250,000 to \$499,999	farms \$1,000	3,286 1,182,066	1.8 1.9	\$10,000 to \$24,999farms \$1,000	6,722 106,401	3.6 3.6
\$500,000 to \$999,999	farms \$1,000	2,662 1,922,804	3.0 3.7	\$25,000 to \$49,999	2,603 90,525	2.2 2.0
\$1,000,000 or more	farms	4,272 13.578.074	3.0	\$50,000 or more farms	1,996	4.4
	\$1,000	13,576,074	2.6	\$1,000	379,193	8.9
Farms by legal status for tax purposes: Family or individual	farms	45,401	2.1	Livestock and poultry: Cattle and calves inventoryfarms	13,984	3.7
Partnership	acres	8,956,083 3,177	3.3 4.5	number Beef cows inventoryfarms	770,048 9,990	4.0 6.7
Corporation:	acres	2,369,872	3.1	number Milk cows inventoryfarms	177,730 1,521	1.4 1.7
Family held	farms	3,605	2.9	number	183,176	11.1
Other than family held	farms	2,919,012 471	3.4 5.9	Hog and pigs inventoryfarms number	2,150 4,372,121	3.7 6.5
Other - estate or trust, prison farm, grazing association,		162,535	15.8	Layers inventory farms number	6,009 35,924,482	5.2 1.9 4.2
American Indian Reservation, etc	farms acres	945 194,738	3.7 4.3	Broilers sold	715 51,943,087	4.2 3.2
Tenure:				Aquaculture soldfarms \$1,000	60 11,832	15.9 43.6
Full owners	farms	37,552 3,162,791	2.4 2.3	Selected crops harvested:	11,002	10.0
Part owners	farms	13,753	2.3 2.1 3.1	Corn for grainfarms	19,082 5,376,022	2.2
Tenants		10,491,854	3.3	acres Durum wheat for grainfarms	5,376,022	3.9
	acres	947,595	7.2	acres Other spring wheat for grainfarms	-	-
Producers characteristics by- <sup>1</sup> (see text) Sex of operator:				acres Winter wheat for grainfarms	3,008	1.9
Male	farms	51,113 14,301,769	1.8 2.3	acres Sorghum for grain	262,177 39	3.0 23.5
Female	farms	28,229	2.1	acres	4,366	24.8
D	acres	5,724,456	2.1	Soybeans for beans	18,671 5,687,521	1.9 2.4
Primary occupation: Farming		37,198	1.8	Ricefarms acres	-	-
Other		57,084	2.0			

See footnote(s) at end of table. --continued

## Table B. Reliability Estimates of State Totals: 2022 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

ltem	Total	Coefficient of variation (percent)	Item	Total	Coefficient of variation (percent)
Selected crops harvested: - Con.  Cotton	- - 39 851 133 2,712 18,327 488,227 1,456 37,901 271	25.3 19.9 13.7 12.8 3.5 3.3 5.4 8.3 12.7	Grapes (including muscadine) (see text)	449 3,533 184 69 855 3,382 397 1,636 686 - - 7 7 7	10.3 7.2 7.2 4.6 6.5 7.6 8.4 8.6 6.9 7.3
Tomatoes in the open	6,872 572 8,193	33.8 10.2 18.5	Land in berries farms acres	587 1,083	6.8 4.0

Data were collected for a maximum of four producers per farm.
Farms with total production expenses equal to market value of agricultural products sold, government payments, and farm-related income are included as farms with gains of less than \$1,000.

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2022 [For meaning of abbreviations and symbols, see introductory text.]

Page	[For meaning of abbreviations and symbols, see introductory text.]  Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Industry	ALL FARMS (NUMBER)						
Country	State Total						
Advans	Indiana	53,599	993	40.9	17.4	14.7	8.9
Alementementementementementementementemen	Counties						
Alementementementementementementementemen	Adams	1 305	51	40.5	24 9	12.5	3.1
Berlon	Allen	1,497	81	42.6	22.1	15.2	5.4
Store		390	29	33.3	5.4		16.9
Brown			25 20				
Case	Brown		28	48.4	21.2	20.2	7.0
Section	Cass	633	36	38.1	5.9	5.7	26.4
Christon	Clark					20.0	
Crawford							
Decalur	Crawford	374	25	45.7	24.0	17.5	4.2
DeCable		520	72 25	46.2	18.5	21.2	6.4
Delayare		552 818	20 68				
Ekhart     1,809   97   48.9   23.2   20.3   5.4	Delaware	506	44	36.2	18.3	14.8	3.1
Flyde			97				
Fourish		298	28				
Fulton							
Clasen	Franklin		32				
Green	Gibson	477	56	39.4	9.6	14.8	15.0
Hancock	Greene	788	42	43.8	18.5	18.8	6.5
Herrifors   September   Sept							
Hendricks		990	44	44.6	20.2	13.5	10.9
Howard	Hendricks	544	27	44.1	24.7	14.0	
Jackson   607   52   39.0   16.3   14.5   6.2   Jasper   608   32   39.0   16.3   14.5   6.2   Jasper   608   34   39.8   12.2   12.9   14.0   Jerming   613   34   39.8   12.2   12.9   14.0   Jerming   613   34   39.8   12.2   12.9   14.0   Jerming   613   31   31.8   31.8   Jehnen   700   700   700   700   700   700   700   Jackson   700   700   700   700   700   700   Jackson   700   700   700   700   700   700   Jackson   700   700   Jackson		427	21	35.6	15.9	14.9	4.8
Jasper   608   32   39.1   12.2   12.9   14.0			15 52				
Jefferson   513   19   40,9   22,6   12,8   5.8     Johnson   520   18   45,0   26,7   13,8   44,4     Krox   447   29   39,4   14,9   18,4   6.1     Kosciusko   1,079   25   43,7   23,2   15,3   5.2     LaGrange   2,474   103   50,3   30,7   16,9   2.7     Lake   347   36   42,1   12,6   11,9   17,6     LaFrott   6,000   6,000   6,000   6,000     LaFrott   6,000   6,000   6,000     LaFrott   6,000   6,000   6,000     LaFrott   6,000   6,000   6,000     LaFrott   6,000     LaFrott   6,000   6,000     LaFrott   6,000   6,000     LaFrott   6,000     LaFrott   6,000   6,000     LaFrot	Jasper		32				14.0
Johnson	Jefferson	513	19	40.9	22.6	12.8	5.6
Knox	Jennings						
Kosciusko							
Lake         347         36         42.1         12.6         11.9         17.8           LaPorte         677         20         40.5         17.7         17.9         4.8           Lawrence         706         76         41.5         19.1         17.2         5.2           Macison         862         33         42.5         18.4         17.2         6.2           Marishall         779         43         40.2         16.5         11.1         12.5           Marin         249         18         42.2         14.4         18.6         9.1           Marin         613         40         36.9         11.1         11.6         14.1           Morigomery         681         32.2         41.3         20.4         16.0         4.8           Mevido         361         32.2         41.3         20.4         16.0         4.8           Noble         1067         103         41.5         20.1         15.3         6.2           Ohio         123         9         26.8         17.6         7.8         14.4           Owen         372         34         42.2         5.6         8.4         28.	Kosciusko		25 103				5.2
Lawrence	Lake	347	36	42.1	12.6	11.9	17.6
Marion         169         7         45.6         25.0         18.9         1.7           Marshall         779         43         40.2         16.5         11.1         12.5           Marin         249         18         42.2         11.4         18.6         9.1           Marin         613         40         36.2         11.1         11.6         0.1           Marin         613         40         36.2         11.1         11.6         0.1           Morigon         651         32         37.9         16.8         13.5         6.7           Morgan         506         42         44.1         19.2         16.5         8.3           Newton         372         34         42.2         5.6         8.4         28.2           Noble         1,067         103         41.5         20.1         15.3         6.2           Ohio         123         9         26.8         17.6         7.8         1.4           Orange         425         49         41.9         20.3         17.2         4.4           Orange         666         51         44.6         15.9         17.3         11.4	Lawrence	706	76	41.5	19.1	17.2	5.2
Martin         249         18         42.2         14.4         18.6         9.1           Miami         613         40         36.9         11.1         11.6         14.1           Monroe         419         22         41.3         20.4         16.0         48.8           Montgan         651         32         37.9         16.8         13.5         7.7           Morgan         506         42         44.1         19.2         16.5         8.3           Newton         372         34         42.2         56         8.4         28.2           Noble         1,067         103         41.5         20.1         15.3         6.2           Ohio         123         9         26.8         17.6         7.8         1.4           Orange         425         49         41.9         20.3         17.2         4.4           Owen         425         49         41.9         20.3         17.2         4.4           Owen         426         45         41.4         55.6         13.5         11.2         10.9           Parke         466         51         44.6         15.9         17.3							
Miami	Marshall	779	43	40.2	16.5	11.1	12.5
Montgome							
Morgan   506   42   44.1   19.2   16.5   8.3     Newton   372   34   42.2   5.6   8.4   8.2     Noble   1.067   103   41.5   20.1   15.3   6.2     Noble   123   9   26.8   17.6   7.8   6.2     Orange   425   49   41.9   20.3   17.2   4.4     Orange   435   41   35.6   13.5   11.2   4.9     Parke   646   51   44.6   15.9   17.3   11.4     Perry   417   33   38.4   15.7   13.2   9.5     Pike   279   38   34.1   11.1   11.7   11.3     Porter   462   21   42.6   14.6   19.4   8.6     Pulaski   507   38   39.6   8.5   11.7   19.4     Pulaski   508   507   38   39.6   8.5   11.7   19.4     Pulaski   508   507   38   39.6   8.5   11.7   19.4     Pulaski   508   509   38.8   14.6   18.6   5.6     Pulaski   509   509   38.8   14.6   18.6   5.6     Pulaski   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509   509   509     Pulaski   509   509   509   509   509   509   509   509   509   509   509   509   509   509   509   509   509	Monroe	419	22	41.3	20.4	16.0	4.8
Noble		506	32 42	44.1			8.3
Ohio         123         9         26.8         17.6         7.8         1.4           Orange         425         49         41.9         20.3         17.2         4.4           Owen         435         41         35.6         13.5         11.2         10.9           Parke         646         51         44.6         15.9         17.3         11.4           Perry         417         33         38.4         15.7         13.2         9.5           Pike         279         38         34.1         11.1         11.7         11.3           Potter         462         21         42.6         14.6         19.4         8.6           Posey         462         28         41.6         17.0         18.9         5.6           Pulaski         507         38         39.6         8.5         11.7         19.4           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         14.6         18.6         5.6           Rush         473         22         36.4         9.9         17.0         9.5							28.2 6.2
Owen         435         41         35.6         13.5         11.2         10.9           Parke         646         51         44.6         15.9         17.3         11.4           Perry         417         33         38.4         15.7         13.2         9.5           Pike         279         38         34.1         11.1         11.7         11.3           Porter         462         21         42.6         14.6         19.4         8.6           Posey         462         28         41.6         17.0         18.9         5.6           Pulaski         507         38         39.6         8.5         11.7         19.4           Putnam         728         64         38.3         17.4         12.9         8.1           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         18.0         14.7         6.1           Rush         473         22         36.4         9.9         17.0         9.5           St. Joseph         547         40         38.2         14.5         13.5         10.2	Ohio	123	9	26.8	17.6	7.8	1.4
Perry         417         33         38.4         15.7         13.2         9.5           Pike         279         38         34.1         11.1         11.7         11.3           Porter         462         21         42.6         14.6         19.4         8.6           Posey         462         28         41.6         17.0         18.9         5.6           Pulaski         507         38         39.6         8.5         11.7         19.4           Putram         728         64         38.3         17.4         12.9         8.1           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         14.5         13.5         10.2           St. Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2 </td <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Porter         462         21         42.6         14.6         19.4         8.6           Posey         462         28         41.6         17.0         18.9         5.6           Pulaski         507         38         39.6         8.5         11.7         19.4           Pulnam         728         64         38.3         17.4         12.9         8.1           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         18.0         14.7         6.1           Rush         473         22         36.4         9.9         17.0         9.5           St. Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         588         39         37.1         17.9         14.5         4.7           Starke         304         15         30.7         13.4         9.7         7.7 <td>Parke</td> <td></td> <td>51</td> <td>44.6</td> <td></td> <td></td> <td></td>	Parke		51	44.6			
Porter         462         21         42.6         14.6         19.4         8.6           Posey         462         28         41.6         17.0         18.9         5.6           Pulaski         507         38         39.6         8.5         11.7         19.4           Pulnam         728         64         38.3         17.4         12.9         8.1           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         18.0         14.7         6.1           Rush         473         22         36.4         9.9         17.0         9.5           St. Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         588         39         37.1         17.9         14.5         4.7           Starke         304         15         30.7         13.4         9.7         7.7 <td>Perry Pike</td> <td>417 279</td> <td>33 38</td> <td></td> <td></td> <td></td> <td>9.5 11.3</td>	Perry Pike	417 279	33 38				9.5 11.3
Pulaski         507         38         39.6         8.5         11.7         19.4           Putnam         728         64         38.3         17.4         12.9         8.1           Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         18.0         14.7         6.1           Rush         473         22         36.4         9.9         17.0         9.5           St. Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         558         39         37.1         17.9         14.5         47           Starke         334         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Switzerland         339         35         40.1         16.2         19.3         4	Porter		21		14.6 17.0		8.6
Randolph         675         29         38.8         14.6         18.6         5.6           Ripley         835         30         38.8         18.0         14.7         6.1           Rush         473         22         36.4         9.9         17.0         9.5           St. Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         558         39         37.1         17.9         14.5         4.7           Starke         394         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Switzerland         339         35         40.1         16.2         19.3         4.6           Tipton         416         24         38.0         10.9         16.8         10.3           Tipton         416         24         38.0         10.9         16.8	Pulaski	507	38	39.6	8.5	11.7	19.4
Rush         473         22         36.4         9.9         17.0         9.5           St Joseph         547         40         38.2         14.5         13.5         10.2           Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         558         39         37.1         17.9         14.5         4.7           Starke         394         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Sullivan         411         23         42.1         8.1         11.3         22.7           Switzerland         339         35         40.1         16.2         19.3         4.6           Tippecanoe         712         43         42.4         20.0         14.4         8.0           Tipton         416         24         38.0         10.9         16.8         10.3           Union         94         19         37.1         14.7         11.8 <td< td=""><td>Randolph</td><td>675</td><td>29</td><td>38.8</td><td>14.6</td><td>18.6</td><td>5.6</td></td<>	Randolph	675	29	38.8	14.6	18.6	5.6
St. Joseph     547     40     38.2     14.5     13.5     10.2       Scott     283     37     40.3     18.2     11.9     10.2       Shelby     548     33     40.5     15.9     17.5     7.0       Spencer     558     39     37.1     17.9     14.5     4.7       Starke     394     15     30.7     13.4     9.7     7.7       Steuben     461     29     40.6     15.5     18.6     6.5       Sullivan     411     23     42.1     8.1     11.3     22.7       Switzerland     339     35     40.1     16.2     19.3     4.6       Tippcanoe     712     43     42.4     20.0     14.4     8.0       Tipton     416     24     38.0     10.9     16.8     10.3       Union     194     19     37.1     14.7     11.8     10.7       Vanderburgh     204     33     31.9     14.0     16.3     1.5	Ripley		30 22				
Scott         283         37         40.3         18.2         11.9         10.2           Shelby         548         33         40.5         15.9         17.5         7.0           Spencer         558         39         37.1         17.9         14.5         4.7           Starke         394         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Sullivan         411         23         42.1         8.1         11.3         22.7           Switzerland         339         35         40.1         16.2         19.3         4.6           Tippecanoe         712         43         42.4         20.0         14.4         8.0           Union         416         24         38.0         10.9         16.8         10.3           Union         194         19         37.1         14.7         11.8         10.7           Vanderburgh         204         33         31.9         14.0         16.3         1.5							
Spencer         558         39         37.1         17.9         14.5         4.7           Starke         394         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Sullivan         411         23         42.1         8.1         11.3         22.7           Switzerland         339         35         40.1         16.2         19.3         4.6           Tippecanoe         712         43         42.4         20.0         14.4         8.0           Tipton         416         24         38.0         10.9         16.8         10.3           Union         194         19         37.1         14.7         11.8         10.7           Vanderburgh         204         33         31.9         14.0         16.3         1.5	Scott	283	37	40.3	18.2	11.9	10.2
Starke.         394         15         30.7         13.4         9.7         7.7           Steuben         461         29         40.6         15.5         18.6         6.5           Sullivan         411         23         42.1         8.1         11.3         22.7           Switzerland         339         35         40.1         16.2         19.3         4.6           Tippecanoe         712         43         42.4         20.0         14.4         8.0           Tipton         416         24         38.0         10.9         16.8         10.3           Union         194         19         37.1         14.7         11.8         10.7           Vanderburgh         204         33         31.9         14.0         16.3         1.5		558	39	37.1	17.9	14.5	4.7
Switzerland     339     35     40.1     16.2     19.3     4.6       Tippecanoe     712     43     42.4     20.0     14.4     8.0       Tipton     416     24     38.0     10.9     16.8     10.3       Union     194     19     37.1     14.7     11.8     10.7       Vanderburgh     204     33     31.9     14.0     16.3     1.5	Starke		15 29				
Tipton     416     24     38.0     10.9     16.8     10.3       Union     194     19     37.1     14.7     11.8     10.7       Vanderburgh     204     33     31.9     14.0     16.3     1.5	Sullivan	411	23	42.1	8.1	11.3	22.7
Tipton     416     24     38.0     10.9     16.8     10.3       Union     194     19     37.1     14.7     11.8     10.7       Vanderburgh     204     33     31.9     14.0     16.3     1.5	Tippecanoe	712		42.4	20.0	14.4	8.0
Vanderburgh				38.0	10.9	16.8	10.3
	Vermillion	291	36				

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2022 (continued) [For meaning of abbreviations and symbols, see introductory text.]

ALFAMMS (AUMBER) - Cor.    Courties	[For meaning of abbreviations and symbols, see introductory text.]  Geographic area	Total (number)	Standard error	Adjustment as percent	Percent of total adjustment	Percent of total adjustment from	Percent of total adjustment from
Countries    148	ALL FADMC (NUMPED). Com	(number)	CHO	of total	from coverage	nonresponse	misclassification
Victor	. ,						
Warren	Counties - Con.						
Warren			23				
Warred   338		421	54 46				
Words	Warrick		35				
Wells			44				
Wolley	Wells	527	34	35.1	14.2	17.1	3.8
Substitution   Subs			37				
Indams							
Indians	LAND IN FARMS (ACRES)						
Counties  Agains  114,772 17,580 28.0 18.0 19.0 19.0 19.0 19.0 19.0 19.0 19.0 19	State Total						
Alien	Indiana	14,602,240	336,018	27.0	2.9	8.2	15.9
Alben   329,722   30,886   304   77, 27.6   4.2   Billackford   75,000   75,000   15,050   14.0   3.1   10.0   6.8   Billackford   75,000   75,000   17,010   16.0   3.1   13.0   2.0   Billackford   75,000   17,000   16.0   13.0   2.0   Billackford   75,000   13.0   2.0   12.0   2.0   Billackford   75,000   13.0   2.0   2.0   12.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2	Counties						
Alben   329,722   30,886   304   77, 27.6   4.2   Billackford   75,000   75,000   15,050   14.0   3.1   10.0   6.8   Billackford   75,000   75,000   17,010   16.0   3.1   13.0   2.0   Billackford   75,000   17,000   16.0   13.0   2.0   Billackford   75,000   13.0   2.0   12.0   2.0   Billackford   75,000   13.0   2.0   2.0   12.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2.0   2.0   2.0   2.0   2.0   2.0   Billackford   75,000   2.0   2	Adama	214 724	17 550	25.0	6.5	16.2	2.2
Benden	Allen	329,722		39.4			4.2
Blackford	Bartholomew	129,104					
Bone	Blackford						2.6
Carroll	Boone						
Clark   86,066   21,281   26,1   7,5   17,8   2.9   Clark   168,912   44,986   16,8   2.5   11,1   3.2   Clarkon   205,912   44,986   16,8   2.5   11,1   3.2   Clarkon   205,912   44,986   16,8   2.5   11,1   3.2   Clarkon   44,833   41,0   44,1   3.7   24,4   3.6   Clarkon   44,833   44,8   3.5   10,7   44,4   Clarkon   44,833   44,8   3.5   10,2   0.7   Clarkon   44,833   44,8   3.5   0.2   0.7   18,0   Clarkon   160,447   22,448   11,0   17,0   18,0   Clarkon   150,448   33,367   24,8   61,1   17,0   18,0   Clarkon   150,448   33,367   24,8   61,1   17,0   18,0   Clarkon   150,449   33,400   33,400   33,400   Clarkon   150,449   33,400   Clarkon   150,449   33,400   33,400   Clarkon   150,449   Clarkon   150,449   Clarkon   150,449   Clarkon   150,449   Clark							
Chulchin	Cass	224,621	29,103	29.6	0.3	1.0	28.3
Clinion   205,912   44,986   48.8   2.9   11.1   3.7   2.5   2.5   1.1   3.7   2.5   3.7	Clark	60,005	21,201	20.1	7.5	17.0	2.9
Cawbord	Clay						
Dearborn	Crawford	68,274	10,784	44.9	13.7	24.4	6.7
Decatur							
Delayare						0.7	
Dubois   150,866   13,811   24.6   4.7   12.6   7.3							
Payes							
Flyd	Elkhart	195,094	13,299	32.4	3.4	10.3	18.6
Fouritain							
Franklin							
Cibson	Franklin	144,173	8.642	28.0	3.7	7.1	17.1
Grant   159,502   10,340   23.7   2.6   15.7   5.4   Greene   1592,510   13,821   40.8   12.1   22.0   6.7   Hamillon   132,195   15,547   28.1   6.7   17.7   3.6   Hamillon   14,430   13,919   31.5   4.5   21.0   Harison   164,421   28,563   31.8   4.2   5.5   22.2   Hendricks   115,423   12,949   20.5   5.4   11.3   3.8   Henry   178,215   14,328   27.3   3.8   8.5   15.0   Howard   199,488   12,344   24.4   3.3   18.9   2.3   Humington   199,488   12,344   24.4   3.3   18.9   2.3   Humington   199,488   12,345   24.4   3.3   18.9   2.3   Humington   199,488   12,345   24.4   3.3   18.9   2.3   Humington   199,488   12,345   24.4   3.5   25.6   24.4   Hasper   312,985   47,331   30.1   2.5   8.4   19.2   Jay   198,780   12,780   24.7   3.7   15.8   5.2   Jay   198,780   12,780   24.7   3.7   15.8   5.2   Jefferson   84,233   9,328   20.7   8.6   7.7   4.3   Jennings   113,373   9,799   20.2   5.4   8.0   6.7   Johnson   212,228   60,081   37.2   10.7   22.1   4.3   Knox   327,292   18,810   30.5   3.6   18.1   8.8   Ksociusko   288,904   38,890   37.0   9.2   20.7   7.1   LaGrange   193,616   18,262   30.0   13.0   12.3   4.7   LaForte   170,099   10,355   22.2   7.4   8.7   LaForte   170,099   10,355   22.2   7.4   8.7   Marishal   201,037   21,638   3.9   2.1   Marishal   201,037   21,638   3.9   2.2   7.7   3.1   Marishal   201,037   21,638   3.9   3.9   2.2   3.0   Marin   201,037   21,638   3.9   3.9   3.9   3.0   3.0   3.0   Marin   201,037   201,037   3.5   3.9   Marin   201,037   202,038   3.9   3.9   3.0   3.0   3.0   Marin   201,039   30.9   30.9   30.9   30.0   30.9   30.0   Marin   201,039   30.9   30.9   30.9   30.9   30.9   Marin   201,039   30.9   30.9   30.9   30.9   30.9   30.9   Marin   201,039   30.9   30.9   30.9   30.9   30.9   30.9   Marin   201,039   30.9   30							
Hamilton	Grant	159,502	10,340	23.7	2.6	15.7	5.4
Hancock							
Hendricks							
Henry	Harrison	154,221	28,563	31.8	4.2	5.5	22.2
Howard							
Jackson   168,778   50,034   29.2   5.9   16.0   7.4   Jasper   312,985   47,331   30.1   2.5   8.4   19.2   Jay   198,780   12,780   24.7   3.7   15.8   5.2   Jay   32,882   20.7   8.6   7.7   4.3   Jenning   33,328   20.7   8.6   7.7   4.3   Jenning   33,328   20.7   8.6   7.7   4.3   Jenning   32,228   60,081   37.2   10.7   22.1   4.3   3.5							
Jasper							
Jefferson							
Jennings							
Knox         327,292         18,810         30.5         3.6         18.1         8.8           Kosciusko         288,904         33.89         37.0         9.2         20.7         7.1           LaGrange         193,616         18,262         30.0         13.0         12.3         4.7           Lake         123,589         10,911         21.5         0.4         1.4         19.7           LaPorte         277,850         24,080         30.0         6.0         18.6         5.3           Lawrence         117,099         13,835         22.2         7.4         8.7         6.1           Macison         196,215         33,319         17.0         3.5         10.9         2.6           Marion         14,595         4,072         21.9         3.2         18.1         0.6           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7 </td <th></th> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Knox         327,292         18,810         30.5         3.6         18.1         8.8           Kosciusko         288,904         33.89         37.0         9.2         20.7         7.1           LaGrange         193,616         18,262         30.0         13.0         12.3         4.7           Lake         123,589         10,911         21.5         0.4         1.4         19.7           LaPorte         277,850         24,080         30.0         6.0         18.6         5.3           Lawrence         117,099         13,835         22.2         7.4         8.7         6.1           Macison         196,215         33,319         17.0         3.5         10.9         2.6           Marion         14,595         4,072         21.9         3.2         18.1         0.6           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7         4.5         13.6         7.7           Marin         5,900         6,497         25.7 </td <th>Johnson</th> <td>122 228</td> <td>60.081</td> <td>37.2</td> <td>10.7</td> <td>22 1</td> <td>43</td>	Johnson	122 228	60.081	37.2	10.7	22 1	43
LaGrange       193,616       18,262       30.0       13.0       12.3       4.7         Lake       123,589       10,911       21.5       0.4       1.4       19.7         LaPorte       277,850       24,080       30.0       6.0       18.6       5.3         Lawrence       117,099       13,835       22.2       7.4       8.7       6.1         Maction       196,215       33,319       17.0       3.5       10.9       2.6         Marion       14,595       4,072       21.9       3.2       18.1       0.6         Marshall       201,037       21,663       29.3       0.9       2.1       26.3         Martin       57,900       6,497       25.7       4.5       13.6       7.7         Miami       201,899       21,914       34.9       2.4       10.8       21.6         Montroe       63,216       3,978       39.2       2.0       5.7       31.5         Morgan       130,356       11,998       31.0       6.8       4.6       11.2       5.0         Morgan       130,356       11,998       31.0       6.8       4.8       1.5       7.9         Newton <th>Knox</th> <td>327,292</td> <td>18.810</td> <td>30.5</td> <td>3.6</td> <td>18.1</td> <td>8.8</td>	Knox	327,292	18.810	30.5	3.6	18.1	8.8
Lake         123,589         10,911         21.5         0.4         1.4         1.97           LaPorte         277,850         24,080         30.0         6.0         18.6         5.3           Lawrence         117,099         13,835         22.2         7.4         8.7         6.1           Marison         196,215         33,319         17.0         3.5         10.9         2.6           Marison         14,595         4,072         21.9         3.2         18.1         0.6           Marison         201,037         21,663         29.3         0.9         2.1         26.3           Marison         57,900         6,497         25.7         4.5         13.6         7.7           Marison         57,900         6,497         25.7         4.5         13.6         7.7           Mismin         201,889         21,914         34.9         2.4         10.8         21.6           Morrore         63,216         3,978         39.2         2.0         5.7         31.5           Mortone         130,356         11,998         31.0         6.8         16.3         7.9           Newton         189,934         11,658							
Lawrence         117,099         13,835         22.2         7.4         8.7         6.1           Madison         196,215         33,319         17.0         3.5         10.9         2.6           Marion         14,595         4,072         21.9         3.2         18.1         0.6           Marshall         201,037         21,663         29.3         0.9         2.1         26.3           Martin         57,900         6,497         25.7         4.5         13.6         7.7           Miami         201,899         21,914         34.9         2.4         10.8         21.6           Morror         63,216         3,978         39.2         2.0         5.7         31.5           Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Mewton         189,934         11,658         18.7         0.8         1.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         2	Lake	123,589	10,911	21.5	0.4	1.4	19.7
Madison       196,215       33,319       17.0       3.5       10.9       2.6         Marion       14,595       4,072       21,9       3.2       18.1       0.6         Marshall       201,037       21,663       29.3       0.9       2.1       26.3         Martin       57,900       6,497       25.7       4.5       13.6       7.7         Miami       201,899       21,914       34.9       2.4       10.8       21.6         Morroce       63,216       3,978       39.2       2.0       5.7       31.5         Morgan       252,762       25,206       20.8       4.6       11.2       5.0         Morgan       130,356       11,998       31.0       6.8       16.3       7.9         Newton       189,934       11,658       18.7       0.8       1.9       16.0         Noble       174,349       14,025       26.5       6.0       11.5       9.0         Ohio       16,420       664       15.0       8.6       4.8       1.9         Orange       95,336       11,974       20.8       8.0       9.3       3.5         Parke       174,867       20,394							
Marshall         201,037         21,663         29.3         0.9         2.1         26.3           Martin         57,900         6,497         25.7         4.5         13.6         7.7           Miami         201,899         21,914         34.9         2.4         10.8         21.6           Monroe         63,216         3,978         39.2         2.0         5.7         31.5           Mortgam         252,762         25,206         20.8         4.6         11.2         5.0           Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Movelon         189,934         11,658         18.7         0.8         19.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Porter         66,411         6,260	Madison	196,215	33,319	17.0	3.5	10.9	2.6
Martin         57,900         6,497         25.7         4,5         13.6         7,7           Miami         201,899         21,914         34.9         2.4         10.8         21.6           Monroe         63,216         3,978         39.2         2.0         5.7         31.5           Mortgomery         525,762         25,206         20.8         4.6         11.2         5.0           Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Newton         189,934         11,658         18.7         0.8         1.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Ohio         16,420         64         15.0         8.6         4.8         1.6           Owen         16,420         64         15.0         8.6         4.8         1.6           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         6,641         6,260         30.5	Marion						
Miami         201,899         21,914         34.9         2.4         10.8         21.6           Monroe         63,216         3,978         39.2         2.0         5.7         31.5           Monroe         252,762         25,206         20.8         4.6         11.2         5.0           Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Newton         189,934         11,658         18.7         0.8         1.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Ohio         16,420         664         15.0         8.6         4.8         1.6           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4							
Monroe         63.216         3.978         39.2         2.0         5.7         31.5           Montgomery         252,762         25,206         20.8         4.6         11.2         5.0           Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Newton         189,934         11,658         18.7         0.8         1.9         16.0           Noble         189,934         11,658         18.7         0.8         1.9         16.0           Ohio         16,420         664         15.0         8.6         4.8         1.6           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20.394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         8,848.3         21,190         28.4         3.6         11.0         13.8           Posey         256,130         23,399         37.9							
Morgan         130,356         11,998         31.0         6.8         16.3         7.9           Newton         189,934         11,658         18.7         0.8         1.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Ohio         664         15.0         8.6         4.8         1.6           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4         3.6         11.0         13.8           Porter         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         256,130         23,399         37.9         7.3         27.7         2.9           Pulnam         245,345         46,918         33.8         1.7	Monroe	63,216	3,978	39.2	2.0	5.7	31.5
NewTon         189 934         11,658         18.7         0.8         1.9         16.0           Noble         174,349         14,025         26.5         6.0         11.5         9.0           Ohio         16,420         664         15.0         8.6         4.8         1.6           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         8,8483         21,190         28.4         3.6         11.0         13.8           Poster         22,238         14,732         20.7         2.5         11.3         6.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         245,345         46,918         33.8         1.7         5.9         26.2           Pulmam         214,4378         29,275         18.8							
Ohio         16,420         664         15.0         8.6         4.8         1.6           Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4         3.6         11.0         13.8           Posey         22,238         14,732         20.7         2.5         11.3         6.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         245,345         46,918         33.8         1.7         5.9         26.2           Putnam         2174,378         29,275         18.8         4.8         9.2         4.8           Randolph         238,870         24,795         27.5         3.1         21.2         3.2           Ripley         175,750         26,525         32.5	Newton	189,934	11,658	18.7	0.8	1.9	16.0
Orange         95,336         11,974         20.8         8.0         9.3         3.5           Owen         76,206         5,107         23.8         5.9         6.7         11.3           Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4         3.6         11.0         13.8           Porter         21,238         14,732         20.7         2.5         11.3         6.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         245,345         46,918         33.8         1.7         5.9         26.2           Putnam         21,438         29,275         18.8         4.8         9.2         4.8           Randolph         238,870         24,795         27.5         3.1         21.2         3.2           Ripley         199,580         27,321         26.9         2.2         12.6         12.1		174,349 16.420					
Parke         174,867         20,394         27.3         5.4         10.5         11.4           Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4         3.6         11.0         13.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         245,345         46,918         33.8         1.7         5.9         26.2           Putnam         214,378         29,275         18.8         4.8         9.2         4.8           Randolph         238,870         24,795         27.5         3.1         21.2         3.2           Ripley         175,750         26,525         32.5         7.7         19.3         5.5           Rush         189,580         27,321         26.9         2.2         12.6         12.1	Orange	95,336	11,974	20.8	8.0	9.3	3.5
Perry         66,411         6,260         30.5         9.6         11.1         9.9           Pike         88,483         21,190         28.4         3.6         11.0         13.8           Porter         12,238         14,732         20.7         2.5         11.3         6.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaski         245,345         46,918         33.8         1.7         5.9         26.2           Putnam         174,378         29,275         18.8         4.8         9.2         4.8           Randolph         238,870         24,795         27.5         3.1         21.2         3.2           Ripley         175,750         26,525         32.5         7.7         19.3         5.5           Rush         189,580         27,321         26.9         2.2         12.6         12.1	Owen	76,206	5,107	23.8	5.9	6.7	11.3
Pike     88,483     21,190     28.4     3.6     11.0     13.8       Porter     22,238     14,732     20.7     2.5     11.3     6.8       Posey     256,130     23,399     37.9     7.3     27.7     2.9       Pulaski     245,345     46,918     33.8     1.7     5.9     26.2       Putnam     247,347     29,275     18.8     4.8     9.2     4.8       Randolph     238,870     24,795     27.5     3.1     21.2     3.2       Ripley     175,750     26,525     32.5     7.7     19.3     5.5       Rush     189,580     27,321     26.9     2.2     12.6     12.1							
Porter         122,238         14,732         20.7         2.5         11.3         6.8           Posey         256,130         23,399         37.9         7.3         27.7         2.9           Pulaskii         245,345         46,918         33.8         1.7         5.9         26.2           Putnam         174,378         29,275         18.8         4.8         9.2         4.8           Randolph         238,870         24,795         27.5         3.1         21.2         3.2           Ripley         175,750         26,525         32.5         7.7         19.3         5.5           Rush         189,580         27,321         26.9         2.2         12.6         12.1							
Pulaski     245,345     46,918     33.8     1.7     5.9     26.2       Putnam     21,4378     29,275     18.8     4.8     9.2     4.8       Randolph     238,870     24,795     27.5     3.1     21.2     3.2       Ripley     175,750     26,525     32.5     7.7     19.3     5.5       Rush     189,580     27,321     26.9     2.2     12.6     12.1	Porter	122,238	14,732	20.7	2.5	11.3	6.8
Putnam     174,378     29,275     18.8     4.8     9.2     4.8       Randolph     238,870     24,795     27.5     3.1     21.2     3.2       Ripley     175,750     26,525     32.5     7.7     19.3     5.5       Rush     189,580     27,321     26.9     2.2     12.6     12.1							
Ripley	Putnam	174,378	29,275	18.8	4.8	9.2	4.8
Rush 189,580 27,321 26.9 2.2 12.6 12.1	Randolph						3.2 5.5
St. Joseph	Rush	189,580	27,321	26.9	2.2	12.6	12.1
continued	St. Joseph	153,034	9,112	27.2	2.7	6.4	

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Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2022 (continued) [For meaning of abbreviations and symbols, see introductory text.]

[For meaning of abbreviations and symbols, see introductory text.]  Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
LAND IN FARMS (ACRES) - Con.						
Counties - Con.						1
	45.293	32,578	18.6	5.5	6.1	7.0
Scott	209,675	33,420	23.8	2.6	11.3	7.0 9.9
Spencer	162,031	29,207	24.9 16.9	5.6	15.4	3.9
Starke Steuben	98,815 96,550	13,059 6,667	17.9	3.8 4.5	7.5 9.6	5.5 3.8
Sullivan	176,644	14,429	36.8	3.4	12.5	20.9
Switzerland Tippecanoe	53,933 237,534	1,966 38,165	31.0 19.8	10.7 3.4	15.1 9.8	5.2 6.6
Tipton	163,401	7,333	20.2	1.9	13.6	4.7
Union	69,029	27,617	29.5	5.8	15.8	7.9
Vanderburgh	51,839	20,204	13.6	2.7	10.4	0.5
Vermillion	104,913 105,310	10,821 41,393	23.3 15.7	3.1 1.4	12.0 4.3	8.3 10.0
Wabash	186,071	24,370	27.6	4.4	19.6	3.6
Warren Warrick	204,198 123,966	21,588 30,494	24.5 41.9	3.6 5.5	8.2 16.6	12.7 19.9
Washington	190,434	18,684	24.6	7.3	12.1	5.2
Wayne	154,498	19,345	31.8 22.5	4.1	9.2	18.5
Wells	201,538 304,558	23,696 32,295	27.6	2.8 2.2	18.5 10.0	1.3 15.4
Whitley	162,338	16,419	20.4	3.7	12.8	3.9
SALES (\$1,000)						
State Total						
Indiana	18,029,033	397	23.3	4.5	8.0	10.7
Counties						
AdamsAllen	366,136 310,503	21 43	20.8 38.1	8.0 7.3	10.3 26.8	2.4 4.0
Bartholomew	128,770	10	15.1	3.1	11.0	1.0
Benton	298,356 78,176	12 16	8.1 22.3	0.3 2.7	5.3 16.0	2.5 3.6
Boone	230,230	7	13.0	2.6	8.6	1.8
Brown	4,973 299.907	1 28	29.5 22.6	7.5 3.3	19.1 13.6	3.0 5.8
Carroll	252,949	29	26.4	0.3	0.8	25.2
Clark	58,899	20	18.8	7.5	9.8	1.5
Clay	143,694	78	31.4	6.1	21.2	4.1
Clinton	274,170	53	18.6	4.8	10.5	3.2
Crawford	28,049 403,143	7 17	35.7 22.0	6.9 4.4	26.4 5.3	2.3 12.3
Dearborn	13,094	2	27.2	7.3	15.8	4.1
Decatur DeKalb	290,732 166,606	34 19	13.7 34.6	0.1 10.5	0.4 17.5	13.2 6.7
Delaware	156,243	39	22.1	2.9	16.4	2.9
DuboisElkhart	487,689 497,787	16 42	21.3 31.9	16.4 8.6	4.2 13.3	0.7 10.0
FayetteFloyd	78,720 6,921	21 1	22.1 15.5	3.4 5.7	12.9 9.4	5.7 0.4
Fountain	175,818	21	16.8	2.0	12.1	2.7
Franklin	103,017 195,306	8 26	20.5 15.5	0.9 2.9	2.4 7.9	17.2 4.6
FultonGibson	268,746	67	33.5	7.7	18.6	7.1
Grant	167,757	15	22.3	2.0	16.0	4.3
Greene	180,126 140,769	16 9	40.5 14.8	13.2 8.9	23.9 5.2	3.4 0.7
Hancock	206,814	23	32.7	7.7	21.8	3.2
Harrison	107,955	22	18.2	5.0	3.0	10.2
Hendricks	122,231	16	19.6	7.3	8.7	3.6
Henry Howard	200,884 137,389	13 13	24.6 19.2	4.1 4.2	12.9 13.3	7.6 1.7
Huntington	303,036	22 25	25.1	7.8	14.6	2.7
Jackson Jasper	264,705 589,674	25 39	15.4 21.2	5.6 4.6	2.2 9.9	7.6 6.7
Jay	602,966	14	16.6	3.8	11.9	0.9
Jefferson	42,544 96,569	5 9	11.7 13.5	4.0 3.6	5.4 1.4	2.2 8.6
·						
Johnson Knox	122,619 416,833	62 26	37.3 25.0	8.4 7.0	23.4 12.8	5.5 5.2
Kosciusko	428,903	17	29.3	11.6	13.3	4.4
LaGrange Lake	494,017 99,957	56 9	34.7 19.6	16.9 0.5	14.1 2.3	3.7 16.7
LaPorte	308,802	22 7	25.5	6.8	14.9	3.8
Lawrence	50,796 206.059	7 41	18.0 12.6	3.6 2.5	4.8 5.6	9.6 4.6
Marion	16,336	3	22.5	6.7	14.9	0.9
Marshall	262,735	23	23.9	1.6	1.5	20.8
Martin Miami	109,809 269,146	9 28	28.7 29.0	8.3 5.8	18.4 8.0	2.0 15.2
Monroe	16,643	2	24.1	8.5	14.5	1.1
Montgomery Morgan	235,467 122,372	21 12	17.2 31.0	5.4 6.3	8.7 18.4	3.1 6.4
Newton	442,405	16	18.7	2.2	3.5	13.1
Noble	199,872	15	23.2	6.6	12.2	4.4
Ohio Orange	4,831 220,924	(Z) 7	5.5 14.4	2.0 4.1	3.2 9.5	0.3 0.7
	,	• 1			5.0	continued

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2022 (continued) [For meaning of abbreviations and symbols, see introductory text.]

Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
SALES (\$1,000) - Con.						
Counties - Con.						
Owen Parke Perry Pike Porter Posey Pulaski Putnam Randolph Ripley	31,996 135,834 47,495 85,118 101,951 222,383 369,273 144,173 328,813 133,546	4 19 8 24 14 16 36 22 32 26	16.1 23.7 25.5 21.7 11.8 31.7 28.2 19.0 30.3 31.1	3.4 4.9 12.5 12.0 2.7 5.4 5.0 3.3 4.8 8.3	5.7 7.5 8.5 7.8 7.8 24.3 7.5 12.2 22.1	6.9 11.2 4.6 1.9 1.2 2.0 15.7 3.5 3.4
Rush St. Joseph Scott Shelby Spencer Starke Steuben Sullivan Switzerland Tippecanoe	222,694 162,244 28,073 208,193 148,680 75,483 82,622 171,052 23,591 244,176	28 13 5 34 19 11 8 16 2 2 30	27.8 25.2 11.9 21.3 22.5 16.0 12.7 34.8 26.0 17.9	3.5 4.3 2.7 3.1 5.5 2.5 3.1 8.2 4.5	18.8 8.4 3.8 12.1 14.2 6.2 7.2 9.8 12.1 10.3	5.6 12.5 5.4 6.2 2.7 7.3 2.6 22.0 5.7 3.1
Tipton Union Vanderburgh Vermillion Vigo Wabash Warren Warrick Washington Wayne	203,027 66,832 50,097 92,473 92,349 394,401 216,652 103,676 258,198 132,839	8 30 20 6 35 26 16 31 23 27	16.0 32.8 11.3 13.6 8.4 18.0 13.4 46.1 21.5 33.1	1.6 4.5 2.5 1.9 2.2 5.8 2.7 3.8 8.4 3.9	9.9 18.5 8.4 9.3 2.2 10.5 3.4 12.9 8.0	4.6 9.9 0.5 2.4 4.0 1.7 7.3 29.4 2.2 21.2
Wells	313,500 439,323 187,697	60 27 26	23.6 27.0 22.3	5.8 5.4 2.6	17.0 12.1 15.3	0.8 9.5 4.4

### Table D. American Indian or Alaska Native Producers: 2022

[For meaning of abbreviations and symbols, see introductory text.]

	American Indian or Alaska Native farm producers			American Indian or Alaska Native farm producers			
Geographic area	Total	Individually reported 1	Other <sup>2</sup>	Geographic area	Total	Individually reported 1	Other <sup>2</sup>
State Total				Counties - Con.			
Indiana	344	344	-	Lawrence	21	21	-
Counties				Madison Marion	9	9	
Adams	6	6	-	Marshall Martin	6 1	6	
Allen Bartholomew	10 1	10 1	-	Miami Monroe	8	8	-
Blackford	2	2	-	Montgomery	2	2	-
Cass	1	1	-	Noble	13	13	
Clay	3	3	-	Orange	3	3	-
Clinton	8	8	-	Owen	2	2	-
Daviess	2	2	-	Perry	6	6	
Delaware	2 3	2 3	-	Porter Pulaski	1 14	1 14	
DuboisFloyd	2 3	2 3	-	PutnamRandolph	7 3	7 3	-
FountainFulton	7 7	7 7	-	Ripley	2	2	-
Gibson	3	3	-	St. Joseph	5 7	5 7	
Greene	14	14	-	Shelby	3	3	
Hamilton	3	3	-	Starke Sullivan	2	2	
Harrison	4	4	-	Switzerland	2	2	
Hendricks	3	3	-	Tippecanoe	6	6	
Howard	1 4	1 4 -	-	Vigo	4	4	
Jackson	5 2	5 2	_	Wabash Warren	8	8 1	
Jefferson	4	4	-	Warrick Washington	1 3	1 3	
Jennings Johnson	5 1	5 1	-	Wayne Wells	2 8	2 8	
KosciuskoLake	1 4	1 4	-	WhiteWhitley	7 7	7 7	-
LaPorte	3	3	-	,	·		

<sup>&</sup>lt;sup>1</sup> Data were collected for a maximum of four producers per farm.
<sup>2</sup> Data represent American Indian or Alaska Native farm or ranch producers on reservations who did not report individually. Data obtained by reservation officials.