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 service 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 preidentified 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 for 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-bysection 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 for 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 π_C is of interest:

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

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 $\pi_{\rm C}$. 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,

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

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 π_C may be written as

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

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 of these 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 *h*th 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 *h*th group $C_{in-scope,h}$ = the number of completed and in-scope census records in the *h*th group

 C_h = the number of completed census records in the *h*th group

 U_h = number of operations of unknown eligibility in the *h*th 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, and 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
Farmsnumb		6,407	44.0	15.5	16.2	12.2
Land in farmsacr		656,869	33.9	7.5	12.0	14.4
Farms by size: 1 to 9 acresfarr	ns 4,799	1,646	54.8	21.7	21.9	11.2
acr	ns 24,349	7,405	55.1	23.4	20.5	11.3
10 to 49 acresfarr		2,852	51.5	21.7	17.9	11.9
acr	ns 7,099	59,369	50.3	20.4	17.6	12.4
50 to 69 acresfarr		539	44.1	15.1	16.3	12.8
acr	ns 7,257	31,566	44.1	15.1	16.1	12.8
70 to 99 acresfarr		536	40.5	12.6	13.9	14.0
acr	ns 7,176	43,407	40.5	12.6	13.8	14.0
100 to 139 acresfarr		391	38.7	11.7	14.7	12.2
acr	ns 4,237	46,548	38.5	11.6	14.6	12.2
140 to 179 acresfarr		210	36.9	10.0	15.3	11.7
acr	ns 3,017	32,699	36.8	10.0	15.2	11.7
180 to 219 acresfarr		200	33.7	7.9	16.1	9.7
acr	ns 1,998	39,373	33.5	7.9	16.0	9.7
220 to 259 acresfarr		140	33.2	7.1	12.6	13.5
acr	ns 4,867	33,595	33.3	7.1	12.7	13.6
260 to 499 acresfarr		382	32.8	6.4	12.9	13.5
acr	ns 2,530	138,536	32.9	6.2	12.9	13.8
500 to 999 acresfarr		300	37.4	4.2	15.3	17.9
acr	1.261	201,987	38.3	4.1	15.4	18.8
1,000 to 1,999 acresfarr		124	43.6	5.7	19.5	18.4
acr	ns 835	167,498	43.1	5.6	18.8	18.6
2,000 acres or morefarr		32	22.3	1.7	2.7	18.0
acr	es 3,048,492	74,618	18.8	1.2	2.0	15.6
Irrigated land use: Harvested cropland farr	ns 2,378	1,041	30.3	7.4	14.1	8.8
acr	ns 232	4,583	9.7	1.5	4.0	4.1
Pastureland and other landfarr		21	54.3	13.2	23.4	17.7
acr		472	58.3	8.7	25.1	24.5
Market value of agricultural products sold\$1,0	8,005,745	479	18.8	3.2	5.0	10.6
Farms by value of sales: Less than \$1,000farr	ns 19,270	1,998	63.8	20.6	22.4	20.7
\$1,00	3.045	(Z)	65.1	33.8	19.8	11.5
\$1,000 to \$2,499		1,640	51.5	22.4	18.0	11.1
\$1,000 to \$4,999	13,018	3	51.3 44.0	22.2 20.8	18.0 14.2	11.1 9.0
\$1,0 \$5,000 to \$9,999	26,393	1,343	43.6	20.6 17.6	14.0 14.9	8.9 8.8
\$1,00	00 64,328	10	40.8	17.5	14.7	8.7
\$10,000 to \$19,999		452	25.2	8.0	10.2	7.0
\$1,0	104,809	6	25.2	8.0	10.3	6.9
\$20,000 to \$24,999farr		132	27.3	8.0	11.7	7.6
\$1,0 \$25,000 to \$39,999farr	0 55,298	3	27.3 31.4	8.0 7.8	11.7 14.8	7.6 8.8
\$1,0	0 137,081	11	31.5	7.8	14.8	8.9
\$40,000 to \$49,999		198	33.4	9.0	15.6	8.8
\$1,0 \$50,000 to \$99,999farr	81,542	9	33.3 26.4	9.1 5.5	15.4 13.3	8.8 7.5
\$1,0	244.936	18	27.2	5.7	13.9	7.5
\$100,000 to \$249,999farr		134	28.9	7.1	11.0	10.7
\$1,0	368,994	23	29.0	6.7	11.2	11.1
\$250,000 to \$499,999farr		289	34.9	3.5	20.0	11.4
\$1,0	409.601	107	35.3	3.4	20.0	11.9
\$500,000 to \$999,999		132	34.1	2.7	16.6	14.8
\$1,00 \$1,000,000 or more	693,367	92	34.0 18.6	2.7 3.2	15.8 4.9	15.5 10.5
\$1,0		256	13.7	2.4	2.6	8.7
Farms by legal status for tax purposes: Family or individualfarr	ns 63,204	5,838	44.1	16.5	15.4	12.2
acr	9 358 085	575,268	35.4	8.8	11.7	14.9
Partnershipfarr		299	42.3	9.1	22.7	10.5
Corporation:		83,714	27.2	3.7	11.5	11.9
Family heldfarr	es 756,923	154	40.9	8.5	20.2	12.2
acr		27,883	31.4	4.1	13.8	13.5
Other than family held farr		71	50.2	6.4	25.2	18.5
acr		25,093	44.4	3.8	19.2	21.4
Other - estate or trust, prison farm, grazing association, American Indian Reservation, etc farr acr	ns 566	87 23,860	43.5 34.5	11.2 4.6	17.2 13.8	15.0 16.1
Tenure:						
Full ownersfarr	es 6,015,982	5,368 419,315	46.1 41.8	17.6 11.7	16.5 14.4	12.1 15.7
Part ownersfarr	es 5,924,025	844	33.7	4.4	14.9	14.5
acr		394,623	25.8	1.8	9.5	14.5
Tenantsfarr		252	42.7	9.3	20.3	13.2
acr		46,672	34.6	9.0	14.9	10.8
Producers characteristics by- ¹ (see text) Sex of operator: Male	ns 64,916	5,835	43.8	14.7	16.9	12.3
Femalefarr	es 11,969,466	623,883 3,808	33.7 43.3	7.0 18.5	12.2 19.5	14.5 5.2
acr		250,833	35.5	11.7	18.0	5.8
Primary occupation: Farmingfarr	ns 43,697	3,659	38.9	13.3	17.9	7.7
Otherfarr	ns 75,435	7,538	48.4	15.2	23.2	9.9

See footnote(s) at end of table.

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.]				-	-	
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
Producers characteristics by- ¹ (see text) - Con.						
Hispanic, Latino, or Spanish originfarms acres	802 123,134	95 12,205	52.1 41.8	11.4 4.3	27.2 24.5	13.5 13.0
Race: American Indian or Alaska Native	235	84	43.0 39.1	21.5	15.8	5.7
acres Asianfarms acres	41,313 157 23,877	12,322 36 2,676	45.9 58.6	8.3 12.1 9.3	19.1 16.8 11.8	11.7 17.0 37.6
Black or African Americanfarms acres	312 24,044	91 3,682	31.7 14.7	9.7 4.2	14.4 7.0	7.6 3.5
Native Hawaiian or Other Pacific Islanderfarms	46	. 11	47.8	25.6	15.8	6.4
acres White acres	2,225 68,804 12,359,082	1,683 6,329 647,084	56.9 44.0 33.9	32.9 15.6	14.7 16.2	9.2 12.3 14.5
More than one race reportedfarms acres	12,339,082 558 86,312	156 35,368	40.0 36.6	7.5 11.7 10.7	12.0 20.7 17.8	7.5
Military service: Never served or only on active duty for training in the Reserves or National Guard (see text)	108,347 10,785	10,040 1,121	45.0 44.2	14.3 15.7	21.5 19.3	9.1 9.1
All producers by age group ¹ : Under 25 years	2,367	577	58.0	15.9	33.0	9.1
25 to 34 years	9,274 15,551	1,725 1,983	57.7 50.7	10.0 14.4	34.4 24.1	13.4 12.3
45 to 54 ýearsfarms 55 to 64 yearsfarms	19,912 30,292	2,216 2,522	45.5 44.8	13.3 13.7	21.7 22.7	10.5 8.3
65 to 74 yearsfarms 75 years and overfarms	27,042 14,694	1,723 898	39.6 37.7	17.7 17.9	14.8 14.8	7.1 5.1
Net cash farm income of operations: Farms with gains of- ² Less than \$1,000farms	2,531	317	46.0	18.7	16.7	10.6
\$1,000 to \$4,999 farms \$1,000 to \$4,999	1,215 6,523 18,032	(Z) 919	45.3 41.9 40.9	17.2 16.0 15.4	17.7 15.2 14.9	10.4 10.7 10.7
\$5,000 to \$9,999farms	4,086	516 4	33.5 32.7	10.8 10.6	12.7	10.7 10.0 9.8
\$10,000 to \$24,999	5,332 87,025	394 7	30.3 30.2	8.2 8.1	11.8 11.9	10.3 10.2
\$25,000 to \$49,999	3,210 113,231	243 8	25.8 25.7	6.3 6.2	10.6 10.7	9.0 8.8
\$50,000 or morefarms \$1,000	5,968 2,863,479	514 175	26.7 17.7	3.9 2.5	11.9 6.0	10.9 9.2
Farms with losses of- Less than \$1,000\$arms \$1,000	3,427 1,752	366 (Z)	51.9 52.3	22.4 22.1	15.6 15.9	13.8 14.3
\$1,000 to \$4,999	13,137 37,828	1,288 4	52.5 52.6	20.7 20.4	18.8 19.0	13.0 13.2
\$5,000 to \$9,999 farms \$1,000	9,735 70,546	872 6	51.9 51.7	19.9 19.8	17.4 17.5	14.6 14.5
\$10,000 to \$24,999	10,025 155,753 3,390	822 13 313	49.7 49.8 47.5	19.0 18.6 13.5	18.8 19.3 19.1	11.8 11.8 14.9
\$25,000 to \$45,555 \$1,000 \$50,000 or more \$1,000 \$60,000 or more \$1,000	116,029 2,061	10 189	47.3 47.3 44.1	13.4 10.9	19.3 19.9	14.5 14.6 13.3
\$1,000	273,721	26	40.0	9.0	17.6	13.5
Livestock and poultry: Cattle and calves inventoryfarms number	31,060 1,876,383	1,371 31,551	36.3 38.7	20.2 15.5	6.5 8.8	9.6 14.4
Beef cows inventoryfarms number	28,073 914,865	1,124 20,777	36.3 39.3	20.0 17.3	6.7 9.0	9.6 12.9
Milk cows inventoryfarms number	1,062 45,904	65 832	25.4 23.4	14.7 6.2	4.6 8.1	6.1 9.2
Hog and pigs inventoryfarms number	1,564 454,797	585 229,100	43.9 14.9	13.7 0.5	14.2 1.5	16.1 12.9
Layers inventory farms number Broilers sold	8,586 5,542,366 796	2,053 1,076,954 204	47.9 10.8	17.5 5.6	18.2 1.5	12.2 3.7 9.8
Aquaculture sold	262,581,637 45	33,530,393 18	23.6 4.4 33.3	6.1 0.8 5.0	7.7 0.5 25.5	9.8 3.1 2.8
\$1,000	3,497	1	0.4	0.4	(Z)	(Z)
Selected crops harvested: Corn for grain farms	6,291	432	28.7	7.6	12.5	8.5
acres Durum wheat for grainfarms acres	1,411,522	64,324	15.2	1.6	5.2	8.4
Other spring wheat for grainfarms acres	-	-	-	-	-	-
Winter wheat for grainfarms acres	1,368 429,697	157 29,891	20.2 11.2	2.7 0.7	8.8 3.2	8.7 7.3
Sorghum for grainfarms acres	10 456	2 108	10.0 14.5	0.6 0.7	3.0 5.8	6.4 8.0
Soybeans for beansfarms acres	6,098 1,928,881	910 187,673	23.7 16.4	3.6 0.8	11.2 6.4	9.0 9.2
Ricefarms acres Cottonfarms	-	-	-	-	-	-
acres	-	-		-		

See footnote(s) at end of table.

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	-	-	-	-	-	-
acres Barley farms	- 16	- 4	6.2	0.8	2.5	3.0
acres Oats	1,818 24 365	242 5 34	1.4 20.8 6.8	0.2 9.7 3.4	0.1 2.7 0.6	1.1 8.5 2.8
Forage - land used for all hay and haylage,	37,930	2,546	39.8	20.6	13.2	6.0
grass silage, and greenchop	1,792,405	94,278	36.7	15.3	13.6	7.8
acres Land in vegetables (see text)farms	2,173	(H)	20.3	6.6	12.8	0.9
acres	7,186	3,634	10.6	2.6	7.3	0.7
Potatoes farms	609	491	22.2	8.2	12.4	1.5
acres	371	206	24.6	6.9	11.1	6.6
Tomatoes in the openfarms	1,072	(H)	16.8	4.8	11.5	0.4
acres	666	367	9.6	2.2	7.1	0.4
Sweet corn (see text) farms	786	(H)	17.0	5.4	11.2	
acres	1,339	666	8.4	2.4	5.7	0.2
Lettucefarms	329	288	12.5	3.7	8.4	
acres	125	65	16.0	3.1	12.6	0.2
Land in orchards (see text) farms	1,309	483	40.7	8.1	17.3	15.4
acres	4,303	1,031	31.7	5.7	12.4	13.6
Applesfarms	683	249	39.1	7.8	18.0	13.4
acres	1,276	311	21.9	4.6	8.2	9.1
Grapes (including muscadine) (see text)farms	327	179	33.6	7.8	13.7	12.1
acres Orangesfarms	525	173	28.6	5.6	8.9	14.1
acres Almondsfarms	17	- 6	35.3	11.9	14.1	9.2
acres	10	1	60.2	12.7	32.9	14.6
Land in berriesfarms	965	407	34.2	6.5	16.0	11.7
acres	986	374	22.7	3.9	11.7	7.2

¹ Data were collected for a maximum of four producers per farm. ² 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)
Farmsnumber Land in farmsacres	69,425 12,431,190	9.2 5.3	Producers characteristics by- 1 (see text) - Con.		
	12,401,100	0.0	Hispanic, Latino, or		
Farms by size: 1 to 9 acres	4.799	34.3	Spanish origin	802 123,134	11. 9.
acres	24,664	30.0		125,154	5.
10 to 49 acresfarms acres	24,349 623,475	11.7 9.5	Race: American Indian or		
50 to 69 acres farms	7,099	7.6	Alaska Native farms	235	35.
acres 70 to 99 acresfarms	410,777 7,257	7.7 7.4	acres Asianfarms	41,313 157	29. 23.
acres	601,134	7.2	acres	23,877	11.
100 to 139 acresfarms acres	7,176 830,736	5.5 5.6		312 24,044	29. 15.
140 to 179 acres farms	4,237	4.9	Native Hawaiian or		
acres 180 to 219 acresfarms	665,353 3,017	4.9 6.6		46 2.225	23 75
acres	595,401	6.6	White farms	68,804	9
220 to 259 acres farms acres	1,998 475,989	7.0 7.1	Acres More than one race reportedfarms	12,359,082 558	5 27
260 to 499 acres farms	4,867 1,692,583	7.9	acres	86,312	41
acres 500 to 999 acresfarms	2,530	8.2 11.8			
acres 1,000 to 1,999 acresfarms	1,734,783	11.6	Never served or only on active duty for training	100 247	
00500	1,261 1,727,803	9.8 9.7	Active duty now or in the past (see text) producers	108,347 10,785	9 10
2,000 acres or more	835	3.9			
acres	3,048,492	2.4	Under 25 years farms	2,367	24
Irrigated land use: Harvested cropland farms	0.070	42.0	25 to 34 years	9,274	18
acres	2,378 81,064	43.8 5.7	35 to 44 yearsfarms 45 to 54 yearsfarms	15,551 19,912	12 11
Pastureland and other land farms	232	9.2	55 to 64 years farms	30,292	8
acres	2,394	19.7	65 to 74 yearsfarms 75 years and overfarms	27,042 14,694	6 6
Market value of agricultural products sold\$1,000	8,005,745	6.0	Net cash farm income of operations:	,	-
Farms by value of sales:			Farms with gains of- ²		
Less than \$1,000 farms	19,270	10.4	Less than \$1,000 farms	2,531	12
\$1,000 to \$2,499farms	3,045 7,913	13.7 20.7	\$1,000 \$1,000 to \$4,999farms	1,215 6,523	13 14
\$1,000	13,018	20.6	\$1,000	18,032	14
\$2,500 to \$4,999farms \$1,000	7,391 26,393	19.9 19.8	\$1,000	4,086 29,288	12 12
\$1,000 \$5,000 to \$9,999farms \$1,000	9,011	14.9	\$10,000 to \$24,999farms	5,332	7.
\$1,000 \$10,000 to \$19,999farms	64,328 7,382	15.0 6.1	\$1,000 \$25,000 to \$49,999farms	87,025 3,210	7. 7.
\$1,000 \$20,000 to \$24,999farms	104,809	6.0	\$1,000	113,231	7.
\$1,000	2,491 55,298	5.3 5.4		5,968 2,863,479	8. 6.
\$25,000 to \$39,999	4,355 137,081	8.0 8.0		,,	-
\$40,000 to \$49,999 farms	1,835	0.0 10.8		3,427	10.
\$1,000 \$50,000 to \$99,999farms \$1,000	81,542 3,483	10.7 8.1		1,752 13,137	10 9
\$50,000 to \$99,999	244,936	7.4	£1.000	37,828	9
\$100,000 to \$249,999	2,405 368,994	5.6 6.1	\$5,000 to \$9,999	9,735 70,546	9
\$250,000 to \$499,999farms	1,166	24.8	\$10,000 to \$24,999farms	10,025	8
\$1,000 \$500,000 to \$999,999farms	409,601 970	26.2 13.6	\$1,000 \$25,000 to \$49,999farms	155,753 3,390	8 9
\$1,000	693,367	13.2	\$1,000	116,029	9
\$1,000,000 or more	1,753 5,803,333	3.6 4.4	\$50,000 or more	2,061 273,721	9. 9.
	-,,			,	
Farms by legal status for tax purposes: Family or individualfarms	63,204	9.2	Livestock and poultry: Cattle and calves inventory farms	31,060	4.
acres Partnership farms	9,358,085 3,430	6.1		1,876,383	1.
Partnership larnis acres	2,041,586	8.7 4.1	number	28,073 914,865	4.
Corporation: Family held farms	1,789		Milk cows inventoryfarms	1,062	6. 1.
acres	756,923	8.6 3.7	number Hog and pigs inventoryfarms	45,904 1,564	37.
Other than family held farms	436	16.3		454,797 8,586	50. 23.
acres Other - estate or trust, prison farm, grazing association,	125,590	20.0	number	0,500 5,542,366	19
American Indian Reservation, etc farms acres	566 149,006	15.3 16.0		796 262,581,637	25. 12.
	149,000	10.0	Aquaculture soldfarms	202,561,037	39
Tenure: Full owners farms	55,671	9.6	\$1,000	3,497	34
acres	6,015,982	7.0	Selected crops harvested:		
Part ownersfarms acres	11,506 5,924,025	7.3 6.7	Corn for grainfarms	6,291 1,411,522	6 4
Tenants farms	2,248	11.2	Durum wheat for grain farms		4
acres	491,183	9.5	Other spring wheat for grainfarms	-	
Producers characteristics by- ¹ (see text)			acres	-	
Sex of operator: Male	64,916	9.0	Winter wheat for grain farms acres	1,368 429,697	11.
acres	11,969,466	5.2	Sorghum for grain farms	10	16
Femalefarms acres	38,425 5,493,023	9.9 4.6		456 6,098	23 14
	3,493,023	4.0	acres	1,928,881	9.
Primary occupation: Farmingfarms	43,697	8.4	Ricefarms acres	-	
Other	75,435	0.4 10.0		-	1

See footnote(s) at end of table.

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

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

Item	Total	Coefficient of variation (percent)	Item	Total	Coefficient of variation (percent)
Selected crops harvested: - Con.			Selected crops harvested: - Con. Land in vegetables (see text) - Con.		
Cotton farms	-	-			
acres		-	Sweet corn (see text) farms	786	(H)
Peanutsfarms	-	-	acres	1,339	49.7
acres		-	Lettuce farms	329	87.5
Barley farms	16	23.0	acres	125	52.1
acres		13.3	Land in orchards (see text) farms	1,309	36.9
Oats farms	24	20.5	acres	4,303	23.9
acres	365	9.4	Apples farms	683	36.5
			acres	1,276	24.4
Forage - land used for all hay and haylage, grass silage, and greenchopfarms			Grapes (including muscadine) (see text)farms	327	54.7
grass silage, and greenchop farms	37,930	6.7	acres	525	32.9
acres	1,792,405	5.3	Oranges farms	-	-
Land in vegetables (see text) farms	2,173	(H)	acres	-	-
acres		5Ò.6	Almonds farms	17	36.2
Potatoesfarms		80.6	acres	10	10.2
acres		55.6	Land in berries farms	965	42.2
Tomatoes in the open farms	1,072	(H)	acres	986	38.0
acres		55.Ź			

¹ Data were collected for a maximum of four producers per farm. ² 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.]

[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
ALL FARMS (NUMBER)						
State Total						
Kentucky	69,425	6,407	44.0	15.5	16.2	12.2
Counties						
Adair	1,074	81	43.7	15.6	13.7	14.4
Allen	906	132	39.6	15.3	13.8	10.5
Anderson	705	86	46.4	18.3	16.5	11.6
Ballard	307	50	37.8	9.4	18.2	10.2
Barren	1,621	103	42.0	18.0	13.7	10.3
Bath	626	71	44.2	16.5	16.6	11.2
Bell	77	29	53.2	14.6	13.7	24.9
Boone	727	146	48.4	19.8	20.5	8.0
Bourbon	846	49	46.9	17.9	21.5	7.5
Boyd	187	17	50.3	18.6	19.3	12.3
Boyle	491	41	43.8	17.4	15.2	11.2
Bracken	557	40	44.7	15.5	22.9	6.3
Breathitt	150	47	54.0	11.0	15.8	27.2
	1,249	153	42.0	15.3	14.1	12.5
Breckinridge Bullitt	420	51	48.3	21.3	17.2	9.8
Butler	648	55	43.1	14.2	16.6	12.3
Caldwell	441	45	38.3	13.3	15.8	9.2
Calloway	821	65	43.2	13.8	17.1	12.4
Campbell	493	68	43.6	19.1	16.2	8.3
Carlisle	248	33	37.1	10.0	12.9	14.2
Carroll	226	30	37.2	8.1	9.8	19.2
Carter	681	64	47.6	19.0	16.3	12.3
Casey	975	58	45.0	18.0	16.1	10.9
Christian	1,095	80	39.7	12.0	13.6	14.1
Clark	804	89	43.7	18.1	15.0	10.6
Clay	178	48	44.4	20.2	15.9	8.3
	374	47	36.6	15.9	13.8	6.9
Crittenden	512	84	42.0	11.7	14.5	15.8
Cumberland	409	58	48.2	17.8	15.8	14.5
Daviess	974	133	40.5	11.6	19.2	9.7
Edmonson	552	59	44.7	15.0	14.4	15.3
Elliott	310	21	43.5	20.3	14.4	8.9
Estill	349	54	46.4	14.9	11.8	19.7
Fayette	682	76	49.7	13.7	22.1	13.9
Fleming	898	80	42.5	17.3	14.4	10.9
Floyd	61	27	37.7	14.9	12.7	10.1
Franklin	532	98	44.7	15.6	17.9	11.2
Fulton	175	37	43.4	11.5	18.1	13.8
Gallatin	157	23	40.8	18.9	13.7	8.2
Garrard	647	42	42.3	14.3	13.6	14.5
	787	63	47.6	22.8	16.3	8.5
Grant Graves	1,129	113	39.9	11.1	10.8	17.9
Grayson	1,283	77	45.8	17.6	15.9	12.2
Green	902	51	41.5	12.1	16.9	12.4
Greenup	475	64	46.1	15.9	18.8	11.4
Hancock	328	30	45.4	13.2	22.8	9.5
Hardin	1,255	89	44.8	19.8	16.3	8.7
Harlan	37	10	51.4	26.7	19.0	5.7
Harrison	1,051	83	45.5	18.8	17.5	9.2
Hart	1,283	77	48.3	13.5	18.2	16.6
Henderson	438	76	34.5	10.0	16.6	7.9
	719	53	43.3	12.4	16.3	14.6
Hickman	226	35	29.6	7.7	8.4	13.5
Hopkins	623	70	42.4	13.2	15.9	13.3
Jackson	460	49	46.1	13.9	13.2	19.0
Jefferson	264	73	48.1	16.9	18.2	13.0
Jessamine	619	92	46.4	11.1	19.9	15.4
Johnson	199	32	51.3	17.4	13.6	20.2
Kenton	453	63	45.3	20.1	15.8	9.4
Knott	49	10	46.9	8.8	7.2	31.0
Knox	293	60	50.5	19.3	15.5	15.7
	701	65	43.5	14.2	16.5	12.9
Larue Laurel	871	115	46.8	19.8	14.9	12.1
Lawrence	255	39	48.2	20.0	12.2	16.1
	127	39	48.0	13.0	14.5	20.6
Leslie	23	11	56.5	26.9	10.0	19.6
	71	24	45.1	12.8	11.1	21.2
Lewis	489	65	43.1	15.1	16.0	12.1
Lincoln	984	77	42.5	18.4	13.4	10.7
Livingston	360	57	47.2	13.0	14.7	19.5
Logan	1,017	76	44.9	13.0	14.2	17.7
Lyon	158	21	36.1	19.9	9.6	6.6
McCracken	339	71	43.4	14.0	13.7	15.6
McCreary	171 346	37 70	48.0	22.8 6.6	16.0	9.2 9.1
McLean Madison	1,164	105	29.2 47.8	18.9	13.5 18.2	10.7
Magoffin	316	53	51.3	22.9	13.8	14.5
	955	54	43.6	14.4	19.9	9.3
Marshall	787	62	45.9	14.1 6.2	17.3	14.4
Martin	21	6	52.4		4.9	41.3
	541	54	40.5	16.9		8.1
Mason Meade	731	71	45.6	19.1	15.5 14.3	12.1
Menifee	213	29	40.4	20.3	13.3	6.8

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
ALL FARMS (NUMBER) - Con.						
Counties - Con.						
Mercer	978	80	44.9	18.6	15.4	11.0
Metcalfe	799	41	43.6	15.3	13.9	14.4
Monroe	674 528	53 52	39.9 40.3	15.3 16.6	15.9 13.0	8.7 10.7
Montgomery Morgan	560	67	40.3 50.7	22.2	15.3	13.3
Muhlenberg	583	63	46.0	15.5	17.8	12.6
Nelson Nicholas	1,241 467	128 51	46.4 41.8	20.2 19.4	14.6 16.1	11.6 6.2
Ohio	746	90	39.8	12.6	12.2	15.0
Oldham	410	48	45.9	18.8	17.2	9.9
Owen	674	88	46.7	16.5	18.8	11.4
Owsley	84	19	38.1	12.6	14.3	11.2
Pendleton Perry	878 53	88 39	45.8 54.7	20.1 9.6	18.8 16.2	6.9 29.0
Pike	66	13	48.5	17.0	13.4	18.1
Powell	165	25	42.4	17.6	12.0	12.8
Pulaski Robertson	1,600 163	103 18	46.3 34.4	17.0 15.8	19.6 11.6	9.7 7.0
Rockcastle	585	62	43.1	21.1	11.5	10.5
Rowan	277	43	45.5	19.9	16.2	9.4
Russell	639	68	42.1	18.3	16.3	7.5
Scott	781	125	47.4	15.3	18.6	13.5
Shelby Simpson	1,350 400	157 61	45.0 40.0	17.1 15.0	17.2 13.9	10.7 11.1
Spencer	578	50	45.7	15.8	14.5	15.3
Taylor Todd	663 551	102 56	38.0 36.5	17.6 10.1	11.8 13.6	8.6 12.8
Trigg	406	34	42.4	8.8	28.4	5.2
Trimble	393	58	39.2	15.1	12.4	11.7
Union	290	46	32.8	10.4	12.6	9.7
Warren	1,530	186	45.8	17.8	13.7	14.4
Washington Wayne	998 708	128 49	46.5 41.5	14.0 17.0	17.0 16.5	15.5 8.0
Wayne	502	43 97	38.8	10.3	14.7	13.8
Whitley	476	38	46.8	16.5	18.6	11.8
Wolfe	243 688	34 96	45.7 46.5	19.9 10.0	21.3 24.8	4.4 11.7
			10.0	10.0	21.0	
LAND IN FARMS (ACRES)						
State Total						
K enderslar	40,404,400	050 000	00.0	7.5	10.0	
Kentucky	12,431,190	656,869	33.9	7.5	12.0	14.4
Counties						
Adair	142,751	13,907	37.1	6.1	12.0	19.0
Allen	136,286	12,433	36.2	11.1	10.5	14.6
Anderson Ballard	59,410 93,696	6,407 22,647	35.9 17.1	13.5 2.5	11.2 7.5	11.2 7.2
Barren	230,539	20,168	35.5	10.5	11.4	13.6
Bath	124,643	15,366	42.6	15.7	18.1	8.8
Bell Boone	20,545 71,293	10,772 9,846	61.6 45.8	13.2 15.1	15.7 24.7	32.7 5.9
Bourbon	183,749	22,140	43.6	12.1	18.4	13.1
Boyd	23,843	1,449	52.3	13.0	28.5	10.8
Boyle	96,306	4,187	40.3	7.1	20.0	13.2
Bracken	90,102	9,758 10,940	46.1	15.0	23.2	7.8
Breathitt Breckinridge	33,617 244,558	38,242	54.3 30.1	5.5 7.4	12.4 11.0	36.4 11.7
Bullitt	29,789	7,830	40.4	18.0	15.6	6.9
Butler Caldwell	172,711 122,775	21,902 6,316	37.7 17.9	8.3 4.9	18.4 8.0	11.1 5.0
Calloway	143,172	24,722	20.5	3.4	7.9	9.2
Campbell	38,744	9,782 20,097	39.0 21.7	14.0	17.2 4.0	7.8 16.2
Carlisle	107,565	20,097	21.7	1.6	4.0	10.2
Carroll	44,115	8,325	34.5	5.2	8.5	20.7
Carter Casey	82,568 188,753	9,022 26,199	39.1 45.2	15.0 12.5	13.2 16.9	10.9 15.8
Christian	345,270	19,465	18.9	3.5	6.4	9.0
Clark	135,849	12,672	44.2	14.3	15.1	14.8
Clay Clinton	38,581 56,133	12,164 3,116	47.2 29.2	22.2 12.1	15.2 10.5	9.8 6.6
Crittenden	133,842	20,365	25.4	5.3	9.1	11.0
Cumberland Daviess	92,797 271,336	6,589 44,298	50.5 20.3	11.5 1.8	14.5 5.3	24.5 13.1
Edmonson	86,574	17,771	37.8	8.4	12.3	17.1
Elliott Estill	41,226 49,684	3,396 10,001	34.2 40.2	12.4 11.6	13.4 8.7	8.4 19.9
Fayette	124,247	7,626	37.9	6.8	15.9	15.2
Fleming Floyd	157,806 6,898	18,595 2,452	39.8 42.9	15.5 11.1	15.5 10.6	8.7 21.2
Franklin	63,623	6,169	41.4	11.1	17.2	12.8
Fulton	91,864	31,065	18.3	2.1	11.6	4.6
Gallatin Garrard	26,928 108,923	3,016 28,668	41.8 44.4	17.2 13.3	17.8 11.3	6.7 19.8
Grant	84,737 255,830	10,456 20,147	40.7 24.1	17.7 1.3	15.9 3.5	7.1 19.3
Graves	200,030	20,147	24.1	1.3	3.5	
						continued

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

Charles (ACREs) - Con. Cardies - Con. <thcardies -="" con.<="" th=""> Cardies - Con. <thc< th=""><th>[For meaning of abbreviations and symbols, see introductory text.] Geographic area</th><th>Total</th><th>Standard</th><th>Adjustment as percent</th><th>Percent of total adjustment</th><th>Percent of total adjustment from</th><th>Percent of total adjustment from</th></thc<></thcardies>	[For meaning of abbreviations and symbols, see introductory text.] Geographic area	Total	Standard	Adjustment as percent	Percent of total adjustment	Percent of total adjustment from	Percent of total adjustment from
Counter Counter <t< th=""><th></th><th>(number)</th><th>error</th><th></th><th></th><th></th><th>misclassification</th></t<>		(number)	error				misclassification
Operation 6223 15 6240 433 153 464 154 Corona 4277 1439 423 153 464 154 142 164 Corona 4277 1439 423 151 424 164 142 164							
Grade 145 130 4 44 332 85 442 104 Horszki H2 530 H2		232 159	12 240	13.8	13.0	16.4	13 5
Consep 7288 10.543 921 84 145 153 Heigh 18223 12.00 62.2 85.0 12.3 10.4	Green						
Hattora 48/20 48/20 49/20 48/20 22/2 100 22/6 10 Header 10/20/2 3/363 6/25 10 22/6 10 Header 10/20/2 3/363 6/25 10 22/6 10 Header 10/20/2 3/363 6/25 10 10 14 30 11/3 Header 10/20/2 13/363 6/25 6/5 10 4/20 Header 10/20/2 13/363 6/5 10 10 10/20 Advance 10/20/2 20/20 6/3 6/3 10/20 Advance 10/20/2 20/20 6/3 6/3 10/20 Advance 10/20/2 20/20 6/3 6/3 10/20 Advance 10/20/2 20/20 6/3 10/20 10/20 Advance 20/20 20/20 20/20 10/20 10/20 Advance 20/20 20/20 10/20 1	Greenup		10,543	42.7		14.8	19.3
Hada 188.723 23.725 35.7 36.7 35.7 36.7 35.7 36.7 35.7 36.7 35.7	Hancock						
binton 196/200 11/800 45/2 15/2	Hardin						
Hart Here 1405 455 450 156 154 Here 111500 14,765 45,10							
Hendrench 100.079 20.669 12.5 12 3.5 7.8 Herron 110.0679 3.706 4.30 0.5 1.3 4.00 Herron 110.06 14.705 4.63 0.6 1.3 4.00 Herron 110.06 14.705 4.63 0.6 1.44		164,233					
Henry 125/77 5.789 41.1 5.4 10.2 19.5 Hedram 215.59 13.52 15.5 6.4 3.5 12.5 13.5 14.5 3.5 12.5 13.5 14.5 3.5 12.5 13.5 14.5 3.5 14.5 3.5 14.5 13.5 14.5							
Partini 111 500 14 700 65 0.5 1.2 4.20 Jackson 777.92 13.252 6.43 6.53 14.43 77 Jackson 777.92 13.252 6.43 6.53 14.44 77 Jackson 777.92 13.252 6.43 6.53 14.44 77 Jackson 777.92 13.252 6.43 6.53 14.44 73 Jackson 777.91 13.252 6.43 14.44 73 73 Kenton 26.9510 6.150 5.34 14.44 73 73 Level 77.971 6.266 14.2707 75.25							
Hophan 210580 22.195 41.0 8.8 12.3 20.0 Jenemin 71.777 21.627 23.1 5.3 8.4 13.0 Jenemin 71.777 21.627 23.1 5.3 8.4 13.0 Monta 35.84 4.77 23.3 5.3 8.4 13.0 Monta 35.82 4.77 23.3 6.0 14.4 13.3 Monta 35.82 4.77 23.5 20.7 13.3 10.0 Lawe 75.751 6.490 16.7 14.3 10.0 10.0 Lawe 75.751 6.260 16.7 72.6 25.6 10.7 13.3 Lawe 16.7 72.6 25.6 10.7 13.6 10.0 <td< td=""><td></td><td>.20,011</td><td>0,100</td><td></td><td>0.1</td><td></td><td>10.0</td></td<>		.20,011	0,100		0.1		10.0
Jackson 77,701 13.362 64.9 13.55 14.44 27.1 Jackson 77,701 13.362 43.3 17.3 8.4 16.0 Jackson 77,771 12.362 43.3 17.3 8.4 10.0 Jackson 77,771 12.362 43.1 13.0 11.0 10.0 Abron 77,771 12.4 13.0 14.4 32.0 12.0 Kox 12.00 4.715 12.0 14.4 12.0 14.4 12.0 Kox 12.00 4.715 12.0 </td <td></td> <td></td> <td></td> <td></td> <td>0.5</td> <td></td> <td></td>					0.5		
Jefferson 13.269 1976 44.0 17.4 15.8 10.8 Jenson 22.070 2.070 2.070 2.01 13.1 3.9 17.0 Kenton 2.070 2.01 13.1 3.9 17.0 2.00 17.0							
Josentring 1 1/171 2/1602 23.3 5.3 6.4 1/46 Kottin 3650 6.55 4.51 11.1 6.9 13.1 Kottin 3650 6.777 20.8 4.4 32.1 13.1 Kottin 3650 6.777 20.8 4.4 32.1 13.1 Lawe 77.971 6.460 4.6 19.7 19.0 10.0 Lewe 4.525 12.60 5.6 2.7 13.0 2.1 Lewer 4.527 12.60 4.6 13.0 2.1 12.5 2.0 4.4 10.0 12.5 2.0 13.0 2.1 12.5 2.0 4.6 13.0 2.1 12.5 2.5 2.2							
Johnson 342300 3297 461 135 116 326 Kook 3659 6.727 263 114 32 132 Kook 32034 4.115 512 147 443 221 Kook 32034 4.115 512 147 143 100 Lard							
kenton 22810 6.150 38.1 11.1 93 771 Acci 32.031 6.147 33.0 6.0 14.4 10.4 Laur							
Kota 3.989 6.727 20.8 4.4 3.2 3.2 Leared 7773 5.03 6.05 1.4 10.0 Leared 7773 5.03 6.07 14.9 10.0 Learence 20.65 3.67 16.8 10.0 10.0 Learence 20.65 3.67 10.0 10.0 10.0 Learence 20.65 3.67 10.0 <							
Koza 1200 11000 1713 310 607 143 221 Laurel 17071 300 6.697 143 101 Laurel 17071 6.494 165 52 137 325 Letter 26091 165 52 137 325 325 Letter 26093 107 723 285 360 31 Letter 26093 107 723 285 360 31 Letter 147519 15362 37 134 107 135 Letter 147519 15363 31 44 34 31 Letter 147519 15363 31 44 34 31 Letter 35222 2333 10 45 143 134 MacTearan 69,709 2344 325 165 415 MacTearan 90,409 3344 325 164 145 MacT							
Lawrine 797.79 9.49 41.65 67.7 14.9 100 Lewine 29.483 321.7 83.8 22.3 33.7 82.3 33.7 82.3 33.7 82.3 33.7 82.3 33.7 82.3 33.7 82.3 10.0							22.1
Lawrence S4.568 (2.907) S5.5 20.7 180 90.7 Lether - 36.683 367 72.5 12.5 12.6 50.5 51.5 Lether - 4.021 1.024 30.0 6.4 56.5 20.7 10.7 12.5 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 11.5 10.7 12.55 11.5 10.7 12.55 11.5 10.7 12.55 11.5 12.55 11.5 12.55 <	Larue	111,006	7,713	30.9	6.0	14.4	10.4
Lawrence S4.568 (2.907) S5.5 20.7 180 90.7 Lether - 36.683 367 72.5 12.5 12.6 50.5 51.5 Lether - 4.021 1.024 30.0 6.4 56.5 20.7 10.7 12.5 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 10.7 10.7 12.55 11.5 10.7 12.55 11.5 10.7 12.55 11.5 10.7 12.55 11.5 12.55 11.5 12.55 <	l eurol	70 701	0.400	44.0	40 -	44.0	10.0
Lee 29.660 3.621 55.5 12.2 13.7 32.6 Levis 4912 1.64 55.5 12.2 13.7 32.6 Levis 12.337 30.614 45.7 14.0 19.1 12.7 Levis 12.337 30.614 45.7 14.0 19.1 12.7 Lovis 26.727 25.752 21.1 4.2 7.0 9.0 Logan 26.727 25.532 21.1 4.2 7.0 9.0 McCrackon 60.700 1.363 44.1 12.0 7.3 13.1 McCrackon 60.700 1.365 44.1 12.0 7.3 13.1 Magdin 10.1746 12.655 44.1 12.0 7.3 13.1 Magdin 10.1746 12.655 44.1 12.0 7.3 13.1 14.4 Marka 9.88 13.059 25.7 13.3 14.1 14.9 14.1 14.9 14.1 14.1<							
Lettic 26.053 107 72.8 28.8 35.0 91 Linoin 12.957 20.64 45.7 64.6 16.7 12.7 Linoin 14.7510 15.862 37.9 13.7 10.7 13.6 Linoin 26.922 22.334 22.9 10.8 6.6 86.6 Lyön 26.922 22.334 22.9 10.8 6.6 86.6 Lyön 26.922 22.334 22.9 10.8 6.5 86.6 Lyön 13.453 15.5 6.7 7.6 13.43 14.7 McCann 19.878 22.84 41.6 22.7 16.3 14.5 Martin 18.878 22.84 41.6 22.7 16.3 14.5 Martin 94.48 19.677 25.4 6.5 11.1 5.8 Martin 18.878 22.84 12.8 14.4 14.5 Martin 18.472 12.8 13.4 14.4 <td></td> <td>24,526 20.460</td> <td></td> <td></td> <td></td> <td></td> <td></td>		24,526 20.460					
Lether 4.021 1.024 30.0 0.4 5.6 20.0 Lendman 147.25 26.44 30.0 0.4 15.6 12.7 Longston 147.25 25.752 21.1 4.2 2.0 30.0 Longston 33.222 21.5 21.1 4.2 2.0 30.0 Lyon 33.222 21.3 31.1 4.4 13.4 31.4 McCasken 33.22 13.453 45.5 20.7 16.7 16.4 Madson 131.20 13.453 45.5 20.7 16.3 13.4 Madson 131.20 13.453 45.5 20.7 16.3 13.4 Madson 131.20 13.453 45.1 20.7 16.3 13.4 Madson 131.20 13.453 45.1 45.1 45.1 16.8 16.2 16.8 16.2 16.8 16.2 16.8 16.8 16.8 16.8 16.8 16.8 16.8 <td< td=""><td></td><td></td><td></td><td></td><td></td><td></td><td></td></td<>							
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Lingson 14.492 38.809 36.6 6.4 11.6 21.6 Logan 33.222 23.332 23.33 23.333 70.6 6.3 6.6 Lyon 33.222 23.332 23.33 23.33 70.6 6.3 6.6 Lyon 7.0 1.3.453 45.5 2.7 8.7 6.1 Macloan 113.120 13.453 45.5 2.7 8.7 6.1 Macloan 119.746 12.854 44.1 12.2 7.8 13.1 Macloan 119.746 12.854 2.4 1.5 0.7 8.7 16.1 Macloan 12.848 12.869 3.3.7 9.3 10.1 14.4 Macloan 13.489 13.89 3.3.5 6.6 17.5 1.6 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14.5 14							12.7
Logan 286,727 28,782 21,1 4,2 7,0 9,8 McCrackon 53,709 12,336 31,1 4,4 13,4 13,4 McCrackon 17,96 12,336 31,1 4,4 13,4 13,4 McCrackon 17,96 12,336 31,1 4,4 13,4 13,4 Machan 11,146 12,583 14,1 12,9 17,8 13,5 Martin 16,370 28,874 80,0 8,5 16,8 10,8 Martin 16,370 28,874 80,0 8,5 11,1 5,4 Martin 9,484 13,08 33,7 9,8 10,1 14,4 Martin 12,3,96 13,08 33,7 9,8 10,1 14,4 Merine 24,724 12,806 24,4 12,8 8,4 8,2 Martin 12,3,74 12,30 10,1 7,1 14,1 13,3 11,1 5,4 Martin	Lincoln						
Lyön 35,222 23,324 23.9 10.8 6.5 6.6 McCashy 17,956 1,183 48.7 20.4 17.3 13.4 McCashy 11,956 1,183 46.7 20.4 17.3 13.4 Machan 19,978 28.974 41.6 12.7 16.5 14.6 Machan 19,979 23.444 24.6 25.5 16.4 17.6 Machan 18,089 16.87 12.0 41.2 28.6 11.5 16.6 Machan 12.0,044 13.0,493 36.5 64.1 15.7 16.6 Machan 12.0,044 13.0,493 36.5 16.4 17.6 17.6 16.9 16.9 16.9							
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McCeary 1183 183 183 183 184 204 17.3 110 McCan 99.376 28.874 61.6 28.7 16.5 14.5 Magorin 99.376 28.874 61.6 28.7 16.5 14.5 Marban 61.69 28.874 61.6 28.7 16.5 14.5 Marban 81.08 28.497 26.8 17.4 65.6 11.1 55.6 Machan 91.09 13.487 25.6 27.5 66.6 116.5 Machan 24.724 12.806 29.4 12.8 8.4 82.2 Marban 13.209 13.342 30.0 14.4 28.2 66.137 16.0 Machan 12.4721 15.01 13.0 27.7 10.0 8.9 8.6 Morgan 76.674 27.20 31.1 13.0 0.5.1 16.6 15.4 17.4 Marban 76.674 27.200 31.1 <	Суоп	35,222	23,324	23.9	10.0	0.0	0.0
McCeary 1183 183 183 183 184 204 17.3 110 McCan 99.376 28.874 61.6 28.7 16.5 14.5 Magorin 99.376 28.874 61.6 28.7 16.5 14.5 Marban 61.69 28.874 61.6 28.7 16.5 14.5 Marban 81.08 28.497 26.8 17.4 65.6 11.1 55.6 Machan 91.09 13.487 25.6 27.5 66.6 116.5 Machan 24.724 12.806 29.4 12.8 8.4 82.2 Marban 13.209 13.342 30.0 14.4 28.2 66.137 16.0 Machan 12.4721 15.01 13.0 27.7 10.0 8.9 8.6 Morgan 76.674 27.20 31.1 13.0 0.5.1 16.6 15.4 17.4 Marban 76.674 27.200 31.1 <	McCracken	59 709	12 336	31.1	44	13.4	13.4
McLaan 113,120 13,433 155 0.7 8.7 8.1 Mathon 197,746 12,834 4.1 12.7 13 134 Mathon 198,756 20,67 6.6 20,77 16.8 10.4 Martin 64,88 057 55.8 7.3 31 45.3 Martin 64,88 057 55.8 7.3 31 45.3 Martin 24,88 125,88 13,699 32.7 93 10.1 14.4 Merce 24,724 12,806 22.4 12.8 4.8 4.2 Merce 142,753 22.34 32.2 6.6 13.5 16.6 Monze 124,964 13,489 35.5 7.6 13.4 13.4 Monze 124,934 22.629 35.4 7.6 12.9 15.9 Monze 124,941 124,941 13.489 35.5 10.4 7.7 14.8 Monze 124,941							
Madison 191.746 12.853 44.1 12.9 17.8 13.8 Magolfn 593.76 22.853 61.6 27 16.8 14.4.6 Marshal 69.160 22.484 22.4 5.5 16.8 14.4.6 Marshal 94.88 637 55.8 7.3 3.0 45.4 Masce 94.88 10.877 25.4 8.3 11.1 5.4 Mesce 142.272 15.010 44.2 2.4 8.4 8.2 Mercer 142.722 15.010 4.12 8.4 8.2 14.4 Morigone 144.753 22.234 3.2 6.6 17.5 16.4 Morigone 114.4753 3.00 11.4 11.3 13.0 13.0 13.1 Ncholas 76.674 22.244 3.20 14.1 13.0 13.1 13.0 13.0 13.0 13.0 13.0 13.0 13.0 13.0 13.0 13.0 13.0							
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Marshall B8:160 23,484 224 55 64 17.6 Martin 9,488 637 55.8 7.3 3.0 45.8 Martin 9,488 13.09 23.7 6.3 10.1 14.4 Martin 24,724 12.806 23.4 12.8 8.4 6.2 Mercine 24,724 12.806 23.4 12.8 8.4 6.2 Mercine 142,724 12.806 23.44 3.2 6.6 17.7 9.0 Morigonery 144,753 23.234 33.2 6.6 17.7 9.0 Morigonery 70,931 20,820 5.6 17.6 12.9 15.3 Nicholas 76,674 27,200 27.7 10.0 13.0 5.1 Nicholas 76,674 27,200 31.1 13.0 13.0 5.1 Othe 163,888 14,485 22.7 3.3 6.1 17.3 Othe 163,89							
Martin 9488 637 55.8 7.3 3.0 45.4 Mason 9488 13871 25.4 8.5 11.1 5.4 Meade 120.388 13.09 33.7 8.3 10.1 144.4 Mercle 120.388 13.09 33.7 8.3 10.1 144.4 Mercle 142.272 15.501 41.2 8.2 18.4 14.4 Mercle 142.272 15.501 41.2 8.2 18.4 14.4 Morigonery 60.311 22.066 51.5 18.6 15.4 17.4 Muhenberg 122.431 22.620 33.1 13.0 13.0 5.1 Obio 138.638 13.465 26.7 3.3 6.1 17.3 Obiom 138.638 13.465 26.7 3.3 6.1 17.3 Obiom 20.800 7.48 20.20 10.4 7.6 14.1 6.5 Owain 20.850 7							
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Webster 184/753 16.270 19.2 3.7 7.6 7.9 Whitley 62,190 10,902 46.3 12.1 18.2 16.0 Wolfe 37,779 13,250 40.0 16.9 19.0 4.2 Woodford 103,650 17,027 33.8 4.0 19.7 10.0 SALES (\$1,000) Sate Total 8,005,745 479 18.8 3.2 5.0 10.6							
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Wolfe 37,779 13,250 40.0 16.9 19.0 4.2 Woodford 103,650 17,027 33.8 4.0 19.7 10.0 SALES (\$1,000) Sate Total 8,005,745 479 18.8 3.2 5.0 10.6	Whitley						
Woodford 103,650 17,027 33.8 4.0 19.7 10.0 SALES (\$1,000) Sate Total Kentucky 8,005,745 479 18.8 3.2 5.0 10.6	Wolfe						
SALES (\$1,000) State Total Aug	Woodford		17,027				
State Total Kentucky 8,005,745 479 18.8 3.2 5.0 10.6							
Kentucky 8,005,745 479 18.8 3.2 5.0 10.6							
continued	Kentucky	8,005,745	479	18.8	3.2	5.0	

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
SALES (\$1,000) - Con.						
Counties						
Adair	103.297	11	29.7	1.4	6.2	22.1
Allen	76,484	6	29.5	10.3	6.1	13.1
Anderson Ballard	13,399 99,341	2 13	38.7 5.0	13.9 1.2	16.6 0.7	8.2 3.0
Barren	181,330	13	21.2	3.8	5.1	12.4
Bath	25,205 1,280	3 1	43.2 32.8	13.7 4.5	16.2 11.0	13.3 17.4
Bell Boone	14,792	2	21.3	4.5	11.0	3.2
Bourbon	250,819	13	28.5	8.4	10.1	9.9
Boyd	1,068	(Z)	26.9	9.9	14.2	2.9
Boyle	54,742	4	37.6	7.2	9.8	20.6
Bracken	12,402	2 1	34.3	10.4	18.4	5.5
Breathitt Breckinridge	1,391 117,942	17	22.6 10.0	8.1 2.0	6.5 2.7	8.0 5.4
Bullitt	9,360	3	30.9	8.3	16.0	6.7
Butler Caldwell	63,943 67,377	3 5 3	15.7 6.0	5.1 1.4	4.7 2.6	5.9 1.9
Calloway	132,115	21	9.0	0.8	0.7	7.5
Campbell	5,781	1 23	14.1	9.2 1.2	4.0	1.0
Carlisle	129,193		17.8	1.2	2.7	13.8
Carroll	4,595	(Z) 2	6.9	1.8	2.9	2.1
Carter Casey	7,897 48,447	2 5	32.2 29.4	10.2 7.3	16.2 10.4	5.8 11.7
Christian	263,771	15	18.2	3.6	6.3	8.2
Clark Clay	45,348 3,680	6 1	34.8 17.5	10.5 5.3	15.5 9.0	8.8 3.3
Clinton	48,309	12	23.2	5.3 4.8	9.0	3.3 16.1
Crittenden	64,544	4	13.0	5.6	3.5	3.9
Cumberland Daviess	10,704 335,931	2 36	24.2 15.4	6.6 0.7	9.0 1.5	8.6 13.2
EdmonsonElliott	59,378 3,035	10 (7)	18.5 18.0	2.7 7.5	6.5 6.6	9.3 4.0
Estill	3,647	(Z) 2	14.8	4.5	6.8	3.5
Fayette	333,101	13 17	33.1 36.4	4.8 13.7	23.7 13.5	4.6 9.1
Fleming Floyd	48,914 327	(Z)	13.9	4.1	7.8	1.9
Franklin	20,746	(Z) 3	38.9	18.5	12.8	7.6
Fulton Gallatin	87,814 11,322	13 3	21.7 30.2	3.4 12.8	11.5 11.1	6.8 6.3
Garrard	36,926	13	48.0	13.9	12.4	21.7
Cront	9,627	1	36.2	15.6	13.4	7.1
Grant Graves	473,755	98	6.7	0.8	0.8	5.1
Grayson	82,704	13	32.4	7.2	11.8	13.3
Green	78,774 6,604	8 1	27.6 22.3	8.0 4.4	6.6 6.3	13.1 11.6
Hancock	26,221	12	46.1	30.0	6.9	9.2
Hardin	81,020 577	20 (Z)	22.7 20.6	5.7 6.5	9.3 3.2	7.8 11.0
Harlan Harrison	35,290	(2)	33.3	11.7	12.8	8.8
Hart	51,639	6	25.2	5.4	6.8	13.0
Henderson	149,142	19	9.0	0.6	2.8	5.6
Henry	30,793	2	27.8	6.8	13.0	8.0
Hickman Hopkins	198,760 211,057	28 14	3.0 23.4	0.6 10.4	0.2 4.9	2.3 8.2
Jackson	6,953	1	31.7	10.0	14.3	7.5
Jefferson	4,380	2 7	13.9	3.8	8.5	1.6
Jessamine Johnson	77,622 1,803	1	6.7 38.7	1.3 6.2	1.5 10.2	3.9 22.3
Kenton	4,069	1	18.7	8.9	7.6	2.2
Knott	517	(Z)	10.7	2.8	5.7	2.2
Knox	2,684	1	32.1	10.2	11.7	10.2
Larue	60,512 16,989	6 2	23.0 30.1	3.0 6.3	6.3 20.2	13.6 3.6
Laurel Lawrence	1,902	1	41.6	14.6	16.4	10.6
Lee	948	(Z) (Z) (Z) 3 7	22.5	6.6	13.0	2.9
Leslie Letcher	199 650	(2)	19.6 27.4	9.9 4.7	2.1 6.0	7.6 16.7
Lewis	16,282	3	23.9	5.8	14.2	3.9
Lincoln	83,497 46,594	7	36.8 31.3	7.3 9.6	26.7 6.0	2.9 15.8
		2	51.5	9.0	0.0	15.0
Logan	225,081	14	8.3	1.3	3.0	3.9
Lyon McCracken	11,316 38,219	4	13.3 13.7	7.4 2.4	3.7 3.9	2.3 7.4
McCreary	1,453	(Z) 39	30.9	12.6	9.8	8.5
McLean	281,993	39 9	5.1 36.4	0.7 9.6	1.4 8.6	3.0
Madison Magoffin	63,620 1,919	9	33.1	9.0 11.4	11.7	18.2 9.9
Marion	81,642	7	31.7	7.7	10.1	13.9
Marshall Martin	82,886 168	19 (Z)	2.7 23.5	0.1 4.0	(Z) 1.7	2.5 17.8
						17.0
Mason	40,963	5 6	25.1	5.1	14.3	5.7
Meade Menifee	55,447 2,618	6 2	14.7 14.0	2.8 4.9	4.1 6.0	7.8 3.1
Mercer	57,723	25	36.5	5.1	26.1	5.3
Metcalfe	50,277 108 704	13 9	24.1 14.5	2.0 4.1	9.5	12.6
Monroe Montgomery	108,704 15,698	9	25.5	4.1 10.1	3.2 8.6	7.3 6.9
		-	25.0		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.						
Morgan Muhlenberg Nelson Nicholas Ohio	5,681 149,024 79,478 31,981 172,009 35,220 34,463 1,455 10,355	1 55 7 10 14 10 6 (Z) 2	34.3 19.7 17.6 35.5 7.2 44.3 23.2 30.7 22.8	12.0 5.2 6.0 16.1 3.2 10.7 6.7 8.5 8.8	14.6 8.7 6.8 14.2 1.8 9.6 13.0 9.2 10.0	7.7 5.8 4.8 5.2 24.0 3.6 13.0 4.0
Perry Pike Powell Pulaski Robertson	730 1,378 5,196 80,512 2,948	1 (Z) 2 6 1	15.8 23.7 38.6 18.5 27.2	2.8 3.5 7.6 5.1 10.5	9.8 2.0 19.6 6.9 9.2	3. 18. 11. 6. 7.
Rockcastle Rowan Russell Scott Shelby Simpson	10,455 5,793 54,891 78,744 91,748 111,041	2 1 6 9 8 14	28.8 29.1 36.0 28.9 15.7 13.3	7.2 9.3 12.3 5.4 3.2 3.1	10.3 7.4 10.6 13.7 6.6 3.0	11. 12. 13. 9. 5. 7.
Spencer Taylor Todd Trigg Trimble Union Warren Warren Washington Wayne	14,722 58,698 224,451 73,415 9,060 191,611 160,664 47,090 78,931 258,956	2 9 11 4 9 14 4 6 18	11.0 15.4 16.9 14.8 12.9 9.0 16.2 39.2 10.9 8.4	3.3 3.0 6.3 5.2 3.1 0.6 3.7 14.8 6.6 2.1	3.8 4.9 6.6 6.1 4.2 4.3 15.1 2.5 0.4	3.5 7.4 4.1 3.7 3.7 4.5 8.2 9.5 9.5 5.5
Webster	238,936 6,143 2,092 235,829	10 1 12	8.4 32.0 25.8 32.5	2.1 13.6 9.6 7.4	0.4 11.3 14.9 18.8	5.3 7. 1.4 6.4

Table D. American Indian or Alaska Native Producers: 2022

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

	American India	an or Alaska Native farn	n producers		American Indian or Alaska Native farm producers		
Geographic area	Total	Individually reported ¹	Other ²	Geographic area	Total	Individually reported ¹	Other ²
itate Total				Counties - Con.			
entucky	739	739	-	Johnson	4	4	
ounties				Knox Larue	6 7	6 7	
dair	19	19	_	Laurel	12	12 5	
len	12	12	-	Lee	2	2	
nderson	14	14	-	Leslie	6	6	
allard arren	1	1	-	Lincoln	9	9	
ath	12	12	-	Logan	11	11	
ell	2	2	-	Lyon	1	1	
ourbon	4	4		McCreary	2	2	
oyle	13	13	-	McLean	2	2	
racken	3	3	-	Madison Magoffin	15	15	
reckinridge	41	41	-	Marion	3	3	
ullitt	7 12	7	-	Marshall	2	2	
utler aldwell	6	6	-	Martin Mason	10	10	
alloway	31	31	-	Meade	10	10	
ampbell	1	1	-	Mercer	17	17	
arroll	1	1	-	Mercel Metcalfe	1	1	
arter	9	9	-	Monroe	6	6	
asey	9	9	_	Montgomery Morgan	8 16	8 16	
nristian	4	4	-	Muhlenberg	6	6	
ark	6	6	-	Nelson	12	12	
linton rittenden	2	2	-	Nicholas Ohio	4 7	4	
umberland	6	6	-	Oldham	7	7	
dmonson	23 10	23 10	-	Owen	6	6	
still	4	4	-	Owen Pendleton	3	3	
éming	27	27	-	Powell	7	7	
anklin	13	13	_	Pulaski Robertson	20	20 3	
arrard	10	10	-	Rockcastle	14	14	
rant	15	15	-	Rowan	5	5	
raves raγson	6	7		Russell Shelby	1	1 15	
reen	2	2	-	Simpson	5	5	
reenup	1 11	1	-	Spanger	F	5	
ardin arlan	2	2	-	Spencer Taylor	3	3	
arrison	20	20	-	Todd	2	2	
art	14	14		Trigg Trimble	2	2	
art enderson	1	14	-	Warren	6	6	
enry	10	10	-	Washington	3	3	
opkins ackson	1	1	-	Wayne Webster	10	10 3	
efferson	4	4	-	Whitley	8	8	
essamine	3	3	-	Woodford	3	3	

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