# Appendix A.

# **Census of Agriculture Methodology**

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

#### THE CENSUS POPULATION

#### The Census Mail List

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

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

minorities but also to increase census awareness and participation.

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

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

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

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

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

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

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

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

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

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

The percentage of farms not represented on the CML

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

# DATA COLLECTION OUTREACH AND PROMOTIONAL EFFORTS

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

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

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

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

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

#### Partnership and Local-Level Outreach

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

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

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

Table D, American Indian and Alaska Native **Producers:** 2022 provides the number of producers (1) reported as American Indian or Alaska Native in the race category, either as a single race or in combination with other races, on the individual census report forms (for up to four per farm) and (2) identified as American Indian or Alaska Native producers farming on reservations by reservation officials. The count from the individual report forms is summarized in the "Individually reported" column. It includes up to four producers on or off reservations. The "Other" column provides counts of producers on reservations as reported by a reservation or tribal official. The "Total" column is simply a sum of the "Individually reported" and the "Other" columns. Tables in other parts of the publication count the reservation-level reports as single farms.

#### **Public Relations**

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

#### Paid Media

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

#### **DATA COLLECTION**

#### **Method of Enumeration**

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

#### **Report Forms**

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

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

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

# **Report Form Mailings**

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

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

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

#### Nonresponse Follow-up

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

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

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

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

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

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

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

#### REPORT FORM PROCESSING

#### **Data Capture**

The Census Bureau's National Processing Center (NPC) in Jeffersonville, IN was contracted to process returned mail packets. NASS staff on site at the NPC provided technical guidance and monitored NPC processing activities. All report forms returned to the NPC were immediately checked in, using bar codes printed on the mailing label, and removed from follow-up report form mailings. All forms with any data were scanned and an image was made of each page of a report form. Optical Mark Recognition (OMR) was used to capture categorical responses and to identify the other answer zones in which some type of mark was present.

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

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

#### **Editing Data**

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

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

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

# **Farm Status Form Editing**

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

## **Imputing Data**

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

Separate system processes were established to efficiently provide data from a similar farm to the edit when donor imputation was required. The farm characteristics used to define similarity between a recipient record and its donor record were determined dynamically by the edit logic.

Euclidean distance was used for similarity computations, with each contributing similarity characteristic scaled appropriately. The most similar farm based on this criterion (the "nearest neighbor") was identified and returned to the edit for use as a donor. The calculated distance between the centroids of the principal counties of production of the donor and recipient was always included as one of the measures of similarity.

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

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

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

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

#### **Data Analysis**

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

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

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

# ACCOUNTING FOR UNDERCOVERAGE, NONRESPONSE, AND MISCLASSIFICATION

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

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

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

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

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

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

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

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

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

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

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

# **Resolving Farm Status**

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

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

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

## **Capture Probabilities**

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

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

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

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

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

#### **Misclassification**

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

#### **CALIBRATION**

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

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

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

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

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

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

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

#### **DISCLOSURE REVIEW**

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

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

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

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

#### **CENSUS QUALITY**

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

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

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

#### **Census Response Rate**

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

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

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

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

where

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

R = number of explicit refusals

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

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

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

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

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

where

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

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

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

## **Census Coverage**

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

#### MEASURED ERRORS IN THE CENSUS PROCESS

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

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

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

The standard error of an estimate is an estimate of the

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

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

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

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

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

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

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

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

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

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

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

# NONMEASURED ERRORS IN THE CENSUS PROCESS

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

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

# **Respondent and Enumerator Error**

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

# **Processing Error**

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

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

# **Item Nonresponse**

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

## **Record Matching Error**

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

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

duplication could be removed.

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

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

[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
Farms		230,662 125,471,325	10,786 7,392,284	48.3 26.8	20.2 2.6	14.0 8.4	14.1 15.8
Farms by size:	,	04.400	4 405	20.0	07.0	4- 4	40.7
1 to 9 acres	acres	24,486 124,041	1,405 6,679 3,745	66.0 64.4	37.9 37.9 31.2	17.4 16.3 13.0	10.7 10.2 11.4
	acres	81,719 1,928,704	93,046 877	55.6 53.9 48.2	29.6 22.1	12.5 12.0	11.4 11.7 14.1
	acres	16,781 967,578	50,722	48.1	22.0 19.9	12.1	14.0
	acres	16,368 1,357,139 16,542	858 70,999 832	45.6 45.5 44.3	19.8 19.8 14.3	12.0 12.0 14.7	13.7 13.7 15.3
	acres	1,903,124 12,251	97,273	44.1 44.0	14.0 12.8	14.7 14.9 14.7	15.3 15.2 16.4
	acres	1,935,564 8,177	773 120,467 704	43.9 39.2	12.8 12.8 11.4	14.7 14.8 12.8	16.4 16.4 15.1
	acres	1,619,508 5,632	139,323 328	39.2 37.7	11.4 11.4 9.7	12.8 11.8	15.1 15.1 16.3
	acres	1,341,125 18,118	78,536 1,270	37.7 36.4	9.7 9.7 6.4	11.9 13.2	16.3 16.1 16.7
	acres	6,453,735 12,674	454,702 763	36.2 33.5	6.3 4.3	13.2 13.2 15.0	16.7 16.7 14.2
	acres	8,781,004 7,939	519,309 474	33.3 33.0	4.2 2.8	15.2 14.5	13.9 15.7
	acres	10,961,232 9,975	668,861 723	33.0 27.4	2.7 1.7	14.6 9.4	15.7 15.3 16.3
	acres	88,098,571	5,842,769	22.3	1.2	6.1	15.0
Irrigated land use: Harvested cropland	farms	15,582	1,399	47.9	11.3	17.3	19.3
	acres	3,126,982 4,849	241,220 321	31.4 50.5	2.0 17.3	13.5 16.4	16.0 16.8
	acres	638,456	117,420	33.9	2.4	13.5	18.0
Market value of agricultural products sold\$	1,000	32,166,561	960	19.9	7.3	3.3	9.3
Farms by value of sales: Less than \$1,000	farms	75,579	6,281	60.2	22.0	19.3	18.9
\$1,000 to \$2,499	1,000 farms	8,162 30,294	1 1,469	60.3 55.9	34.0 32.4	13.6 13.4	12.7 10.1
\$2,500 to \$4,999	1,000 farms	49,708 27,619	2 1,541	55.5 47.8	32.2 27.6	13.3 10.6	10.0 9.5
	1,000	98,085 27,684	5 1,587	47.4 42.3	27.5 22.8	10.6 10.2	9.4 9.3
	1.000	194,298 22,343	11 910	41.9 33.7	22.6 14.0	10.0 9.6	9.3 10.2
\$20,000 to \$24,999	1,000 farms	312,438 6,407	12 262	33.5 33.4	13.6 12.5	9.8 10.6	10.2 10.3
\$25,000 to \$39,999		141,547 10,729	6 421	33.4 32.2	12.6 9.5	10.6 9.5	10.3 13.2
\$40,000 to \$49,999		335,389 3,917	13 129	32.2 30.9	9.4 9.6	9.5 11.8	13.3 9.4
\$50,000 to \$99,999		173,408 8,785	6 521	30.9 30.2	9.5 7.8	11.9 9.7	9.4 12.7
\$100,000 to \$249,999		608,505 7,194	35 771	29.9 41.2	7.6 5.7	9.7 14.0	12.6 21.5
\$250,000 to \$499,999		1,091,839 3,383	118 403	40.2 40.6	5.3 5.0	13.9 18.2	21.0 17.4
\$500,000 to \$999,999	1,000 farms	1,177,741 2,639	137 351	39.9 44.4	4.9 4.4	18.3 19.7	16.7 20.3
\$1,000,000 or more		1,829,022 4,089	246 267	43.6 36.8	4.2 9.2	19.5 8.1	19.9 19.5
·	1,000	26,146,421	551	15.4	6.5	1.6	7.4
Farms by legal status for tax purposes: Family or individual		205,473	9,683	48.5	22.7	12.7	13.1
Partnership		73,252,405 13,566	5,125,544 716	28.4 44.3	3.4 6.8	6.8 19.7	18.2 17.8
Corporation:	acres	32,352,815	1,774,288	24.1	1.6	9.0	13.4
	acres	7,344 14,766,773	270 886,4 <u>21</u>	49.0 26.0	10.6 1.9	21.8 10.5	16.7 13.6
	farms acres	1,486 2,747,461	77 181,675	53.9 18.5	9.8 1.2	17.6 11.1	26.5 6.1
Other - estate or trust, prison farm, grazing association, American Indian Reservation, etc		2,793	209	49.2	13.2	17.0	19.0
	acres	2,351,871	134,623	27.9	2.1	13.1	12.6
Tenure: Full owners		179,127	7,896	52.0	24.1	14.5	13.4
Part owners		50,187,898 40,540	2,344,985 2,166	32.5 33.6	4.6 5.1	10.8 11.3	17.1 17.2
Tenants		58,794,545 10,995	3,930,052 918	22.2 41.8	1.0 6.9	5.6 16.5	15.6 18.3
	acres	16,488,882	1,371,026	25.6	1.9	13.0	10.7
Producers characteristics by- ¹ (see text) Sex of operator:		000 000	10.000		46.5	4	40 :
Male	acres	208,863 119,815,650	10,622 7,229,059	47.5 26.5	19.2 2.4	14.9 8.6	13.4 15.5
Female	farms acres	143,585 59,133,549	3,503 2,541,513	49.6 27.5	24.5 4.3	17.7 14.9	7.4 8.3
Primary occupation:	farm -	450.040	2 222		40.	40 -	10.5
Farming Other		153,043 249,833	6,039 10,189	44.5 52.5	16.1 19.5	16.5 21.3	12.0 11.7

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

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

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

[For meaning of abbreviations and symbols, see introductory text.]			Adjustment	Percent of total	Percent of total	Percent of total
Item	Total	Standard error	as percent of total	adjustment from coverage	adjustment from nonresponse	adjustment from misclassification
Producers characteristics by- ¹ (see text) - Con.						
Hispanic, Latino, or Spanish originfarms acres	28,269	2,886	56.9	25.2	17.1	14.5
	10,128,859	1,316,465	26.7	2.1	8.5	16.1
Race: American Indian or Alaska Native	2,705	119	56.8	31.3	11.7	13.8
	825,480	77,170	36.9	8.7	14.7	13.4
Asian	1,748	113	59.7	27.4	13.5	18.8
	181,705	13,147	37.3	4.9	4.2	28.3
Black or African American	7,235	391	67.1	40.1	12.1	14.8
	855,704	194,609	58.5	10.9	32.2	15.4
Native Hawaiian or Other Pacific Islanderfarms	306	24	58.2	33.3	10.7	14.2
acres White	66,608	30,692	36.7	8.1	8.7	19.9
	221,037	10,474	47.5	19.7	14.0	13.8
More than one race reported	124,062,222	7,277,802	26.5	2.5	8.4	15.7
	3,067	188	59.2	28.0	16.0	15.3
	1,000,462	165,959	42.4	7.8	20.3	14.3
Military service:  Never served or only on active duty for training in the Reserves or National Guard (see text) producers Active duty now or in the past (see text) producers	360,624	13,910	49.5	18.0	19.7	11.8
	42,252	2,132	48.5	20.3	17.1	11.2
All producers by age group ¹: Under 25 yearsfarms	5,549	506	64.6	19.8	34.5	10.3
25 to 34 years farms	19,351	3,255	65.1	17.0	42.8	5.3
35 to 44 years farms	42,184	2,065	57.8	18.7	28.7	10.4
45 to 54 ýears	63,194	2,831	54.2	21.1	16.4	16.7
	105,668	5,183	49.8	19.4	16.4	14.0
65 to 74 yearsfarms	103,310	4,000	44.1	16.7	16.4	11.0
75 years and overfarms	63,620	2,330	41.2	17.5	15.0	8.7
Net cash farm income of operations: Farms with gains of- <sup>2</sup> Less than \$1,000farms	6,312	404	46.1	23.3	12.3	10.5
\$1,000	3,019	(Z)	45.4	22.4	13.1	9.9
\$1,000 to \$4,999	14,311	988	43.1	17.9	12.7	12.5
\$1,000 \$5,000 to \$9,999 \$1,000 \$1,000	39,064 8,254 59,637	588 4	42.5 37.6 37.3	17.1 13.3 12.9	12.9 11.9 11.8	12.5 12.5 12.6
\$1,000	10,278	521	36.3	9.7	12.4	14.2
\$10,000 to \$24,999	166,302	8	36.1	9.6	12.9	14.6
\$25,000 to \$49,999	6,070	357	36.4	9.1	13.6	13.6
	215,619	13	36.6	9.2	13.8	13.6
\$50,000 or more \$1,000	14,365	1,067	40.8	6.4	14.6	19.8
	11,188,014	349	20.1	6.3	3.8	10.0
Farms with losses of-	8,652	534	50.3	24.5	11.0	14.7
Less than \$1,000	4,523	(Z)	50.9	24.4	11.3	15.2
\$1,000 to \$4,999 \$1,000	41,039	2,039	52.8	27.4	12.7	12.7
\$1,000 to \$4,999	121,468	6	52.9	27.6	12.7	12.7
\$5,000 to \$9,999 farms	37,774	1,786	52.5	26.5	13.6	12.5
\$1,000	276,040	13	52.5	26.5	13.4	12.6
\$10,000 to \$24,999	48,786	2,132	51.5	24.5	14.5	12.4
	777,670	34	51.3	24.1	14.7	12.5
\$25,000 to \$49,999	20,098	1,135	48.8	19.5	14.2	15.2
	694,111	40	48.6	19.0	14.3	15.3
\$50,000 or more	14,723	685	44.8	10.0	18.0	16.8
	2,451,499	114	40.6	7.0	16.5	17.2
Livestock and poultry: Cattle and calves inventoryfarms	131,815	5,446	40.4	29.9	4.7	5.8
Beef cows inventorynumber	12,543,300	334,357	22.3	11.9	2.7	7.8
	117,838	4,733	39.4	28.8	4.7	5.9
number Milk cows inventory farms number	4,360,026	142,631	29.7	14.1	5.5	10.1
	479	13	14.4	11.2	1.3	1.9
	639,506	6,536	4.3	3.3	(Z)	0.9
Hog and pigs inventory farms number	5,837	1,636	61.1	26.7	19.5	14.9
	1,188,820	123,966	7.4	2.9	0.4	4.0
Layers inventory farms number	30,288	1,611	54.8	28.7	16.2	9.9
	24,478,507	5,860,019	12.0	4.8	0.4	6.8
Broilers sold	2,086	724	58.5	27.8	16.9	13.8
	709,585,824	64,856,116	46.3	21.0	6.3	19.1
Aquaculture sold farms \$1,000	202 72,328	17	35.6 21.2	11.6 7.9	6.0 0.5	18.1 12.8
Selected crops harvested: Corn for grainfarms	3,714	705	34.7	2.9	11.4	20.4
acres Durum wheat for grain	1,680,377	330,990	17.0	0.9	5.8	10.4
Other spring wheat for grain	124	21	38.7	8.9	6.6	23.1
	9,096	1,796	28.8	4.7	7.1	17.0
Winter wheat for grain	4,008	519	36.2	3.6	11.5	21.1
	1,740,243	168,222	28.2	2.0	8.9	17.3
Sorghum for grain	2,237 994,977	788 134,382	24.6 6.1	2.0 2.0 0.4	9.3 2.1	17.3 13.2 3.6
Soybeans for beans	385	68	30.4	4.4	12.0	14.0
	97,284	12,815	11.6	0.7	6.2	4.7
Ricefarms acres	289	42	40.8	3.7	18.1	19.1
	193,438	30,014	42.7	2.4	18.1	22.2
Cottonfarms acres	4,822	878	40.1	2.3	17.4	20.4
	2,337,631	82,999	7.3	0.4	2.7	4.1

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

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

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

ltem	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		120	15.4	1.1	8.2	6.1
acres Barley farms	37	22,576 6	2.4 40.5	0.1 14.0	1.1 19.2	1.1 7.4
Oatsacres acres	297	1,428 45 10,581	40.9 28.3 24.0	5.9 5.4 0.8	23.9 4.2 2.2	11.1 18.7 21.0
Forage - land used for all hay and haylage, grass silage, and greenchopfarms		5,513 346.292	36.9 36.0	23.5 14.1	3.8 5.8	9.6 16.1
acres Land in vegetables (see text)farms	2,177	595	57.2	17.7	18.2	21.2
Potatoes farms	461	8,787 120	29.4 56.4	3.1 16.8	7.5 19.5	18.9 20.1
Tomatoes in the openfarms	870	212 292	5.3 59.2	2.1 19.4	0.3 18.2	2.9 21.6
Sweet corn (see text)	281	198 64	54.6 52.7	18.2 13.9	17.0 19.9	19.4 18.8
acres Lettuce	247	196 89 36	10.5 59.1 14.8	1.8 15.6 3.4	0.7 28.7 2.7	8.1 14.8 8.7
Land in orchards (see text)	8,286	1,117 17.979	54.0 41.5	18.3 6.5	16.3 10.2	19.4 24.8
Apples	737	77 48	59.3 55.5	20.5 15.2	17.4 18.4	21.5 21.9
Grapes (including muscadine) (see text)	1,378	143 534	59.5 54.2	15.1 4.3	23.7 13.5	20.7 36.3
Orangesfarms	364	40	62.9	14.0	20.9	28.0
Almondsfarms	35	(D) 14	(D) 40.0	12.0 12.0	(D) 10.1	(D) 18.0
acres Land in berries acres acres	1,583	(D) 186 415	(D) 57.9 53.0	(D) 21.7 16.2	(D) 15.6 13.5	(D) 20.6 23.2

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

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

Item	,	Total	Coefficient of variation (percent)	ltem	Total	Coefficient of variation (percent)
Farms		230,662 125,471,325	4.7 5.9	Producers characteristics by- <sup>1</sup> (see text) - Con.		
	40100	120,47 1,020	0.0	Hispanic, Latino, or Spanish originfarms	20 260	10.2
Farms by size: 1 to 9 acres		24,486	5.7	Spanish origin acres	28,269 10,128,859	10.2 13.0
10 to 49 acres	acres farms	124,041 81,719	5.4 4.6	Race:		
50 to 69 acres	acres	1,928,704 16,781	4.8 5.2	American Indian or Alaska Nativefarms	2,705	4.4
70 to 99 acres	acres	967,578	5.2	acres Asian farms	825,480	9.3
	acres	16,368 1,357,139	5.2 5.2	acres	1,748 181,705	6.4 7.2
100 to 139 acres	farms acres	16,542 1,903,124	5.0 5.1	Black or African American	7,235 855,704	5.4 22.7
140 to 179 acres	farms acres	12,251 1,935,564	6.3 6.2	Native Hawaiian or Other Pacific Islander farms	306	7.9
180 to 219 acres	farms	8,177	8.6	acres	66,608	46.1
220 to 259 acres	acres farms	1,619,508 5,632	8.6 5.8	White	221,037 124,062,222	4.7 5.9
260 to 499 acres	acres	1,341,125 18,118	5.9 7.0	More than one race reported	3,067 1,000,462	6.1 16.6
500 to 999 acres	acres	6,453,735	7.0		1,000,402	10.0
	acres	12,674 8,781,004	6.0 5.9	Military service: Never served or only on active duty for training		
1,000 to 1,999 acres	farms acres	7,939 10,961,232	6.0 6.1	in the Reserves or National Guard (see text)producers Active duty now or in the past (see text)producers	360,624 42,252	3.9 5.0
2,000 acres or more	farms acres	9,975 88,098,571	7.3	All producers by age group 1:	,	
Indicate dilay disease	acics	00,030,37 1	0.0	Under 25 years farms	5,549	9.1
Irrigated land use: Harvested cropland	farms	15,582	9.0	25 to 34 years	19,351 42,184	16.8 4.9
Pastureland and other land	acres	3,126,982 4.849	7.7 6.6	45 to 54 years	63,194 105,668	4.5 4.9
	acres	638,456	18.4	65 to 74 years farms	103,310	4.9 3.9 3.7
Market value of agricultural products sold	\$1,000	32,166,561	3.0	75 years and overfarms	63,620	3.7
Farms by value of sales:				Net cash farm income of operations: Farms with gains of- <sup>2</sup>		
Less than \$1,000	\$1 000	75,579 8,162	8.3 10.6	Less than \$1,000	6,312 3,019	6.4 5.7
\$1,000 to \$2,499	farms	30,294	4.8	\$1,000 to \$4,999farms	14,311	6.9
\$2,500 to \$4,999	\$1,000 farms	49,708 27,619	4.9 5.6	\$1,000 \$5,000 to \$9,999farms	39,064 8,254	6.9 7.1
\$5,000 to \$9,999	\$1,000 farms	98,085 27,684	5.6 5.7	\$1,000 \$10,000 to \$24,999farms	59,637 10,278	6.8 5.1
\$10,000 to \$19,999	\$1 000	194,298 22,343	5.6 4.1	\$1,000 \$25,000 to \$49,999	166,302 6,070	4.9 5.9
	\$1.000	312,438	4.0	¶ \$1,000	215,619	6.1
\$20,000 to \$24,999	\$1.000	6,407 141,547	4.1 4.1	\$50,000 or more	14,365 11,188,014	7.4 3.1
\$25,000 to \$39,999	farms \$1,000	10,729 335,389	3.9 3.9	Farms with losses of-		
\$40,000 to \$49,999	farms	3,917	3.3	Less than \$1,000 farms	8,652	6.2
\$50,000 to \$99,999	\$1,000 farms	173,408 8,785	3.2 5.9	\$1,000 \$1,000 to \$4,999farms	4,523 41,039	5.5 5.0
\$100,000 to \$249,999	\$1,000 farms	608,505 7,194	5.7 10.7	\$1,000 \$5,000 to \$9,999farms	121,468 37,774	4.9 4.7
\$250,000 to \$499,999	\$1,000	1,091,839 3,383	10.8 11.9	\$1,000 \$10,000 to \$24,999farms	276,040 48,786	4.7 4.4
	\$1,000	1,177,741	11.6	\$1,000 \$25,000 to \$49,999 farms	777,670	4.4
\$500,000 to \$999,999	\$1,000	2,639 1,829,022	13.3 13.4	\$1,000	20,098 694,111	5.6 5.8
\$1,000,000 or more	farms \$1,000	4,089 26,146,421	6.5 2.1	\$50,000 or more	14,723 2,451,499	4.7 4.6
Farms by legal status for tax purposes:	. ,	., .,		Livestock and poultry:	, , , , , ,	
Family or individual	farms	205,473	4.7	Cattle and calves inventory farms	131,815	4.1
Partnership	acres farms	73,252,405 13,566	7.0 5.3	number Beef cows inventoryfarms	12,543,300 117,838	2.7 4.0
Corporation:	acres	32,352,815	5.5	number Milk cows inventoryfarms	4,360,026 479	3.3 2.8
Family held		7,344	3.7	number	639,506 5,837	1.0
Other than family held		14,766,773 1,486	6.0 5.2	Hog and pigs inventoryfarms number	1,188,820	28.0 10.4
Other - estate or trust, prison farm, grazing association	acres	2,747,461	6.6	Layers inventory farms number	30,288 24,478,507	5.3 23.9
American Indian Reservation, etc		2,793 2,351,871	7.5 5.7	Broilers sold	2,086 709,585,824	34.7 9.1
T	dorco	2,001,071	0.7	Aquaculture soldfarms	202	8.5
Tenure: Full owners		179,127	4.4 4.7	\$1,000	72,328	3.2
Part owners	acres farms	50,187,898 40,540	4.7 5.3	Selected crops harvested:  Corn for grainfarms	3,714	19.0
Tenants	acres	58,794,545 10,995	6.7 8.3	acres  Durum wheat for grain	1,680,377	19.7
ronanto	acres	16,488,882	8.3	acres	-	100
Producers characteristics by- 1 (see text)				Other spring wheat for grainfarms acres	124 9,096	16.9 19.7
Sex of operator:  Male	farms	208,863	5.1	Winter wheat for grain	4,008 1,740,243	12.9 9.7
Female	acres	119,815,650 143,585	6.0 2.4	Sorghum for grain	2,237 994,977	35.2 13.5
ı Ullaic	acres	59,133,549	4.3	Soybeans for beansfarms	385	17.6
Primary occupation:				acres Ricefarms	97,284 289	13.2 14.6
Farming Other		153,043 249,833	3.9 4.1	acres	193,438	15.5
		2.0,000	17.1	JI	1	

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

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

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

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	4,822	18.2			
acres	2,337,631	3.6	Sweet corn (see text)farms	281	22.7
Peanutsfarms	306	39.2	acres	3,292	6.0
acres Barley	118,260 37	19.1 16.8	Lettuce	247 649	35.9 5.6
acres	6,723	21.2	Land in orchards (see text)	8,286	13.5
Oats	297	15.3	acres	194,781	9.2
acres	52,833	20.0	Applesfarms	737	10.5
40100	02,000	20.0	acres	624	7.6
Forage - land used for all hay and haylage,			Grapes (including muscadine) (see text)farms	1,378	10.4
grass silage, and greenchop farms	63,823	8.6	acres	11,546	4.6
acres	4,445,285	7.8	Oranges farms	364	11.0
Land in vegetables (see text) farms	2,177	27.3	acres	(D) 35	(D)
acres	98,815	8.9	Almondsfarms	35	40.3
Potatoesfarms	461	26.1	acres	(D)	(D)
acres	14,670	1.4	Land in berriesfarms	1,583	11.7
Tomatoes in the open farms	870	33.5	acres	3,259	12.7
acres	902	22.0			

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

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

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						
Texas	230,662	10,786	49.0	20.4	14.3	14.3
Counties						
	1,741	142	47.7	23.1	9.8	14.8
Andrews	149	26	50.3	16.0	13.7	20.6
AngelinaAransas	838 79	49 11	52.1 46.9	26.2 29.3	13.5 6.7	12.4 11.0
ArcherArmstrong	457 184	115 41	41.1 37.8	14.6 10.5	8.0 14.8	18.5 12.5
Atascosa	1,673	118	50.7	18.5	17.9	14.4
Austin	1,930 389	125 73	45.4 45.1	25.2 11.7	9.8 21.2	10.5 12.1
Bandera	723	50	56.2	18.9	18.4	18.9
Bastrop	1,871 229	58 22	50.1	25.0	14.8	10.2
Baylor Bee	743	39	47.5 47.8	10.0 23.4	8.5 11.7	29.0 12.7
Bell Bexar	2,330 2,107	134 134	49.5 53.7	26.4 25.2	13.0 14.8	10.1 13.7
Blanco Borden	776 102	47 9	55.1 32.5	21.0 4.4	18.9 9.3	15.1 18.8
Bosque	1,384	92	48.1	20.4	15.3	12.5
Bowie	1,267 2,538	43 145	45.0 54.5	21.5 32.1	9.4 10.9	14.1 11.5
Brazos	1,103	77	46.5	25.6	13.1	7.7
Brewster	205	16	53.1	9.9	8.0	35.1
Briscoe	152 317	10 35	37.3 57.3	9.3 14.4	21.5 33.5	6.6 9.5
Brown	1,680 1,528	212 98	53.5 42.8	23.9 25.9	14.3 8.2	15.3 8.6
Burnet	1,428	91	54.2	26.5	16.2	11.5
CaldwellCalhoun	1,329 257	84 15	48.5 42.6	23.5 24.4	15.2 12.2	9.8 6.0
Callahan	1,050	71	51.6	18.7	13.8	19.2
Cameron	1,248 416	160	55.7 47.1	20.6	14.1 6.6	21.1
Camp	367	59 45	40.1	25.2 4.6	16.8	15.3 18.8
Cass	939 415	53 82	49.5 45.9	22.6 3.6	13.7 14.1	13.3 28.2
Chambers	491 1,411	38 73	52.3 49.3	25.3 23.8	15.5 12.0	11.5 13.5
Cherokee	334	37	45.4	7.6	17.2	20.5
Clay Cochran	881 349	50 64	42.2 39.3	18.9 4.2	8.9 17.0	14.5 18.1
Coke	433	32	52.3	10.8	18.3	23.2
Coleman	1,071	60	47.7	8.9	11.5	27.2
Collin Collingsworth	2,330 285	109 57	53.2 38.8	29.4 6.7	14.3 20.4	9.5 11.7
Colorado	1,702 888	99 52	43.2 55.3	19.5 25.3	11.8 20.8	12.0 9.2
Concho	1,500 400	77 44	44.2 44.1	19.5 7.0	12.6 23.1	12.2 13.9
Cooke	2,188	109	46.1	25.0	8.7	12.4
Coryell	1,435	82	48.9	22.3	14.0	12.7
Cottle	258 44	19 9	40.3 43.2	8.6 12.6	12.5 10.4	19.2 20.2
Crockett	275	21	54.8	11.4	15.6	27.8
Crosby Culberson	440 73	303 11	43.4 40.3	1.9 11.5	20.9 23.4	20.7 5.4
Dallam Dallas	323 647	32 33	43.9 62.5	3.5 26.6	5.6 16.0	34.8 19.9
Dawson Deaf Smith	518 663	124 140	34.5 46.1	5.0 7.4	16.9 15.3	12.7 23.4
Delta	433	56	48.0	21.7	7.6	18.7
Denton	2,936	164	53.6	31.7	13.3	8.6
DeWitt	1,533 498	36 38	40.0 45.2	25.4 11.3	6.9 13.0	7.7 20.9
Dimmit	211	12	54.2	26.1	16.2	11.8
Donley Duval	333 1,044	46 94	46.0 53.2	9.5 15.1	25.5 22.2	11.1 15.9
Eastland Ector	1,210 178	69 20	50.1 53.7	18.4 21.0	18.1 7.9	13.6 24.8
Edwards	456	42	60.6	10.8	23.4	26.4
Ellis	2,563	106	49.9	28.5	10.2	11.2
El Paso Erath	581 2,400	105 111	56.1 50.0	31.2 24.2	13.3 12.2	11.5 13.6
Falls	1,146	99	45.1	19.1	8.9	17.1
Fannin Fayette	2,108 2,905	148 79	46.6 41.1	24.5 25.4	11.3 8.1	10.8 7.5
FisherFloyd	558 457	90 397	45.2 40.6	8.3 5.1	16.3 23.1	20.6 12.4
Foard	184	20 66	39.2 50.9	7.5	7.6	24.0 13.5
Fort BendFranklin	1,233 505	32	46.2	24.8 24.0	12.7 11.5	10.6
Freestone	1,291	48	48.9	26.1	10.2	12.6
Frio Gaines Gaines	592 624	45 118	54.8 39.1	19.7 6.3	18.8 22.5	16.4 10.3
-	024	110	39.1	0.3	22.3	continued

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.						
Galveston	563	41	52.0	21.6	20.3	10.0
Garza	251	34	43.6	8.5	22.2	12.9
Gillespie	2,021 188	114 21	52.2 44.8	19.2 2.3	18.8 22.0	14.1 20.6
Goliad	1,092	68	46.1	21.0	13.4	11.7
Gonzales	1,870 287	96 25	40.3 48.6	22.4 14.7	8.7 22.2	9.2 11.7
Grayson	2,851	160	49.6	25.8	12.2	11.6
Gregg	403 1,668	27 91	59.1 48.3	26.2 21.8	12.0 17.9	20.9 8.6
GuadalupeHale	2,369 779	97 81	49.2 41.0	26.5 7.3	13.2 19.7	9.5 14.0
Hall	407	43	42.3	6.5	16.7	19.1
Hamilton Hansford	964 137	86 94	45.4 28.3	19.6 2.9	13.4 13.7	12.4 11.7
Hardeman	315	34	42.6	9.1	12.6	20.8
Hardin	606 1,531	45 101	54.0 55.8	33.9 26.8	11.8 16.9	8.3 12.1
Harris	1,015	93	51.8	23.4	13.8	14.6
Hartley	224	51	44.3	5.6	27.7	11.0
Haskell	518	45	36.6	6.9	8.5	21.2
Hays	940	38	56.2	26.4	18.6	11.3
Hemphill	213 1,891	15 98	46.2 48.7	12.9 26.2	18.6 9.2	14.7 13.2
Hidalgo	2,045	210	61.5	22.4	15.1	24.0
Hill Hockley	2,011 897	105 146	46.2 44.3	23.0 8.3	9.4 17.4	13.8 18.6
Hood	1,109	67	52.6	30.0	12.1	10.5
Hopkins	1,873 1,411	128 92	45.2 48.2	26.0 19.8	9.1 7.2	10.1 21.2
	·		-			
Howard	407 162	49 25	41.2 46.9	6.3 9.1	13.8 16.7	21.1 21.1
Hunt	3,504	176	48.9	29.4	10.0	9.5
Hutchinson	167 160	15 23	50.8 54.2	18.2 10.0	10.8 13.2	21.8 31.1
Jack	889	35 53	48.9	20.5	9.6	18.8
Jackson	825 919	53 42	44.4 51.7	14.8 25.6	12.2 15.8	17.4 10.3
Jasper	107	15 25	57.6	11.2	9.4	37.0
Jefferson	612	25	48.5	28.3	11.3	8.8
Jim Hogg	208	13	46.2	19.8	18.4	7.9
Jim Wells	960 2,745	102 118	54.5 49.2	23.4 29.3	19.5 9.8	11.5 10.2
Jones	988	57	51.2	15.3	13.7	22.2
Karnes	958 2,478	89 141	42.1 49.5	19.2 31.2	6.4 9.1	16.4 9.1
Kendall	1,142	56	56.1	26.3	19.7	10.0
Kenedy Kent	30 137	4 133	41.7 39.5	12.6 7.4	16.7 13.8	12.4 18.4
Kerr	987	70	58.5	16.8	20.9	20.8
Kimble	610	GE.	56.2	12.0	25.6	16.7
Kimble	619 54	65 13	56.2 38.0	13.8 7.2	25.6 19.9	16.7 10.9
Kinney	190	16 27	55.6	11.8	32.8	10.9
KlebergKnox	380 259	196	51.7 50.0	29.5 3.0	11.2 5.2	10.9 41.8
Lamar	1,865	117	45.8	20.6	11.9	13.3
LambLampasas	879 1,076	174 145	37.3 53.5	6.7 21.7	17.9 16.1	12.7 15.6
La Salle	344	34	57.4	16.2	17.1	24.1
Lavaca	2,735	80	34.3	21.8	6.3	6.2
Lee	1,720	106	42.9	25.7	9.2	8.0
Liberty	1,597 1,321	101 84	46.9 50.4	22.1 31.1	13.4 12.2	11.3 7.0
Limestone	1,263	57	44.9	23.0	10.6	11.3
Live Oak	283 793	30 48	45.9 47.3	8.3 15.7	21.2 25.0	16.4 6.6
Llano	798	57	51.0	21.5	18.5	11.1
Loving	11 1,286	(H) 141	(Z) 55.2	(Z) 12.8	(Z) 22.3	(Z) 20.2
Lubbock	512	62	37.5	5.0	16.0	16.5
	560	20	50.0	44.4	20.7	16.0
McCulloch	562 3,140	28 142	50.8 49.7	14.1 25.8	20.7 14.3	16.0 9.6
McMullen	171	142 22	53.3	12.6	15.0	25.6
Madison	819 244	72 54	45.4 57.0	26.3 26.5	8.2 10.8	10.9 19.7
Martin	395	67	42.3	7.4	15.7	19.2
Mason	650 814	57 57	46.1 42.7	17.3 18.3	15.0 11.8	13.8 12.5
Maverick	234	38	58.5	23.6	20.5	14.5
Medina	2,204	100	51.0	23.2	16.0	11.8
iviculia			50.4	10.5	17.0	21.4
Menard	374	32	52.1	13.5	17.2	
MenardMidland	349	21	58.5	28.0	18.7	11.8
Menard Midland Millam	349 2,048 874	21 138 113	58.5 45.4 53.2	28.0 17.4 18.0	18.7 13.9 15.9	11.8 14.1 19.2
Menard Midland Milam	349 2,048	21 138	58.5 45.4	28.0 17.4	18.7 13.9	11.8 14.1

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.			Oi total		потпооронос	ooidoomoatioH
Counties - Con.						
Moore	218	40	47.2	16.5	11.6	19.1
Morris	335	70	49.0	23.5	9.4	16.1
Motley	213	37	41.8	5.5	14.2	22.1
Nacogdoches	1,014 2,213	64 91	48.4 47.4	24.0 27.1	11.9 9.0	12.6 11.3
Newton	426	26	54.9	25.7	10.7	18.6
Nolan	443	57	47.9	12.6	14.0	21.4
Nueces	549	157	49.3	17.1	14.1	18.2
Ochiltree	285	56 24	44.1	3.2	29.4	11.5
Oldham	178	24	43.6	5.8	14.4	23.4
Orange	513	45	55.0	28.1	21.7	5.3
Palo Pinto	1,147	64	50.6	26.6	15.9	8.0
Panola	744	52	47.7	28.1	9.8	9.7
Parker	4,379	235	53.8	31.1	12.9	9.9
Parmer	477 249	102 158	43.8 48.0	5.5 9.7	22.6 9.5	15.7 28.7
Pecos	594	32	48.7	25.6	13.1	10.0
Potter	243	15	49.5	14.7	9.4	25.5
Presidio	147	15 28	38.1	8.0	12.6	17.4
Rains	631	77	45.2	24.2	9.5	11.6
Dandall	0.40	اددد		40.5	40.0	47.0
Randall	843 91	141 10	55.0 45.2	19.5 10.3	18.6 24.8	17.0 10.1
Real	212	26	61.7	17.0	23.7	21.0
Red River	1,041	63	41.1	9.4	8.1	23.6
Reeves	150	18	52.9	11.3	16.6	24.9
Refugio	315	43	49.5	13.6	24.6	11.3
Roberts	119	21 67	51.8	4.1	11.3	36.3
Robertson	1,351 359	28	45.4 56.1	20.6 30.1	11.2 18.9	13.6 7.1
Runnels	1,039	81	46.5	9.1	15.3	22.1
	,					
Rusk	1,309	64	50.1	24.3	11.7	14.0
Sabine	173	15	49.5	19.1	23.9	6.5
San Augustine	227 588	12 41	49.2 51.2	28.7 27.7	8.8 10.2	11.6 13.3
San Patricio	620	42	47.9	15.3	18.8	13.7
San Saba	865	56	50.6	15.0	16.7	19.0
Schleicher	353	56 38	51.7	6.2	26.0	19.5
Scurry	685	53	49.8	9.8	18.8	21.1
Shackelford	208 799	21 80	41.3 46.4	12.1 25.0	7.9 10.5	21.3 10.8
Sileiby	199	60	40.4	23.0	10.5	10.0
Sherman	282	56	33.9	6.1	15.3	12.4
Smith	2,495	149	53.1	29.0	13.7	10.4
Somervell	320	42	52.4	27.2	12.6	12.6
Starr	1,126	137 37	57.6 48.4	18.2 15.1	27.3 13.1	12.2 20.1
Stephens	454 70	6	50.0	13.8	16.1	20.1
Stonewall	344	37	49.2	9.6	15.8	23.8
Sutton	289	44	55.3	10.8	25.0	19.4
Swisher	441	116	37.4	6.3	18.4	12.8
Tarrant	1,000	55	56.7	29.6	17.1	9.9
Taylor	1,222	105	54.8	20.0	15.0	19.8
Terrell	60	16	42.4	4.4	33.9	4.1
Terry	669	232	43.3	5.1	24.5	13.8
Throckmorton	185	128	48.0	7.8	15.0	25.1
Titus	687	104	45.4	23.3	10.4	11.7
Tom Green	1,392 870	92 60	60.3 52.2	22.5 26.7	23.5 14.5	14.3 11.0
Trinity	444	39	46.0	27.1	8.7	10.2
Tyler	652	33	49.5	26.8	13.5	9.2
Úpshur	1,373	62	50.8	30.3	9.3	11.2
Linton	404		40.0	40.7	00.0	40.0
Uvalde	101 580	17 38	46.9 55.2	12.7	22.2 20.7	12.0
Val Verde	333	30 22	55.2 59.1	13.7 18.8	20.7	20.9 20.0
Van Zandt	3,206	131	48.1	28.9	9.1	10.1
Victoria	1,412	77	46.5	21.6	11.7	13.1
Walker	1,222	28	50.4	30.1	12.2	8.2
Waller	1,545	100	47.4	26.9	11.2	9.3
Ward	52 2,137	14   116	50.7 42.9	7.2 24.3	9.1 9.9	34.4 8.7
	659	182	42.9 55.5	10.9	11.7	32.9
	009	102	55.5	10.9	11.7	52.9
Webb	1,472	88	46.7	15.2	12.6	18.9
Wharton		51	36.7	11.2	17.1	8.5
Wharton	467			21.7	9.7	19.0
Wharton	467 632	55	50.4			10.0
Wharton Wheeler Wichita Wilbarger	467 632 374	55 29	40.5	10.6	16.6	13.3
Wharton Wheeler Wichita Wilbarger Willacy	467 632 374 345	55 29 66	40.5 53.8	10.6 16.4	16.6 12.2	25.2
Wharton	467 632 374 345 2,352	55 29 66 137	40.5 53.8 49.8	10.6 16.4 25.7	16.6 12.2 12.6	25.2 11.5
Wharton Wheeler Wichita Wilbarger Willacy Williamson	467 632 374 345	55 29 66	40.5 53.8	10.6 16.4	16.6 12.2	25.2 11.5
Wharton Wheeler Wichita Wilbarger Willary Williamson Wilson Winkler Wise	467 632 374 345 2,352 2,503 38 3.528	55 29 66 137 105 18 145	40.5 53.8 49.8 47.5 50.0 50.7	10.6 16.4 25.7 28.7 20.3 30.4	16.6 12.2 12.6 9.6 13.4 10.0	25.2 11.5 9.2 16.3 10.4
Wharton Wheeler Wichita Wilbarger Willacy Williamson Wilson Winkler	467 632 374 345 2,352 2,503 38	55 29 66 137 105 18	40.5 53.8 49.8 47.5 50.0	10.6 16.4 25.7 28.7 20.3	16.6 12.2 12.6 9.6 13.4	25.2 11.5 9.2 16.3
Wharton Wheeler Wichita Wilbarger Willary Willary Willary Wilson Winkler Wise Wood	467 632 374 345 2,352 2,503 38 3,528 1,357	55 29 66 137 105 18 145 85	40.5 53.8 49.8 47.5 50.0 50.7 46.5	10.6 16.4 25.7 28.7 20.3 30.4 27.2	16.6 12.2 12.6 9.6 13.4 10.0	25.2 11.5 9.2 16.3 10.4 9.0
Wharton Wheeler Wichita Wilbarger Willacy Willianson Wilson Winkler Wise Wood Yoakum	467 632 374 345 2,352 2,503 38 3,528 1,357	55 29 66 137 105 18 145 85	40.5 53.8 49.8 47.5 50.0 50.7 46.5	10.6 16.4 25.7 28.7 20.3 30.4 27.2	16.6 12.2 12.6 9.6 13.4 10.0 10.3	25.2 11.5 9.2 16.3 10.4 9.0
Wharton Wheeler Wichita Wilbarger Willacy Willacy Williamson Wilson Winkler Wise Wood	467 632 374 345 2,352 2,503 38 3,528 1,357	55 29 66 137 105 18 145 85	40.5 53.8 49.8 47.5 50.0 50.7 46.5	10.6 16.4 25.7 28.7 20.3 30.4	16.6 12.2 12.6 9.6 13.4 10.0	25.2 11.5 9.2 16.3 10.4 9.0

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
LAND IN FARMS (ACRES)						
State Total						
Texas	125,471,325	7,392,284	30.4	2.9	9.6	17.9
Counties						
Anderson	361,026	65,699	40.3	10.5	8.0	21.8
Andrews	879,802	50,552	5.5	0.7	0.5	4.3
	77,346	5,164	35.8	10.1	12.8	12.8
Aransas	42,886	292	11.9	8.2	1.6	2.1
Armstrong	577,879	383,414	39.7	3.8	4.1	31.8
	461,617	115,026	26.5	4.2	10.0	12.3
Atascosa	688,382	125,901	32.8	6.9	11.2	14.7
Austin	258,883	39,269	35.6	15.7	9.9	10.0
Bailey	529,253	58,858	38.1	5.0	20.9	12.2
Bandera	191,495	16,087	47.4	9.1	24.5	13.8
		,				
Bastrop	263,123	22,555	36.9	12.9	10.0	14.0
	555,156	37,476	30.6	5.0	5.9	19.7
Bee	437,238	121,157	32.3	5.4	9.0	17.9
	496,484	67.350	24.0	6.8	9.2	8.0
Bexar	248,545	12,492	42.2	9.8	12.8	19.5
	361,697	178,783	52.3	7.5	26.5	18.2
Borden	572,829	27,304	17.9	2.7	4.5	10.7
Bosque	586,420	114,436	40.8	10.7	18.1	11.9
	256,027	29,976	44.8	5.8	10.6	28.4
Brazoria	419,260	39,158	37.5	8.8	12.5	16.2
Brazos	277,682	26,213	39.3	16.3	15.2	7.9
Brewster	2,259,266	213,724	23.3	1.2	1.7	20.4
Briscoe	585,760	660	15.0	0.9	11.0	3.1
	372,375	85,212	11.9	3.7	4.1	4.1
Brooks	475,421	98,768	42.2	5.9	10.5	25.8
Burleson	300,620	32,373	37.7	12.2	12.5	13.0
	425,682	130,158	46.0	13.6	17.4	15.0
Caldwell	244,313	69,028	35.8	9.8	12.8	13.1
	129,971	31,036	13.1	3.6	6.0	3.5
Callahan	468,449	195,699	42.9	4.0	14.1	24.9
Cameron	208,701	45,149	31.0	1.6	9.5	19.9
Camp	53,316	11,463	26.3	6.8	1.8	17.7
	582,593	153,065	24.2	1.3	11.3	11.7
Cass	139,124	10,639	45.4	13.1	17.7	14.7
	570,818	228,618	35.1	2.1	12.3	20.7
Chambers Cherokee	199,088	30,458	27.7	2.9	7.7	17.1
	325,551	59,323	39.3	13.7	15.5	10.0
Childress	444,942	55,813	33.0	3.9	15.5	13.6
Clay	680,467	53,867	33.5	6.9	5.8	20.8
Cochran	434,001	70,692	25.6	1.3	7.5	16.9
Coke	478,560	177,208	38.4	4.9	10.6	22.8
Coleman	758,719	106,112	43.6	4.4	10.0	29.3
	197,374	25,734	25.5	5.3	4.2	16.0
Collingsworth	537,442	94,083	39.3	5.4	24.7	9.2
	452,829	117,857	39.9	6.4	8.9	24.6
Comal	107,388	8,854	61.3	1.4	59.4	0.5 18.2
Concho	596,256 629,378	136,821 32,338	37.4 31.5	9.6 3.6	9.5 18.4	9.5
Cooke	513,278	55,824	36.2	11.7	6.4	18.1
	511,451	63,144	35.4	4.4	6.3	24.8
Cottle	569,008	60,151	13.9	3.1	2.1	8.7
Crane	291,025	126,423	15.5	2.8	2.3	10.5
	1,768,834	188,932	30.2	3.1	7.4	19.7
Crosby	576,011	149,241	27.3	0.6	9.6	17.0
Culberson Dallam	1,932,918	151,197	14.3	0.4	13.1	0.9
	961,047	108,369	35.6	1.7	2.7	31.2
Dallas	67,030	6,380	62.7	13.5	21.2	28.0
	574,896	102,134	23.4	2.2	10.8	10.4
Deaf Smith Delta	957,798	204,527	37.6	2.2	12.6	22.8
	108,877	29,198	30.7	8.3	4.4	18.0
Denton	272,184	85,862	27.9	7.5	5.3	15.1
DeWitt	411,339	77,180	33.4	13.7	9.1	10.5
Dickens  Dimmit	575,827	22,216	22.9	2.8	9.2	11.0
	344,379	84,792	33.9	4.1	12.4	17.3
Donley	585,161	153,936	25.6	2.7	13.5	9.5
	1,115,787	46,490	23.0	4.2	8.0	10.9
Eastland	519,189	139,357	42.2	11.6	16.6	14.0
Ector	417,245	227,737	14.1	3.2	1.4	9.6
Edwards	1,011,179	426,776	40.6	3.6 5.2	13.1	23.9
Ellis	377,200	37,876	24.7		3.1	16.4
El Paso	269,479	29,298	34.8	1.8	18.1	14.8
Erath	675,439	153,744	37.7	7.8	8.8	21.1
FallsFannin	488,283	72,777	30.8	0.9	1.0	28.9
	417,464	54,865	37.0	13.8	7.7	15.6
Fayette	470,955	34,838	38.6	16.2	10.1	12.3
FisherFloyd	387,119	76,361	28.2	3.7	9.5	15.0
	634,965	273,609	23.7	1.9	9.3	12.5
FoardFort Bend	441,647	131,286	19.0	0.6	1.2	17.2
	320,377	23,615	31.2	4.5	10.3	16.4
Franklin	110,438	19,811	37.5	12.8	9.2	15.6
Freestone	372,086	33,376	35.3	7.8	5.6	22.0
Frio	566,717	67,888	38.1	3.6	30.1	4.5
	810,019	174,423	27.2	1.5	14.4	11.3
	1					continued

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

[For meaning of abbreviations and symbols, see introductory text.]  Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
LAND IN FARMS (ACRES) - Con.						
Counties - Con.						
Galveston	34,117	4,832	31.4	7.2	13.5	10.7
GarzaGillespie	407,281 548,817	46,591 83,094	24.3 39.5	3.7 8.8	16.1 16.8	4.5 13.9
Glasscock	517,077	71,082	40.0	0.9	6.4	32.8
Goliad Gonzales	416,291 630,773	33,110 56,175	42.3 30.6	5.9 13.2	12.0 9.4	24.4 7.9
Gray	541,538	76,818	29.6	6.4	12.2	11.0
Grayson Gregg	394,985 26,043	53,496 5,341	34.7 60.5	7.8 12.5	15.5 6.8	11.4 41.3
Grimes	502,510	29,789	49.1	10.9	17.9	20.3
Guadalupe	291,287	23,815	37.4	14.6	11.6	11.1
Hale	575,527	62,226	21.2	2.0	8.9	10.4
Hall Hamilton	359,028 515,913	29,022 61,798	29.7 36.2	3.1 11.4	12.4 12.9	14.3 11.9
Hansford	645,303	93,809	17.8	1.5	6.7	9.6
Hardeman Hardin	420,820 36,858	50,682 3,065	26.9 44.6	2.5 26.1	13.8 10.1	10.6 8.3
Harris	193,556	28,267	57.9	2.7	25.7	29.6
Harrison Hartley	121,801 935,417	15,375 38,950	45.7 22.0	10.0 3.5	17.0 10.4	18.8 8.1
Haskell Hays	542,383 142,428	62,080 11,298	19.7 47.3	1.7 11.8	4.6 21.9	13.5 13.6
Hemphill	579,694	59,054	37.2	6.3	9.8	21.1
Henderson Hidalgo	263,600 535,588	60,196 31,419	38.0 29.2	13.6 2.9	10.8 4.8	13.7 21.5
Hill	566,852	92,961	24.1	7.5	7.5	9.2
Hockley Hood	546,993 124,769	159,162 28,303	31.5 50.3	2.0 17.5	12.5 10.7	17.1 22.1
Hopkins	317,431	21,153	34.0	16.7	8.8	8.5
Houston	483,598	82,508	35.3	4.1	4.4	26.8
HowardHudspeth	575,487 2,642,028	57,992 370,669	25.0 12.4	1.1 0.7	12.9 1.9	11.0 9.8
Hunt	355,339	27,058	34.4	13.7	12.1	8.6
Hutchinson	560,153 672,190	95,910 80,486	26.3 25.6	3.7 1.5	3.7 4.1	19.0 19.9
Jack	573,752	64,831	36.0	7.5	9.7	18.9
Jackson	353,038 63,695	82,325 3,197	33.7 31.6	4.8 17.3	15.6 7.3	13.3 7.0
Jeff Davis	1,420,886	77,875	8.5	1.5	0.7	6.4
Jefferson	347,504	125,719	18.9	6.2	8.5	4.1
Jim Hogg	587,474	98,744	18.6	7.8	5.0	5.8
Jim Wells	398,796 287,921	47,698 47,958	31.3 32.9	4.1 3.9	18.3 1.9	9.0 27.1
Jones	564,608	93,644	30.9	2.6	5.0	23.4
Karnes	389,854 280,030	47,937 150,938	36.2 42.6	10.6 17.5	12.8 8.3	12.7 16.9
Kendall	269,055	45,011	40.3	12.3	17.5	10.5
Kenedy Kent	1,000,174 589,592	54,768	35.9 23.9	1.7 0.7	27.5 1.3	6.7 21.9
Kerr	390,194	218,789	51.1	6.8	18.0	26.3
Kimble	421,491	72,079	39.8	7.1	19.5	13.3
King Kinney	562,164 615,924	162,201 27,181	13.4 28.3	0.8 1.9	2.9 19.4	9.7 7.0
Kleberg	470,997	3,219	4.1	0.3	0.5	3.3
KnoxLamar	544,231 513,465	146,968 54.446	11.6 38.5	0.1 4.2	0.2 18.2	11.3 16.0
Lamb	511,619	113,897	28.9	2.2	17.9	8.9
LampasasLa Salle	448,284 552,478	236,266 129,927	45.1 52.7	2.3 4.1	3.5 10.6	39.2 38.0
Lavaca	540,742	56,576	35.3	10.8	13.6	10.9
Lee	341,764	99,507	35.0	7.2	18.5	9.3
Leon Liberty	423,117 234,400	117,885 71,488	37.3 27.0	11.9 6.7	17.8 3.5	7.5 16.7
Limestone	458,104	37,561	22.3	10.4	4.8	7.2
Lipscomb Live Oak	554,835 414,029	157,126 139,526	43.0 46.5	5.7 3.4	21.8 35.0	15.5 8.1
Llano	521,757	170,836	37.3	8.1	9.7	19.5
Loving Lubbock	424,193 465,867	242,880 148,728	(Z) 29.8	(Z) 1.0	(Z) 13.4	(Z) 15.4
Lynn	566,683	96,679	20.9	1.4	9.2	10.2
McCulloch	547,959	49,481	42.2	1.5	10.2	30.5
McLennan	552,280	91,638	38.8	11.0	11.5	16.3
McMullen	580,772 214,931	136,260 43,186	52.8 30.4	8.9 6.0	26.7 20.6	17.2 3.8
Marion	56,568	20,793	41.3	18.0	10.4	12.9
Martin	576,851 591,985	252,253 50,927	39.0 42.1	0.4 10.2	2.4 20.0	36.3 11.9
Matagorda	545,730	96,516	30.6	2.8	8.6	19.3
Maverick	329,643 634,224	266,310 28,099	35.9 44.1	7.4 7.1	24.1 15.9	4.4 21.1
		·				
Menard Midland	574,274 560,075	50,955 59,070	28.8 32.8	3.6 4.9	13.8 9.4	11.3 18.5
Milam	492,739	33,318	23.4	5.6	8.2	9.6
MillsMitchell	378,004 582,475	49,351 122,693	46.4 20.7	11.0 3.8	14.4 8.9	21.0 8.0
Montague	465,118 100,081	55,821 30,041	35.4 48.9	14.9 16.7	9.8 18.5	10.8 13.7
Montgomery	100,061	30,041	40.9	10.7	10.5	continued

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

ALAD M. ARMS (ACRES). Con.	[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
Story	LAND IN FARMS (ACRES) - Con.						
Months  44 161 17 17 17 17 17 18 18 18 18 18 18 18 18 18 18 18 18 18	Counties - Con.						
Months  44 161 17 17 17 17 17 18 18 18 18 18 18 18 18 18 18 18 18 18	Moore	511.477	150.141	13.5	3.3	4.0	6.1
Name	Morris	45,116	12,497	46.5	18.8	9.3	18.5
Namericon							
Newborn							14.8
Name	Newton	25,609	3,090	24.1	14.5	3.9	5.7
Combine							
Other							
Paid							
Paid	Orange	40.401	18 400	35.4	18.0	7.3	0.3
Papole							11.3
Parmer	Panola	142,072	93,109		19.8	11.8	9.8
Peace							
Pak.   62,888   4,220   37,1   15,4   12,5   9.2   Preside   238,110   16,852   17,6   10,0   16,852   Preside   238,110   17,6   10,0   16,852   Preside   238,110   17,6   17,6   10,0   16,852   Preside   238,110   24,555   37,2   13,7   15,1   8,3   Randall   25,386   24,200   35,5   44   68,8   13,7   Repair   24,555   36,2   10,4   14,2   20,8   7,6   Repair   35,386   10,200   10,4   14,2   20,8   7,6   Repair   36,000   10,4   14,4   20,8   7,6   Repair   36,000   10,4   16,4   16,4   16,4   16,4   16,4   Repair   36,000   14,4   16,4   16,4   16,4   16,4   Repair   36,000   36,4   15,4   16,4   Repair   36,4   16,4   16,4   Repair							
Presido		82,869	4,822	37.1	15.4		9.2
Raines							
Rendall		2,363,110 72 477					
Reagan   74.4 ct   50.04							
Real							
Red Ryes	Real						7.6 12.0
Reves     38,067   144,163   10.7   0.8   1.2   14.7   1	Red River	482,116	164,344	38.1	5.0	6.4	26.7
Roberts							
Robertson							
Runels		459,840					
Reph	Rockwall	23,466					
Sabine	Runnels	6/2,612	68,158	35.5	3.0	9.4	23.1
San Augustine	Rusk			46.8	17.8	13.5	15.4
San Jackson   66,844   7,089   35.8   15.4   9.6   10.8							
San Patricio   330,088   41,262   21,5   1.1   11,1   9.3   330,088   341,262   21,5   1.1   11,1   9.3   330,584   32,27   43,1   23,1   24			7,855 7,080				
Scheicher							
Soury							
Shackelford							
Shelby							
Smith		252,770	15,670	35.4		9.9	9.5
Smith	Sherman	500 226	97 706	10.0	2.2	6.0	10.8
Somervell							
Stephens	Somervell	99,570	34,068		13.5	15.7	10.6
Sterling							
Stonewall							
Sulton   909,743   723,035   327   5.6   10.7   16.3     Sysisher   542,277   84,590   27.1   2.8   14.0   10.3     Tarrant   199,120   20,760   60.2   16.6   16.0   27.7     Tarylor   285,570   102,447   41.1   6.2   9.2   2.5     Tarylor   285,857   102,447   41.1   6.2   9.2   2.5     Tarylor   285,858   179,814   27.2   0.9   24.3   2.0     Tarylor   285,877   28,201   25.9   2.6   15.7   7.5     Titus   139,188   45,332   41.8   81.1   15.5   18.3     Tom Green   937,713   179,174   45.9   5.1   20.4   20.3     Tarylor   197,174   45.9   5.1   20.4   20.3     Tarylor   198,239   43,583   33.0   41.1   12.4   6.5     Tarylor   67,100   9,061   35.2   13.4   11.7   10.1     Tarylor   63,492   41.89   45.6   16.1   12.2   17.3     Upshum   150,383   22,409   41.8   22.5   8.2   11.1     Upshum   150,380   22,121   2.16   4.1   9.6   7.9     Uvalde   993,079   80,652   27.6   3.3   6.6   17.7     Uvalde   993,079   80,652   27.6   3.3   6.6   17.7     Ovalde   993,079   80,652   27.6   3.3   5.6   6.6   17.7     Ovalde   993,079   80,652   27.6   3.3   5.6   6.6   17.7     Ovalde   993,079   80,652   27.6   3.3   5.6   6.6   17.7     Ovalde   993,079   80,652   27.6   3.3   9.9   6.5   7.9     Waller   994,070   996,070	Stonewall	476,804	202,481	37.7	4.9	6.2	26.6
Tarrant	Sutton						
Taylor	Tarrant						
Teirell         801,358         179,814         27.2         0.9         24,3         2.0           Terry         568,831         224,475         39.4         2.2         23.2         124.1           Throckmorton         583,977         28,201         25.9         2.6         15.7         7.5           Tilus         139,188         45,332         41.8         8.1         15.5         18.3           Tom Green         937,713         179,174         45.9         5.1         20.4         20.3           Travis         198,239         43,583         33.0         14.1         12.4         6.5           Tinity         67,100         9,061         35.2         13.4         11.7         10.1           Tyler         63,492         41,69         45.6         16.1         12.2         17.3           Upshur         518,980         221,212         21.6         4.1         9.6         7.9           Upton         518,980         221,212         21.6         4.1         9.6         17.7           Val Verde         14,17,386         52.651         30.6         2.4         21.7         6.5           Val Coria         52,000		·	·	00.2			
Terry         568,831         224,475         39.4         2.2         23.2         14.1           Throckmorton         583,977         28,201         25.9         2.6         15.7         7.5           Tilus         139,188         45,332         41.8         8.1         15.5         18.3           Tom Green         937,713         179,174         45.9         5.1         20.4         20.3           Travis         198,239         43,583         33.0         14.1         12.4         6.5           Trinity         67,100         9061         35.2         13.4         11.7         10.1           Tyler         63,492         4,169         45.6         16.1         12.2         17.3           Upshur         518,980         221,212         21.6         4.1         9.6         7.9           Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1417,386         52,651         30.6         2.4         21.7         6.5           Van Zandt         416,603         28,876         50.0         12.5         14.5         22.9           Walker         194,887							
Throckmorton   583,977   28,201   25,9   2.6   15,7   7.5							
Tom Green         937,713         179,174         45.9         5.1         20.4         20.3           Travis         198,239         43,583         33.0         14.1         12.4         6.5           Trinity         67,100         9,061         35.2         13.4         11.7         10.1           Tyler         63,492         4,169         45.6         16.1         12.2         17.3           Upshur         150,383         22,409         41.8         22.5         8.2         11.1           Upton         518,980         22,1212         21.6         4.1         9.6         7.9           Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,386         52,651         30.6         2.4         21.7         6.5           Van Zanct         416,603         28,76         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Waller         194,887         35,669         32.6         12.9         9.5         10.2           Ward         194,993	Throckmorton	583,977		25.9	2.6	15.7	7.5
Travis         198,239         43,583         33.0         14.1         12.4         6.5           Trinity         67,100         9,061         35.2         13.4         11.7         10.1           Tyler         63,492         41.69         45.6         16.1         12.2         17.3           Uphor         518,980         221,212         21.6         4.1         9.6         7.9           Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,386         52,651         30.6         2.4         21.7         6.5           Var Dandt         416,603         28,876         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         194,887         35,669         32.6         12.9         9.5         10.2           Walre         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,101         32.8         0.3         1.4         31.1           Ward         421,993         19,259 <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Trinity         67,100         9,061         35.2         13.4         11.7         10.1           Tyler         63,492         4,169         45.6         16.1         12.2         17.3           Upshur         150,383         22,409         41.8         22.5         8.2         11.1           Upton         518,980         221,212         21.6         4.1         9.6         7.9           Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,386         52,651         30.6         2.4         21.7         6.5           Van Zandt         416,603         2.8 876         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         124,887         35,669         32.6         12.9         9.5         10.2           Waler         211,993         19,259         24.3         9.9         6.5         7.0           Ward         441,773         11,010         32.8         0.3         1.4         3.1           Washington         374,600         39,	Travis						
Tyler 63,492 4,169 45.6 16.1 12.2 17.3 Upshur 150,333 22,409 41.8 22.5 8.2 11.1 11.0 150,333 22,409 41.8 22.5 8.2 11.1 11.0 150,307.9 80,652 27.6 3.3 6.6 17.7 17.0 17.0 17.0 17.0 17.0 17.0 17.0	Trinity						
Upton         518,880         221,212         21.6         4.1         9.6         7.9           Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,886         52,651         30.6         2.4         21.7         6.5           Van Zandt         416,603         28,876         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         194,887         35,669         32.6         12.9         9.5         10.2           Waller         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         <	Tyler	63,492				12.2	
Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,386         52,651         30.6         2.4         21.7         6.5           Van Zandt         416,603         28,876         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         194,887         35,669         32.6         12.9         9.5         10.2           Waller         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639	Upshur	150,383	22,409	41.8	22.5	8.2	11.1
Uvalde         993,079         80,652         27.6         3.3         6.6         17.7           Val Verde         1,417,386         52,651         30.6         2.4         21.7         6.5           Van Zandt         416,603         28,876         50.0         12.5         14.5         22.9           Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         194,887         35,669         32.6         12.9         9.5         10.2           Waller         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639	Upton	518.980	221,212	21.6	4.1	9.6	7.9
Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         94,887         35,669         32.6         12.9         9.5         10.2           Waller         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wilbarger         586,318         92,177         9.8         0.8         1.7         7.3           Williamson         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         30,148 <t< td=""><td>Uvalde</td><td>993,079</td><td>80,652</td><td>27.6</td><td>3.3</td><td>6.6</td><td>17.7</td></t<>	Uvalde	993,079	80,652	27.6	3.3	6.6	17.7
Victoria         526,006         47,745         25.8         5.5         10.7         9.6           Walker         94,887         35,669         32.6         12.9         9.5         10.2           Waller         211,993         19,259         24.3         9.9         6.5         7.9           Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wilbarger         586,318         92,177         9.8         0.8         1.7         7.3           Williamson         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         30,148 <t< td=""><td></td><td>1,417,386</td><td></td><td></td><td></td><td></td><td>6.5</td></t<>		1,417,386					6.5
Walker       194,887       35,669       32.6       12.9       9.5       10.2         Waller       211,993       19,259       24.3       9.9       6.5       7.9         Ward       441,773       11,010       32.8       0.3       1.4       31.1         Washington       374,608       39,391       39.2       14.9       12.3       12.0         Webb       2,128,507       986,729       24.2       0.7       2.2       21.2         Wharton       553,800       58,641       33.2       2.6       11.2       19.4         Wheeler       584,576       46,055       36.7       6.2       20.4       10.2         Wilbarger       298,639       66,508       30.1       3.6       2.3       24.3         Willagoy       293,861       14,604       7.3       0.5       2.4       4.4         Williamson       293,861       14,604       7.3       0.5       2.4       4.4         Williamson       380,184       74,482       38.7       5.5       6.3       27.0         Wilson       393,148       23,113       40.2       14.2       12.5       13.5         Winkler       365,							9.6
Ward         441,773         11,010         32.8         0.3         1.4         31.1           Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639         66,508         30.1         3.6         2.3         24.3           Wilbarger         586,318         92,177         9.8         0.8         1.7         7.3           Williamson         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         380,184         74,482         38.7         5.5         6.3         27.0           Wilson         393,148         23,113         40.2         14.2         12.5         13.5           Winkler         365,973         124,409         15.8         2.4         1.2         12.5           Wood         193,055         <	Walker	194,887	35,669	32.6	12.9	9.5	10.2
Washington         374,608         39,391         39.2         14.9         12.3         12.0           Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639         66,508         30.1         3.6         2.3         24.3           Wilbarger         9.8         0.8         1.7         7.3         3.6         2.3         24.3           Willary         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         393,148         23,113         40.2         14.2         12.5         13.5           Wilson         393,148         23,113         40.2         14.2         12.5         13.5           Wise         365,973         124,409         15.8         2.4         1.2         12.1           Wise         345,021	Waller						
Webb         2,128,507         986,729         24.2         0.7         2.2         21.2           Wharton         553,800         58,641         33.2         2.6         11.2         19.4           Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639         66,508         30.1         3.6         2.3         24.3           Wilbarger         536,318         92,177         9.8         0.8         1.7         7.3           Willary         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         380,184         74,482         38.7         5.5         6.3         27.0           Wiskon         393,148         23,113         40.2         14.2         12.5         13.5           Winkler         365,973         124,409         15.8         2.4         1.2         12.1           Wise         345,021         121,300         42.0         15.3         13.9         12.8           Wood         193,055         17,504         47.8         12.8         23.2         11.8           Young         411,578         58	Washington	441,773 374 608					
Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639         66,508         30.1         3.6         2.3         24.3           Wilbarger         556,318         92,177         9.8         0.8         1.7         7.3           Willargo         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         380,184         74,482         38.7         5.5         6.3         27.0           Wilson         393,148         23,113         40.2         14.2         12.5         13.5           Winkler         365,973         124,409         15.8         2.4         1.2         12.1           Wise         345,021         121,300         42.0         15.3         13.9         12.8           Wood         193,055         17,504         47.8         12.8         23.2         11.8           Yoakum         41,578         58,329         16.0         3.5         6.4         6.2           Young         483,160         36,613         42.6         9.5         12.7         20.4           Zapata         29,658         40.3 </td <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Wheeler         584,576         46,055         36.7         6.2         20.4         10.2           Wichita         298,639         66,508         30.1         3.6         2.3         24.3           Wilbarger         556,318         92,177         9.8         0.8         1.7         7.3           Willagoy         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         380,184         74,482         38.7         5.5         6.3         27.0           Wilson         393,148         23,113         40.2         14.2         12.5         13.5           Winkler         365,973         124,409         15.8         2.4         1.2         12.1           Wise         345,021         121,300         42.0         15.3         13.9         12.8           Wood         193,055         17,504         47.8         12.8         23.2         11.8           Yoakum         41,578         58,329         16.0         3.5         6.4         6.2           Young         483,160         36,613         42.6         9.5         12.7         20.4           Zapata         29,658         40.3 </td <td>NAME and an</td> <td>550,000</td> <td>50.044</td> <td>20.0</td> <td>0.0</td> <td>44.0</td> <td>40.4</td>	NAME and an	550,000	50.044	20.0	0.0	44.0	40.4
Wichita     298,639     66,508     30.1     3.6     2.3     24.3       Wilbarger     536,318     92,177     9.8     0.8     1.7     7.3       Willacy     293,861     14,604     7.3     0.5     2.4     4.4       Williamson     380,184     74,482     38.7     5.5     6.3     27.0       Wilson     393,148     23,113     40.2     14.2     12.5     13.5       Winkler     365,973     124,409     15.8     2.4     1.2     12.1       Wise     345,021     121,300     42.0     15.3     13.9     12.8       Wood     193,055     17,504     47.8     12.8     23.2     11.8       Yoakum     41,578     58,329     16.0     3.5     6.4     6.2       Young     483,160     36,613     42.6     9.5     12.7     20.4       Zapata     287,324     92,658     40.3     8.3     21.1     10.9							
Wilbarger         536,318         92,177         9.8         0.8         1.7         7.3           Willacy         293,861         14,604         7.3         0.5         2.4         4.4           Williamson         380,184         74,482         38.7         5.5         6.3         27.0           Wilson         393,148         23,113         40.2         14.2         12.5         13.5           Winkler         365,973         124,409         15.8         2.4         1.2         12.1           Wise         345,021         121,300         42.0         15.3         13.9         12.8           Wood         193,055         17,504         47.8         12.8         23.2         11.8           Yoakum         411,578         58,329         16.0         3.5         6.4         6.2           Young         483,160         36,613         42.6         9.5         12.7         20.4           Zapata         287,324         92,658         40.3         8.3         21.1         10.9		298,639					
Williamson     380,184     74,482     38.7     5.5     6.3     27.0       Wilson     393,148     23,113     40.2     14.2     12.5     13.5       Winkler     365,973     124,409     15.8     2.4     1.2     12.1       Wise     345,021     121,300     42.0     15.3     13.9     12.8       Wood     193,055     17,504     47.8     12.8     23.2     11.8       Yoakum     481,160     36,613     42.6     9.5     12.7     20.4       Zapata     287,324     92,658     40.3     8.3     21.1     10.9	Wilbarger	536,318	92,177	9.8	0.8	1.7	7.3
Wilson     393,148     23,113     40.2     14.2     12.5     13.5       Winkler     365,973     124,409     15.8     2.4     1.2     12.1       Wise     345,021     121,300     42.0     15.3     13.9     12.8       Wood     193,055     17,504     47.8     12.8     23.2     11.8       Yoakum     41,578     58,329     16.0     3.5     6.4     6.2       Young     483,160     36,613     42.6     9.5     12.7     20.4       Zapata     287,324     92,658     40.3     8.3     21.1     10.9							4.4
Winkler     365,973     124,409     15.8     2.4     1.2     12.1       Wise     345,021     121,300     42.0     15.3     13.9     12.8       Wood     193,055     17,504     47.8     12.8     23.2     11.8       Yoakum     441,578     58,329     16.0     3.5     6.4     6.2       Young     483,160     36,613     42.6     9.5     12.7     20.4       Zapata     287,324     92,658     40.3     8.3     21.1     10.9	Wilson						
Wood         193,055         17,504         47.8         12.8         23.2         11.8           Yoakum         441,578         58,329         16.0         3.5         6.4         6.2           Young         483,160         36,613         42.6         9.5         12.7         20.4           Zapata         292,658         40.3         8.3         21.1         10.9	Winkler	365,973	124,409	15.8	2.4	1.2	12.1
Yoakum     441,578     58,329     16.0     3.5     6.4     6.2       Young     483,160     36,613     42.6     9.5     12.7     20.4       Zapata     287,324     92,658     40.3     8.3     21.1     10.9							
Zapata	YYUUU	193,055	17,504	47.8	12.8	23.2	11.8
Zapata	Yoakum				3.5		
Zapitia	Young				9.5		
	Zayala	287,324 740,758	92,658 229,470	40.3 40.7	8.3 1.7	21.1 4.4	10.9 34.6

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)						
State Total						
Texas	32,166,561	960	19.0	6.8	3.2	9.0
Counties						
	100 100	40	40.0	05.0	0.7	44.4
Andrews	190,139 9,742	10 (Z)	40.9 7.0	25.8 3.0	3.7 0.5	11.4 3.5
Angelina	69,997 2,190	4	28.1 35.8	12.6 14.0	2.9 8.7	12.6 13.2
Archer	116,409	28 11	41.8	21.9 10.8	5.9	13.9
Armstrong Atascosa	69,350 65,106	4	16.4 33.5	10.7	3.2 7.9	2.5 15.0
Austin	57,353 385,149	20 9	34.2 9.4	13.3 3.8	2.9 0.7	18.1 4.9
Bandera	4,630	(Z)	47.7	12.5	17.1	18.2
Bastrop	58,615	14	43.3	16.2	23.4	3.8
Baylor Bee	53,090 36,323	11 7	26.5 18.2	7.0 4.2	10.4 0.3	9.1 13.7
Bell Bexar	90,098 73,150	24 9	30.1 21.2	7.0 2.8	9.5 0.7	13.7 17.7
Blanco	18,207 27,700	11 2	47.3 3.6	21.3 1.4	17.7 0.6	8.3 1.6
Borden	69,157	14	49.1	21.5	11.3	16.3
Bowie Brazoria	116,782 112,182	19 17	49.5 34.7	20.6 6.9	14.7 10.4	14.3 17.3
Brazos	122,917	4	15.7	13.0	0.9	1.8
Brewster	23,557	15	29.7	2.3	0.6	26.9
Briscoe	54,917 24,206	(Z) 2	6.8 7.8	0.2 1.1	6.2 5.0	0.4 1.6
Brown	41,991 104,390	5 11	27.6 37.7	10.0 16.3	4.3 7.7	13.3 13.8
Burnet	29,942 62,658	7 8	38.5 28.9	14.9 18.0	13.4 4.5	10.2 6.4
Caldwell	31,973	7	24.4	3.6	9.1	11.7
Callahan	22,701	6	42.9	7.2	4.0	31.7
Cameron	128,790 183,019	13 24	28.7 17.6	2.6 6.9	6.9 (Z)	19.2 10.7
Carson	122,173	35	20.1	0.6	6.5	12.9
Cass	144,523 1,839,154	36 56	52.1 3.0	22.7 1.9	18.8 0.3	10.7 0.8
Chambers	53,224 120,896	9 28	39.1 39.2	4.0 20.4	4.9 8.5	30.1 10.3
Childress	26,096 80,929	2 8	23.4 37.1	3.1 11.2	6.1 3.2	14.2 22.7
Clay Cochran	50,851	4	10.4	0.3	1.3	8.8
Coke	10,686	3	57.6	9.2	27.2	21.1
Coleman	44,586 98,779	6 11	43.6 13.1	14.1 7.0	13.5 3.6	16.0 2.5
Collingsworth	30,687 103,726	3 29	18.6 40.5	1.7 6.3	14.3 3.6	2.6 30.7
Comal	5,888	1	40.2	20.8	14.1	5.3 2.2
Concho	268,394 32,270	20 3	9.2 27.1	5.9 6.2	1.1 6.0	14.9
Cooke	109,452 73,508	27 11	42.3 16.3	15.0 3.8	7.5 3.5	19.8 9.0
Cottle	25,751	4	5.4	1.0	1.1	3.4
Crane	1,501	1	2.4	1.9	0.2	0.2
Crockett	30,654 54,410	4 5	26.1 14.4	13.5 0.5	4.7 9.7	7.9 4.3
Culberson Dallam	34,059 1,086,765	1 38	5.9 9.7	1.4 2.2	0.5 0.5	4.0 6.9
Dallas	32,680 52,552	19 5	47.7 22.6	2.7 1.5	0.6 4.4	44.5 16.7
Deaf Smith	1,893,692	84	6.0	5.0	0.3	0.8
Delta	19,812	4	21.9	7.4	4.3	10.2
Denton	135,467 31,438	9 4	25.7 29.5	11.2 14.4	9.3 7.0	5.1 8.1
Dickens Dimmit	17,365 10,612	3 3	22.9 55.2	4.4 27.2	2.5 5.4	16.0 22.5
Donley	85,042	6	20.3	2.3	11.7	6.3
Duval Eastland	15,019 36,976	1 4	31.9 34.8	9.7 11.5	15.0 12.5	7.2 10.8
Ector Edwards	3,822 11,392	2 2 8	22.6 36.1	9.6 4.1	3.2 7.0	9.8 24.9
Ellis	78,345	8	15.2	3.1	0.9	11.1
El Paso	41,340	11	38.2	6.4	25.9	5.9
Erath Falls	490,011 188,869	20 12	15.9 30.2	6.3 1.3	7.4 0.4	2.1 28.5
FanninFayette	103,695 78,747	26 6	25.3 36.6	10.4 16.7	8.5 11.3	6.5 8.6
Fisher Floyd	51,552 165,634		8.1 10.5	3.0 1.3	1.3 4.0	3.7 5.2
Foard	11,719	3 22 3 9	11.8	0.7	0.5	10.6
Fort BendFranklin	64,849 245,380	9 32	40.6 57.2	13.9 33.0	15.0 3.8	11.7 20.4
Freestone	122,796	19	38.4	14.1	11.5	12.8
Frio	167,847	8	14.2	9.7	0.9	3.5
Gaines	169,482	22	10.4	0.9	3.5	6.1 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.						
Galveston	12,771	3	57.7	21.4	17.7	18.6
Garza	12,093	1	13.3	1.7	8.8	2.8
Gillespie	38,189 28,586	4 2	46.0 51.3	6.2 3.3	16.1 14.9	23.6 33.1
Goliad	21,984	3	40.7	7.2	11.3 2.5	22.1 3.7
GonzalesGray	1,002,018 278,342	116 6	22.8 3.8	16.7 0.9	(Z)	2.9
Grayson	87,097 2,688	16	31.5 50.6	15.9 14.0	6.ó 7.8	9.5 28.7
Grimes	83,236	(Z) 22	31.4	18.5	3.5	9.4
Guadalupe	94,061	7	42.5	28.5	5.6	8.5
Hale	481,675	12	3.3	1.1	1.2	1.0
Hall Hamilton	19,092 100,704	1 3	22.0 13.8	1.5 8.0	3.4 3.5	17.0 2.4
Hansford	899,646	11	2.5	1.4	0.2	0.8
Hardeman Hardin	55,995 4,637	3 (Z)	10.5 42.4	1.2 24.6	5.7 14.8	3.7 3.0
Harris	89,039	9	48.0	13.9	8.8	25.2
Harrison Hartley	13,020 1,735,660	1 20	39.0 2.4	19.3 1.2	10.9 0.4	8.7 0.8
•						
Haskell Hays	49,659 29,240	4 2	17.8 31.3	1.2 9.7	1.2 19.6	15.4 1.9
Hemphill	146,527	16 13	53.8	8.0 17.9	5.7 12.9	40.2
Henderson Hidalgo	44,194 386,043	24	42.8 27.1	3.1	3.2	12.0 20.8
Hill	129,941 62,279	33 6	27.4 23.5	8.7 1.0	7.1 6.4	11.5 16.1
Hood	22,550	8	44.8	26.5	9.5	8.8
Hopkins	342,278 89,987	22 12	40.9 18.9	22.2 10.2	4.6 0.5	14.2 8.3
	·					
Howard	32,631 64,412	1 7	9.7 48.5	0.7 4.9	1.7 22.3	7.2 21.4
Hunt	82,418	16	36.9	13.0	15.2	8.7
Hutchinson	62,260 9,915	8 (Z)	22.9 19.2	11.4 4.4	4.9 4.5	6.6 10.3
Jack	42,816	4	36.4	12.4	8.9	15.1
Jackson	80,290 13,151	17 5	21.4 47.3	3.3 8.5	9.5 1.9	8.6 36.9
Jeff Davis	28,574	1	9.0	5.2	0.1	3.7
Jefferson	35,187	5	22.8	8.2	7.4	7.2
Jim Hogg	8,573 72,616	3	20.3 4.6	9.5 1.3	6.6	4.2 2.8
Jim Wells	65,996	11	38.8	3.8	0.4 1.6	33.4
Jones	73,772 39.691	7 16	45.7 40.4	28.7 24.6	5.9 7.1	11.0 8.7
Kaufman	49,371	9	50.8	26.7	13.1	11.1
Kendall Kenedy	14,129 18,849	1 (L)	58.0 14.9	26.3 1.3	19.8 7.7	11.8 6.0
Kent	9,849	1	24.6	0.9	0.6	23.1
Kerr	11,151	5	53.5	16.2	25.8	11.5
Kimble	7,226	1	38.1	6.5	9.2	22.3
King Kinney	13,073 3,788	(Z)	11.9 24.2	0.8 6.1	0.9 13.0	10.3 5.1
Kleberg	51,805 26,742	1 12	3.7 23.4	1.7 0.5	0.6 2.0	1.4 20.9
KnoxLamar	85,538	10	35.2	2.0	20.2	13.0
Lamb Lampasas	565,299 33,116	38 12	6.5 29.3	3.0 11.3	1.5 13.3	2.0 4.7
La Salle	7,667	2	52.1	26.3	18.2	7.6
Lavaca	66,195	10	35.0	17.1	8.9	9.0
Lee	89,196	7	17.6	12.5	3.2	1.9
Leon Liberty	233,517 40,699	28 27	28.3 31.5	18.4 18.7	6.1 5.3	3.8 7.4
Limestone	95,644	21	52.0	8.9	2.3	40.8
Lipscomb Live Oak	80,730 14,965	11 6	32.2 47.5	6.8 5.1	12.1 36.0	13.3 6.3
Llano	27,274	9	37.8	14.6	10.3	12.9
Loving Lubbock	1,547 160,301	(H) 7	(Z) 12.2	(Z) 5.6	(Z) 4.7	(Z) 2.0
Lynn	46,388	4	10.6	0.6	2.7	7.2
McCulloch	19,405	5	36.2	6.0	10.8	19.3
McLennan	210,109 9,466	32 5	34.2 51.9	21.7 12.0	7.2 18.7	5.3 21.3
McMullen	185,143	3	28.2	26.8	0.8	0.6
Marion	7,161 22,746	(H) 2	54.5 26.3	37.8 5.0	8.7 8.3	7.9 13.0
Mason	50,231	5	57.9	23.7	18.3	15.8
Matagorda	157,078	61	28.2	5.1	8.2	14.9
Maverick	44,296 82,644	3 5	5.4 28.8	4.3 16.3	0.6 6.7	0.6 5.8
	12,075		37.3	10.7	14.6	11.9
MenardMidland	19,192	2 5	60.8	39.2	12.8	8.8
Milam	156,432 44,236	15 7	18.5 27.7	7.6 9.8	2.0 10.5	8.9 7.4
MillsMitchell	37,955	2 7	27.0	9.3	5.0	12.6
Montague Montgomery	62,059 25,053	7 4	28.6 59.9	10.4 25.2	14.3 24.9	3.8 9.8
	23,033	4	55.9	23.2	24.9	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.						
Moore Morris Motley Nacogdoches Navarro Newton Nolan Nueces	706,879 55,369 18,727 578,906 64,962 2,079 23,172 139,951	23 21 5 68 10 (Z) 1 8	2.1 52.6 13.5 39.9 35.7 39.7 13.6 4.6	1.9 49.6 2.2 29.3 18.7 25.8 6.4 0.8	0.1 0.8 2.0 2.1 6.6 7.6 2.2 0.5	0.1 2.1 9.2 8.5 10.3 6.4 5.0 3.3
OchiltreeOldham	378,132 99,756	20 7	3.2 12.2	2.4 6.7	0.2 2.3	0.6 3.1
Orange Palo Pinto Panola Parker Parmer Pecos Polk Potter Presidio Rains	4,292 48,564 96,170 68,496 1,375,105 48,942 10,893 47,431 41,521 31,630	4 4 18 14 51 1 10 6 5	47.7 28.2 23.0 35.9 4.1 18.3 40.1 23.3 4.1 30.1	26.8 12.6 19.2 19.5 1.2 2.4 20.1 3.2 2.4 9.2	16.1 5.4 1.7 10.7 1.9 1.8 7.6 5.7 (Z)	4.8 10.1 2.2 5.7 1.1 14.1 12.4 14.4 1.6 19.7
Randall         Reagan         Real         Red River         Reeves         Refugio         Roberts         Robertson         Rockwall         Runnels	730,108 8,810 2,647 99,685 27,790 38,708 23,539 217,662 5,361 61,609	30 12 12 7 9 12 23 (Z) 2	6.3 13.5 41.4 22.7 61.4 13.0 30.5 35.2 14.4 24.9	1.7 2.9 6.5 16.9 4.4 0.6 6.7 8.4 7.5 6.4	0.1 6.6 26.4 1.6 3.5 11.1 16.6 6.7 4.2 8.6	4.4 3.9 8.6 4.2 53.6 1.3 7.2 20.1 2.7 9.9
Rusk Sabine San Augustine San Jacinto San Patricio San Saba Schleicher Scury Shackelford Shelby	105,024 (D) 304,692 9,207 101,209 41,512 27,188 30,605 16,401 625,837	2 (Z) 15 4 12 11 4 3 6 79	30.3 (D) 53.0 37.7 9.0 41.5 34.3 12.0 23.7 37.5	9.5 (D) 13.1 9.8 0.8 6.0 4.6 3.5 6.8 24.7	1.2 (D) 1.9 3.0 3.4 12.9 15.5 4.2 8.4	19.7 (D) 38.1 24.9 4.8 22.7 14.1 4.3 8.5 10.2
Sherman Smith Somervell Starr Stephens Sterling Stonewall Sutton Swisher Tarrant	988,213 70,899 7,272 73,015 9,296 11,037 14,461 20,407 749,528 24,327	43 9 5 12 1 (Z) 8 4 11 5	4.1 54.0 40.9 17.4 33.2 17.5 45.1 34.3 3.0 56.2	3.4 25.7 22.9 0.7 6.9 2.1 13.2 7.0 1.9 25.8	0.1 8.5 11.4 12.7 6.5 2.8 7.8 11.6 0.2 27.6	0.6 19.7 6.7 4.0 19.7 12.6 24.1 15.7 0.9 2.8
Taylor Terrel Terry Throckmorton Titus Tom Green Travis Trinity Tyler Upshur	20,545 6,168 100,210 37,973 222,986 101,976 63,384 8,237 9,365 84,679	3 (Z) 25 1 44 6 18 2 8	36.3 8.8 22.3 20.7 51.3 29.3 46.4 38.4 59.3 68.6	10.1 2.0 0.8 6.6 34.3 4.9 24.8 24.1 27.8 41.2	6.3 5.2 10.5 2.3 10.0 17.9 10.3 4.7 21.1	19.9 1.6 11.1 11.9 7.0 6.5 11.3 9.6 10.5 18.4
Upton Uvalde Val Verde Van Zandt Victoria Walker Waller Ward Washington Webb	10,415 90,644 15,482 168,285 72,034 25,399 106,565 (D) 51,789 31,518	3 15 5 10 9 3 20 (Z) 13 15	10.9 13.6 22.1 34.7 25.6 35.2 11.7 (D) 37.6 18.0	5.1 0.6 6.0 19.7 5.6 11.3 8.9 (D) 19.3 6.0	1.5 1.2 3.9 5.3 11.6 11.9 1.2 (D) 9.9 3.5	4.4 11.7 11.2 9.7 8.4 12.0 (D) 8.4 8.4
Wharton Wheeler Wichita Wilbarger Willacy Williamson Wilson Winkler Wise Wood	393,763 123,503 45,380 42,158 95,391 95,687 146,627 1,799 58,945 225,687	47 5 6 11 9 34 8 (Z) 5 5 28	28.2 11.8 30.7 10.5 9.3 42.0 24.5 6.5 51.7 56.5	0.5 8.2 5.0 2.4 0.6 6.1 1.0 25.5 32.0	1.8 1.2 2.0 1.6 3.9 5.7 3.1 0.8 7.1 11.2	25.9 2.4 23.7 6.6 4.7 30.2 13.1 4.7 19.1 13.2
Yoakum Young Zapata Zavala	56,923 29,820 5,194 86,838	25 4 1 6	34.6 44.8 30.5 14.8	4.9 13.5 11.6 2.4	9.5 10.7 9.9 2.7	20.2 20.6 9.0 9.7

Table D. American Indian or Alaska Native Producers: 2022

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

	American Indian or Alaska Native farm producers				American Indian or Alaska Native farm producers		
Geographic area	Total	Individually reported 1	Other <sup>2</sup>	Geographic area	Total	Individually reported <sup>1</sup>	Other <sup>2</sup>
State Total		·		Counties - Con.			
Texas	5,640	5,640	-	Grayson	143	143	-
Counties				GreggGrimes	10 42	10 42	-
Counties				Guadalupe	57	57	-
AndersonAngelina	29 7	29 7	-	Hale	45 9	45 9	-
Archer	3	3	-	Hamilton	30	30	-
Armstrong	1 69	1 69	-	HansfordHardeman	3 6	3 6	-
Austin	52	52	-	Hardin	5	5	-
Bailey Bandera	21 19	21 19	-	Harris	30	30	_
Bastrop	47	47	-	Harrison	16	16	-
Baylor	10	10	-	Hartley Haskell	7	7 4	-
Bee	11	11	-	Hays	14	14	-
Bell Bexar	84 46	84 46	-	Hemphill Henderson	12 42	12 42	-
Blanco	12	12	-	Hidalgo	8	8	-
Borden	1 38	1 38	-	Hill	54 13	54 13	-
Bowie	63	63	-	,	40	40	
Brazoria Brazos	67 13	67 13	-	Hood Hopkins	43 72	43 72	-
Brewster	19	19	-	Houston	39	39	-
Briscoe	4	4	-	Howard Hudspeth	6 4	6 4	-
Brooks	7	7	-	Hunt	88	88	-
Brown Burleson	51 20	51 20	-	Hutchinson	2 2	2 2	-
Burnet	41	41	-	Jack	25	25	-
Caldwell Calhoun	12	12 8	-	Jackson	11	11	-
Callahan	12	12	-	Jasper	23	23	-
Cameron	24 25	24 25	-	Jeff Davis Jefferson	8	2 8	-
•		-		Jim Wells	15	15	-
Carson	44	7 44	-	Johnson	86 40	86 40	-
Castro	4	4	-	Karnes	14	14	-
Chambers	11 21	11 21	-	Kaufman Kendall	63 42	63 42	-
Clay	29	29	-	Kenedy	2	2	-
Cochran	3 9	3	-	Kent	3	3	-
Coleman	21	21	-	Kerr	20	20	-
Collin	104	104	-	KimbleKinney	5 5	5 5	-
Collingsworth	9	9	-	Kleberg	4	4	-
Colorado Comal	31 17	31 17	-	KnoxLamar	6 143	6 143	-
Comanche	25	25	-	Lamb	19	19	-
Concho	3 53	3 53	-	LampasasLa Salle	19 18	19 18	-
Coryell	42	42	-		10		
Crockett	6 5	6 5	-	Lavaca	19 11	19 11	-
Crosby	3	3	-	Leon	19	19	-
Dallam	1	1	-	Liberty	14 49	14 49	-
Dallas	14	14	-	Lipscomb	7	7	-
Dawson  Deaf Smith	11 14	11 14	-	Live OakLlano	24 24	24 24	-
Delta	18 56	18 56	-	Lubbock	35	35	-
DeNton DeWitt	25	25	-	Lynn	9	9	-
Dickens	22	22 1	-	McCulloch	6 73	6 73	-
Dimmit Donley	23	23	-	McLennan McMullen	3	3	-
Duval	13	13		MadisonMarion	12 22	12 22	-
Eastland	25	25	-	Martin	6	6	-
Edwards	7 86	7 86	-	Mason	44 17	44 17	-
El Paso	21	21 48	-	Matagorda Medina	57	57	-
ErathFalls	48 18	48 18	-	Menard	15	15	-
Fannin	70	70	-	Midland	5	5	-
FayetteFisher	29 18	29 18	-	Milam Mills	17 15	17 15	-
			-	Mitchell	6	6	-
Floyd Foard	4 6	4	<u>-</u>	Montague	57 34	57 34	-
Fort Bend	9	9	-	Moore	10	10	-
FranklinFreestone	17 23	17 23	-	MorrisNacogdoches	2 21	2 21	-
Frio	4	4	-	Navarro	64	64	-
GainesGalveston	3 15	3 15	-	Newton	10	10	
Garza	6	6	-	Nolan	13	13	-
Gillespie	20	20	-	Nueces Ochiltree	26 4	26 4	-
Glasscock	1	1	-	Oldham	14	14	-
Goliad Gonzales	8 20	8 20	<u>-</u>	Orange Palo Pinto	26 20	26 20	-
Gray	7	7	-	Panola	14	14	
See feetnete(s) at end of table				JI.			

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

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

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

	American Indian or Alaska Native farm producers				American Indian or Alaska Native farm producers		
Geographic area	Total	Individually reported 1	Other <sup>2</sup>	Geographic area	Total	Individually reported 1	Other <sup>2</sup>
Counties - Con.				Counties - Con.			
Parker	143	143	-	Swisher	39	39	
Parmer	9	9	-	Tarrant	17	17	
Polk	17	17	-	Taylor	21	21	
Potter	15	15	_	Terry	14	14	
residio	6	6	_	Throckmorton	2	2	
Paine	41	41		Titus	25	25	
lains	21	21	-	Tom Cross	19		
Randall	21	21	-	Tom Green		19	
Reagan	2	2	-	Travis	29	29	
leal	6	6	-	Trinity	3	3	
Red River	54	54	-	Tyler	11	11	
eeves	11	11	_	Upshur	60	60	
efugio	5	5	_	Uvalde	7	7	
oberts	1	1	_	Val Verde	14	1/1	
obertson	41	41		Van Zandt	136	136	
	7 .	7.	-	Viotoria	48	130	
ockwall	2	5	-	Victoria		40	
lunnels	13	13	-	Walker	38	38	
usk	26	26	-	Waller	15	15	
abine	8	8	-	Ward	4	4	
an Augustine	2	2	-	Washington	38	38	
an Jačinto	7	7	-	Webb	6	6	
an Patricio	5	5	_	Wharton	20	20	
an Saba	38	38		Wheeler	24	24	
curry	16	16		Wichita	27	27	
hackelford	10	10	-	Wilbarger	15	15	
	2	2	-		13	13	
helby	Ö	б	-	Willacy	3	.3	
nerman	3	_3	-	Williamson	45	45	
mith	59	59	-	Wilson	49	49	
omervell	5	5	-	Wise	118	118	
tarr	4	4	-	Wood	49	49	
tephens	15	15	-	Yoakum	7	7	
tonewall	4	4	_	Young	8	8	
utton	7	7		Zavala	3	ž	

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