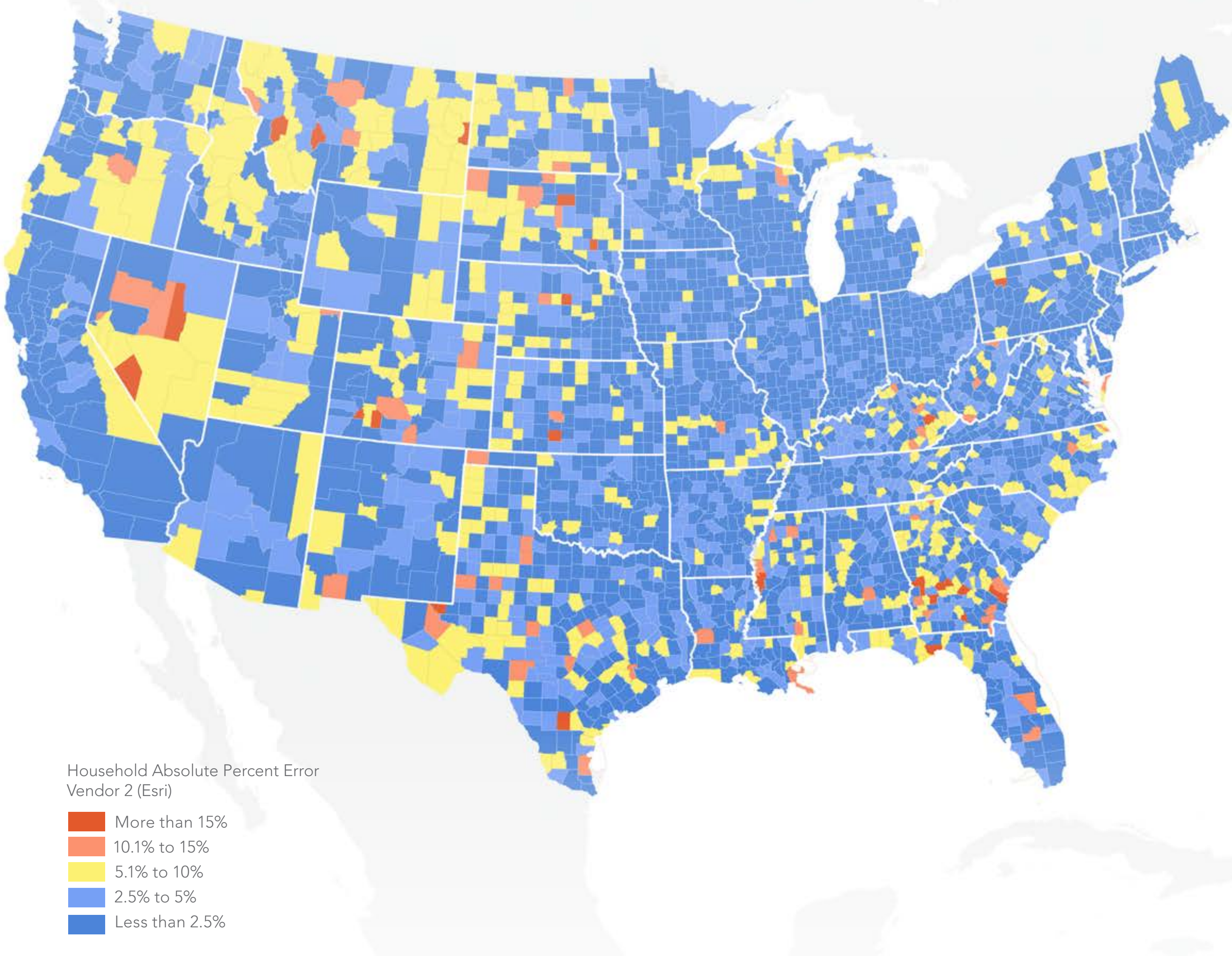
Vendor Accuracy Study

2010 Estimates versus Census 2010



Calculated as the absolute value of the percent difference between 2010 household estimates and Census 2010 household counts

esri

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Introduction By

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Introduction

Vendor Accuracy Study
2010 Estimates versus Census 2010

Data producers work on a 10-year cycle. With every census, we get the opportunity to look back over the previous decade while resetting our annual demographic estimates to a new base. Census counts reveal how well we have anticipated and measured demographic change since the last census. The decade from 2000 to 2010 posed a real challenge. Since 2000, we have experienced both extremes in local change: rapid growth with the expansion of the housing market followed by the precipitous decline that heralded one of the worst recessions in US history.

We know from experience just how difficult it is to capture rapid change accurately—growth or decline. We also understand the difficulty of measuring demographic change for the smallest areas: block groups. Block groups are the most frequently used areas because they represent the building blocks of user-defined polygons and ZIP Codes. Unfortunately, after Census 2000, there was no current data reported for block groups in the past decade.

To capture the change, we used data series that were symptomatic of population change, sources like address lists or delivery counts from the US Postal Service. We revised our models to apply the available data sources to calculate change and investigated new sources of data to measure changes in the distribution of the population. How successful were we? With the release of the 2010 Census counts, we addressed that question.

The answer can depend on the test that is used to compare 2010 updates to 2010 Census counts. There is a test for bias, the Mean Algebraic Percent Error (MALPE), which indicates whether estimates tend to be too low or too high. However, this test can overstate bias, since the lower limit is naturally capped at zero, while the upper limit is infinite. Another test, the Index of Dissimilarity (ID), measures allocation error, a more abstruse measure used by demographers to test the distribution of the population. For example, was the US population distributed accurately among the states? The total may be off, but the allocation of the population to subareas is tested independently of the total. However, data users prefer to know how much the estimated totals differ from the counts. The most common test is for accuracy, simply calculated as the percent difference between the estimate and the count. Summarizing the results is not as simple.

The average—the Mean Absolute Percent Error (MAPE)—represents a skewed distribution and clearly overstates error for small areas. It is deemed suitable for counties or states, but it returns questionable results for census tracts or block groups. A number of alternatives have been tried to retain the integrity of the results without overstating the error. Is one measure better than another?

To obtain an unbiased answer to our questions, we turned to an independent team of investigators. We also added one question, which came from data users: Is one data producer more accurate than another? There are certainly superficial differences among the vendors, but we use similar data sources to derive our demographic updates. Are there real differences in accuracy? The professionals who undertook the study are well experienced in small-area forecasts and measures of forecast accuracy. We asked them to test two variables, total population and households, from five major data vendors including Esri. The data was provided without identifying the individual vendors—a blind study. The following is a summary of their findings.

Results

Methodology

The data used in this project was the 2010 estimates of total population and households produced by Esri and four other major data vendors. The estimates data consisted of the forecast results at four different levels of geography: state, county, census tract, and census block group. The vendors' 2010 estimates, which were provided anonymously to the researchers by Esri, were then compared to the results of the 2010 Census. Error measurements were then calculated for each geographic area and summarized to show the total error for each level of geography. The population and household error measurements were also stratified and analyzed by base size in 2000 and 2000–2010 growth rate quartiles.

All the vendors, including Esri, had created their forecasts using 2000 Census geography. To analyze the accuracy of the vendor forecasts without modifying their data or compromising the original results, the 2010 Census counts were assigned to 2000 Census geography. This enabled the study team to analyze the 2010 Census results versus the vendor forecasts without modifying any vendor datasets. The correspondence of the 2010 Census counts to 2000 geography entailed an extensive quality control and quality assurance process to determine where census geography had changed and to identify the population density of areas that were either divided or consolidated during 2000–2010.

The full research project examined the three dimensions of forecast error: bias (MALPE), allocation (ID), and precision (MAPE). Because precision is the dimension of error on which most data users focus, we follow suit in this paper. In so doing, we use a refinement of MAPE that mitigates the effects of extreme errors (outliers) in trying to assess average precision. This is important because extreme errors, while rare, cause average error to increase, thereby overstating where the bulk of the errors are located (Swanson, Tayman, and Barr 2000). The refinement we use is MAPE-R (Mean Absolute Percent Error—Rescaled), which not only mitigates the effect of extreme errors but also retains virtually all of the information about them, something MAPE and similar measurements don't do (Coleman and Swanson 2007; Swanson, Tayman, and Barr 2000; Tayman, Swanson, and Barr 1999).

Briefly, if standard tests find that the distribution of Absolute Percent Errors (APEs) is right skewed (by extreme errors), then MAPE-R is used to change the shape of the distribution of APEs to one that is more symmetrical. If the tests show that it is not extremely right skewed, MAPE-R is not needed, and MAPE is used. If MAPE-R is called for, the Box-Cox power transformation is used to change the shape of the APE distribution efficiently and objectively (Box and Cox 1964). The transformed APE distribution considers all errors but assigns a proportionate amount of influence to each case through normalization and not elimination, thereby reducing the otherwise disproportionate effect of outliers on a summary measure of error. The mean of the transformed APE distribution is known as MAPE-T. The transformed APE distribution has a disadvantage, however: the Box-Cox transformation moves the observations into a unit of measurement that is difficult to interpret (Emerson and Stoto 1983,124). Hence, MAPE-T is expressed back into the original scale of the observations by taking its inverse (Coleman and Swanson 2007). The reexpression of MAPE-T is known as MAPE-R.

We strongly believe that the MAPE-R transformation represents an optimal technique for dealing with outliers, which are typically found in the error distributions of forecasts and estimates (Swanson, Tayman, and Barr 2000; Tayman, Swanson, and Barr 1999). There are other techniques for dealing with outliers, including trimming and winsorizing; as an alternative, one could turn to a robust measure such as the Median Absolute Percent Error (MEDAPE) or the geometric Mean Absolute Percent Error (GMAPE) (Barnett and Lewis 1994). Like Fox (1991), we are, however, reluctant to simply remove outlying observations (trimming), and are equally averse to limiting them (winsorizing) and ignoring them (MEDAPE and GMAPE). Unlike these methods for dealing with outliers, MAPE-R not only mitigates the effect of outliers, it also retains virtually all of the information about each of the errors (Coleman and Swanson 2007; Swanson, Tayman, and Barr 2000; Tayman, Swanson, and Barr 1999). Hence, we use MAPE-R as the preferred measure of forecast precision.

Reporting

A scorecard was developed to present a summary of each vendor's relative performance. A composite score is calculated within each geographic level, representing the sum of the error measures for population and households for each size and growth quartile (nine values each for population and households). The scores have a minimum value of zero and no upper bounds. These composite scores are then summed to determine which vendor had the lowest overall precision error. The population and households error totals were then added together to find a total overall score. These results showed that Esri had the lowest score in population, households, and overall error.

The lowest scores indicate the highest accuracy.

All Level Population & Household Results

Criteria/Vendor	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
Population	151.8	**127.3**	134.6	148.0	131.4
Households	164.1	**120.4**	142.1	147.7	173.3
Total Precision (MAPE-R)	315.9	**247.7**	276.7	295.7	304.7

Best Possible=0; Worst Possible=+∞

State Population & Household Results

Criteria/Vendor	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
Population	6.9	7.2	7.7	9.2	**5.6**
Households	14.5	**5.4**	10.2	10.1	24.1
Total State Precision (MAPE-R)	21.4	**12.6**	17.9	19.3	29.7

Best Possible=0; Worst Possible=+∞

As is the case in all comparative error procedures, there will be variations from overall results when examining the subcategories. The state level results were one such example (N=51). For total population, Vendor 5 had the lowest total error by 1.3 points; for households, Esri had the lowest total by 4.7 points. When the two scores were combined, Esri had the lowest overall score by 5.3 points.

County Level Population & Household Results

Criteria/Vendor	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
Population	20.2	**19.1**	21.0	20.9	21.6
Households	29.0	**20.7**	31.1	25.6	34.1
Total County Precision (MAPE-R)	49.2	**39.8**	52.1	46.5	55.7

Best Possible=0; Worst Possible=+∞

At the county level (N=3,141), Esri had the lowest population error score, by 1.1 points, and the lowest household error score, by 4.9 points. The results for the total county precision measure show that Esri had the lowest score by 6.7 points.

Census Tract Level Population & Household Results

Criteria/Vendor	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
Population	55.3	**47.1**	48.1	54.9	47.7
Households	51.3	**42.4**	45.2	51.1	51.9
Total Census Tract Precision (MAPE-R)	106.6	**89.5**	93.3	106	99.6

Best Possible=0; Worst Possible=+∞

For census tracts (N=65,334), the results are similar. Esri had the lowest error sum for both population, by 0.6 points, and households, by 2.8 points. As a result, Esri achieved the lowest score for census tracts by 3.8 points.

Block Group Level Population & Household Results

Criteria/Vendor	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
Population	69.4	**53.9**	57.8	63	56.5
Households	69.3	**51.9**	55.6	60.9	63.2
Total Block Group Precision (MAPE-R)	138.7	**105.8**	113.4	123.9	119.7

Best Possible=0; Worst Possible=+∞

Finally, at the block group level (N=208,687), Esri also had the lowest error sum for both population, by 2.6 points, and households, by 3.7 points. Esri had the lowest total error sum at the block group level by 7.6 points.

A review of the results finds several important trends. First, the error scores increase as the level of geography decreases in size and the number of cases significantly increases. Despite the larger number of observations for smaller geographies, the chances of extreme errors affecting the end results increases. The larger number of areas cannot mitigate the effects of extreme error on the overall average. There is also a noticeable difference in the size and distribution of the errors between population and households among the vendors.

Esri tends to have the smallest total error in both population and households, but the difference between Esri and the other vendors is much greater in the households error. Part of this trend may be due to methodological differences.

Since this was a blind study, the researchers had no idea which vendors were included, let alone what methodologies were used by the respective vendors. Therefore, one of the interests in performing the research was not to judge methodology but rather to test how well error measurements performed with a large number of cases like the total number of block groups. The availability of these datasets provided a unique opportunity to perform extensive error testing on extremely large numbers of estimates against census results. While the MAPE-R measurement performed well and did mitigate the influence of extreme errors, the sheer size of the largest errors still had an impact on the final results for all vendors. This situation was evident even when examining block group errors that had over 208,000 cases. Given that an analysis of estimate errors from multiple sources for all observations at the tract and block group levels has never before been undertaken, this procedure provides groundbreaking insight into small-area error analysis and the testing of error measurements.

After reviewing the results for all quartiles at all levels of geography, it is concluded that Esri had the lowest precision error total for both population and households. The results also show that at smaller levels of geography, for which change is more difficult to forecast, Esri tended to perform even better, particularly for households.

Esri tends to have the smallest total error in both population and households at smaller levels of geography, Esri tended to perform even better, particularly for households.

Appendix A

Tables

Results of the MAPE-R tests by vendor, variable, geographic level, and quartiles are included in these tables. Quartiles represent the size of the base population in 2000 and the rates of change from 2000 to 2010. The growth quartiles are defined as being roughly 25 percent of the observations of a geographic level that have the lowest 2000–2010 growth rate (quartile 1) through 25 percent of the observations of a geographic level that have the highest 2000–2010 growth rate (quartile 4). The size quartiles are defined as being roughly 25 percent of the observations of a geographic level that has the smallest 2010 size (quartile 1) through 25 percent of the observations of a geographic level that has the largest 2010 size (quartile 4). Quartile values vary by level of geography, as shown in the appendix tables.

Table 1: Quartiles defined by variable and geography

Block Group Households

Quartile	Size	Growth Rate
1	< 301	< -5.01%
2	301 to 400	-5.01% to 0%
3	401 to 500	0.01% to 4.99%
4	501+	5%+

County Households

Quartile	Size	Growth Rate
1	< 3,500	< 0.00%
2	3,500 to 6,999	0% to 4.99%
3	7,000 to 14,999	5.00% to 9.99%
4	15,000+	10.0%+

Block Group Population

Quartile	Size	Growth Rate
1	< 800	< -5.01%
2	800 to 1,199	-5% to 0%
3	1,200 to 1,599	0.01% to 4.99%
4	1,600+	5%+

County Population

Quartile	Size	Growth Rate
1	< 9,999	< 0.00%
2	10,000 to 19,999	0.0% to 4.99%
3	20,000 to 39,999	5.0% to 9.99%
4	40,000+	10.0%+

Census Tract Households

Quartile	Size	Growth Rate
1	< 999	< -5.01%
2	1,000 to 1,499	-5% to 0%
3	1,500 to 1,999	0.01% to 7.99%
4	2,000+	8%+

State Households

Quartile	Size	Growth Rate
1	< 500,000	< 5.00%
2	500,000 to 1,499,999	5.00% to 9.99%
3	1,500,000 to 2,999,999	10.0% to 14.99%
4	3,000,000+	15.0%+

Census Tract Population

Quartile	Size	Growth Rate
1	< 2,999	< -5.01%
2	2,999 to 3,999	-5% to 0%
3	4,000 to 4,999	0.01% to 7.99%
4	5,000+	8%+

State Population

Quartile	Size	Growth Rate
1	< 1,000,000	< 5.00%
2	1,000,000 to 2,999,999	5.00% to 9.99%
3	3,000,000 to 7,999,999	10.0% to 14.99%
4	8,000,000+	15.0%+

Table 2: Number of areas in each quartile

Block Group Households

Quartile	Size	Growth Rate
1	45,266	45,561
2	47,283	55,088
3	38,664	35,881
4	77,474	72,157

County Households

Quartile	Size	Growth Rate
1	622	782
2	636	760
3	769	646
4	1,114	953

Block Group Population

Quartile	Size	Growth Rate
1	47,311	62,469
2	66,866	41,191
3	42,289	33,529
4	52,221	71,498

County Population

Quartile	Size	Growth Rate
1	695	1,101
2	652	742
3	681	492
4	1,113	806

Census Tract Households

Quartile	Size	Growth Rate
1	13,964	10,995
2	18,373	15,377
3	15,656	17,689
4	17,341	21,273

State Households

Quartile	Size	Growth Rate
1	12	8
2	13	20
3	15	9
4	11	14

Census Tract Population

Quartile	Size	Growth Rate
1	18,491	15,345
2	13,925	13,524
3	12,078	17,021
4	20,840	19,444

State Population

Quartile	Size	Growth Rate
1	8	16
2	14	16
3	18	9
4	11	10

State Population Results

Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All States	0.7	0.8	0.8	1.0	**0.6**
Size					
Quartile 1	**0.6**	0.9	1.0	1.2	0.8
Quartile 2	0.8	0.8	0.8	1.0	**0.7**
Quartile 3	0.5	0.6	0.7	0.9	**0.4**
Quartile 4	0.9	0.9	0.8	0.9	**0.5**
Growth Rate					
Quartile 1	0.8	0.7	0.7	0.8	**0.6**
Quartile 2	**0.4**	0.5	0.6	0.8	0.5
Quartile 3	1.2	0.8	1.4	1.4	**0.6**
Quartile 4	1.0	1.2	**0.9**	1.2	**0.9**
SUM	6.9	7.2	7.7	9.2	**5.6**

State Household Results

Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All States	1.2	**0.6**	1.1	1.1	2.7
Size					
Quartile 1	3.2	**1.1**	1.7	1.8	1.8
Quartile 2	1.8	**0.5**	0.8	1.1	2.4
Quartile 3	1.4	**0.5**	1.0	0.9	3.6
Quartile 4	1.0	**0.4**	0.8	0.8	2.8
Growth Rate					
Quartile 1	1.0	**0.4**	1.5	0.9	2.1
Quartile 2	1.6	**0.5**	0.8	1.0	2.6
Quartile 3	1.3	**0.6**	1.1	1.0	3.1
Quartile 4	2.0	**0.8**	1.4	1.5	3.0
SUM	14.5	**5.4**	10.2	10.1	24.1

County Population Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Counties	2.1	**2.0**	2.2	2.2	2.2
Size					
Quartile 1	3.8	**3.3**	3.9	3.8	4.3
Quartile 2	2.6	**2.3**	2.5	2.5	2.6
Quartile 3	**2.0**	**2.0**	2.1	2.1	2.1
Quartile 4	**1.4**	1.5	1.6	1.6	1.5
Growth Rate					
Quartile 1	2.4	**2.1**	2.4	2.4	2.6
Quartile 2	1.8	**1.7**	1.9	1.9	2.0
Quartile 3	**1.9**	**1.9**	2.1	2.1	2.1
Quartile 4	**2.2**	2.3	2.3	2.3	**2.2**
SUM	20.2	**19.1**	21.0	20.9	21.6

County Household Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Counties	3.0	**2.2**	3.2	2.6	3.7
Size					
Quartile 1	5.0	**3.6**	5.0	5.1	5.0
Quartile 2	3.6	**2.4**	4.0	3.1	3.1
Quartile 3	3.0	**2.2**	3.5	2.4	3.9
Quartile 4	2.3	**1.6**	2.0	1.8	3.5
Growth Rate					
Quartile 1	2.8	**2.3**	5.2	3.4	4.1
Quartile 2	2.9	**1.9**	2.0	2.3	3.3
Quartile 3	3.2	**2.1**	2.8	2.3	3.3
Quartile 4	3.2	**2.4**	2.8	2.6	4.2
SUM	29.0	**20.7**	31.1	25.6	34.1

Census Tract Population Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Census Tracts	5.9	**5.0**	5.2	5.9	5.1
Size					
Quartile 1	7.8	**6.6**	6.7	7.5	6.7
Quartile 2	5.8	**4.8**	5.1	5.7	5.1
Quartile 3	5.4	**4.5**	4.8	5.5	4.8
Quartile 4	5.3	**4.4**	4.7	5.4	4.5
Growth Rate					
Quartile 1	8.8	8.8	7.7	8.2	**7.3**
Quartile 2	4.3	**3.5**	**3.5**	4.4	4.2
Quartile 3	4.2	**3.3**	3.9	4.6	4.2
Quartile 4	7.8	6.2	6.5	7.7	**5.8**
SUM	55.3	**47.1**	48.1	54.9	47.7

Census Tract Household Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Census Tracts	5.4	**4.2**	4.7	5.3	5.4
Size					
Quartile 1	8.1	**6.4**	6.7	7.7	7.4
Quartile 2	5.3	**4.2**	4.6	5.3	5.5
Quartile 3	4.8	**3.8**	4.2	4.8	5.2
Quartile 4	4.7	**3.8**	4.3	4.8	4.9
Growth Rate					
Quartile 1	**7.6**	8.7	8.1	8.0	8.3
Quartile 2	3.9	**2.8**	3.0	4.0	5.4
Quartile 3	4.1	**3.0**	3.7	4.3	4.7
Quartile 4	7.4	5.5	5.9	6.9	**5.1**
SUM	51.3	**42.4**	45.2	51.1	51.9

Block Group Population Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Block Groups	8.4	**6.6**	6.9	7.5	6.8
Size					
Quartile 1	10.3	**8.3**	8.5	9.0	8.5
Quartile 2	8.0	**6.4**	6.6	7.1	6.7
Quartile 3	7.7	**6.1**	6.5	6.8	6.2
Quartile 4	8.0	6.1	6.5	7.3	**6.0**
Growth Rate					
Quartile 1	5.7	**4.6**	5.5	5.5	4.9
Quartile 2	5.9	**3.8**	4.0	5.3	5.0
Quartile 3	5.4	**4.0**	4.7	5.4	4.9
Quartile 4	10.0	8.0	8.6	9.1	**7.5**
SUM	69.4	**53.9**	57.8	63.0	56.5

Block Group Household Results
Best Performing Precision (MAPE-R)

	Vendor 1	Vendor 2 (Esri)	Vendor 3	Vendor 4	Vendor 5
All Block Groups	7.5	**5.5**	6.0	6.6	6.8
Size					
Quartile 1	9.4	**7.0**	**7.0**	8.0	8.6
Quartile 2	7.2	**5.3**	5.8	6.3	7.0
Quartile 3	7.0	**5.1**	5.6	6.1	6.6
Quartile 4	7.2	**5.1**	5.8	6.4	6.0
Growth Rate					
Quartile 1	10.5	10.1	9.9	**9.4**	10.1
Quartile 2	5.5	**3.1**	3.4	4.7	6.3
Quartile 3	5.3	**3.5**	4.5	5.1	5.4
Quartile 4	9.7	7.2	7.6	8.3	**6.4**
SUM	69.3	**51.9**	55.6	60.9	63.2

Appendix B

Citations

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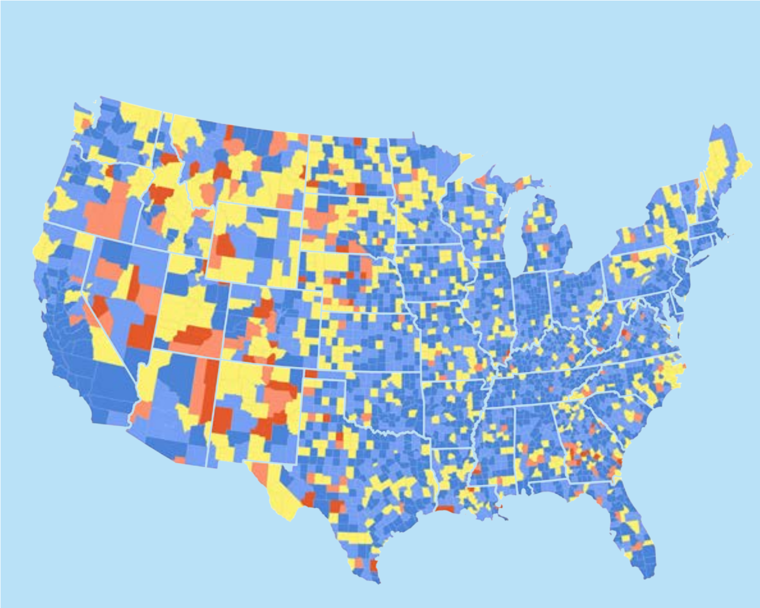
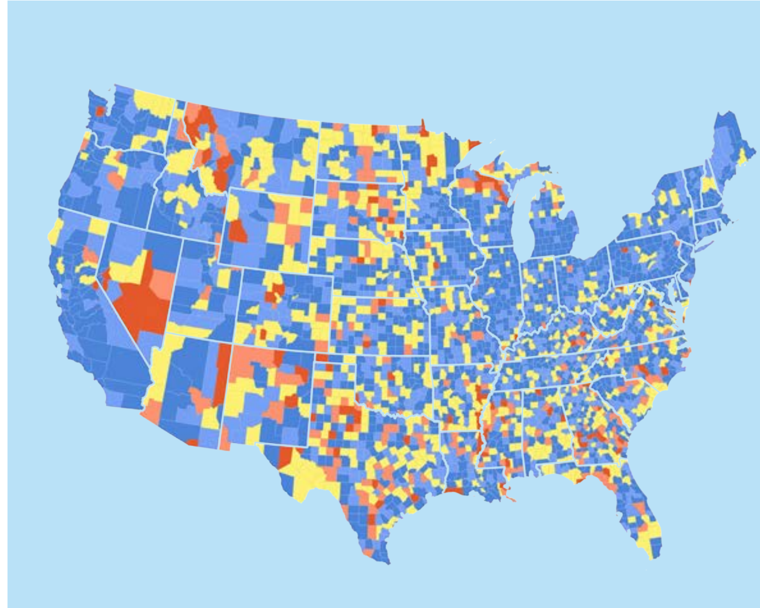
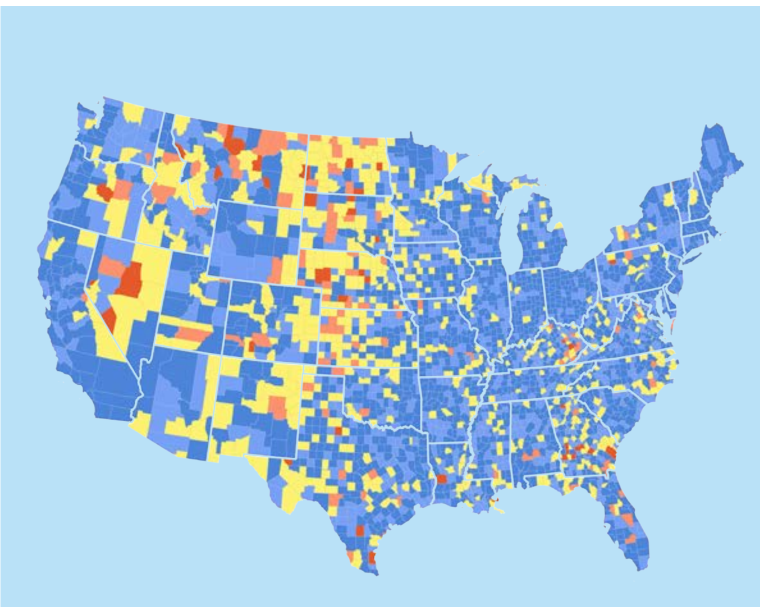
Population and households error totals are then added together to find a total overall score. These results showed that Esri had the lowest score in population, households, and overall error.



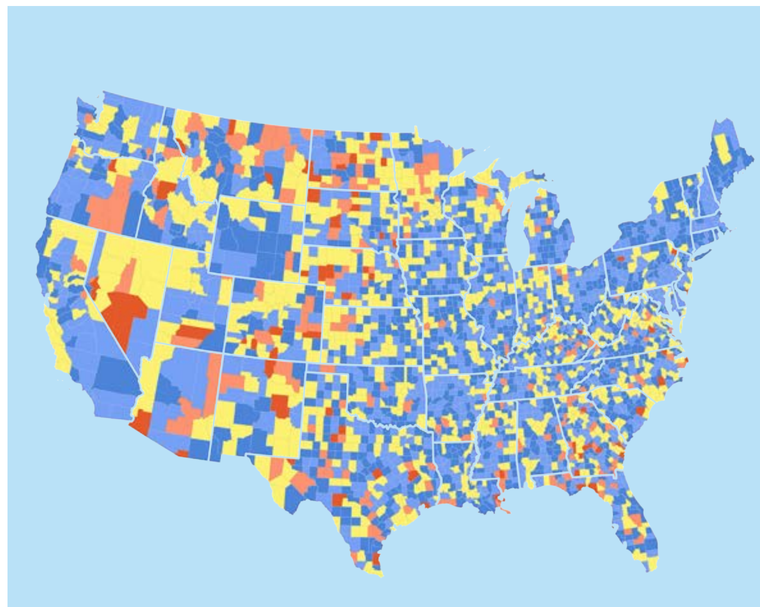
Household Absolute Percent Error
Vendor 1



Household Absolute Percent Error
Vendor 3



Household Absolute Percent Error
Vendor 4



Household Absolute Percent Error
Vendor 5

- More than 15%
- 10.1% to 15%
- 5.1% to 10%
- 2.5% to 5%
- Less than 2.5%

Calculated as the absolute value of the percent difference between 2010 household estimates and Census 2010 household counts

Esri inspires and enables people to positively impact their future through a deeper, geographic understanding of the changing world around them.

Governments, industry leaders, academics, and nongovernmental organizations trust us to connect them with the analytic knowledge they need to make the critical decisions that shape the planet. For more than 40 years, Esri has cultivated collaborative relationships with partners who share our commitment to solving earth's most pressing challenges with geographic expertise and rational resolve. Today, we believe that geography is at the heart of a more resilient and sustainable future. Creating responsible products and solutions drives our passion for improving quality of life everywhere.

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