Incorporating Data Quality Information in Mapping American Community Survey Data

Min Sun and David W. S. Wong

ABSTRACT: This paper proposes a set of methods to map the American Community Survey (ACS) data disseminated by the U.S. Census Bureau. The ACS replaces part of the original census (long form) in the 2010 decennial Census in the U.S. Reliability of estimates should be taken into account when analyzing and mapping ACS data because these estimates are derived from surveys with sample sizes much smaller than those in the decennial censuses. Most maps using ACS data do not include data reliability information. In this article, we review the standard data quality or reliability information accompanying the ACS estimates. We propose a set of techniques to map ACS estimates by incorporating the margin of error (MOE) or related information either on the map display or in the mapping process. The techniques are proposed in two contexts: recognizing the varying degree of reliability among estimates, and determining if estimates are statistically different. They offer cartographers and GIS users some options to map ACS estimates and handle the reliability information simultaneously.

Introduction

Census data have been widely used to support a variety of planning and decision making activities. Academic inquiries ranging from economic and housing analyses to demographic and transportation studies use census data frequently. Among the social sciences heavily relying on census data, geography plays a leading role in mapping census data. The development and availability of the TIGER/Line files in the 1990s provided the necessary digital boundary data to support census mapping (Broome and Meixler 1990; Cooke 1998). Mapping census data has become a relatively straightforward task due to the proliferation of GIS. Among the wide range of data that the U.S. Census Bureau gathers and disseminates through various programs, population and housing data have been used and mapped frequently.

Population and housing data collected during previous decennial censuses were disseminated through various summary files (SFs). Some data such as those in SF1 were tabulated from the census short form, which was received by every household in the U.S., and theoretically these data were derived from the entire population. However, some variables, such as those about economic and housing characteristics, were based upon the long form received by one in six people in the U.S. Even with such a relatively large sample size, long form data do have some data quality issues (Bench 2004). In 1996, the U.S. Census Bureau launched the American Community Survey (ACS), a new continuous measurement program, which gathers data to replace the census long form. When using the ACS data, one should pay extra attention to data quality, especially the sampling error, because the ACS data are survey data based upon a sample size much smaller than those in previous decennial censuses when the long form was used. In their editorial, Heuvelink and Burrough point out that "It is crucially important to know how accurate the data contained in spatial databases really are, because without that knowledge we cannot assess the true value of the derived information, nor the correctness of the decisions it supports." (Heuvelink and Burrough 2002, p. 111)

American Community Survey data have been available to the public since 2006 (for 2005 data), and more data products will be available in the near future. The use of ACS data is likely to increase tremendously as it replaces the long form. The Census Bureau provides a margin of error (MOE) for each estimate of a variable for each census enumeration unit to reflect the magnitude of sampling error, an important aspect of data quality or reliability. While sound analyses using the ACS data should include data quality information, map-

Min Sun and David W. S. Wong, Geography and GeoInformation Science, George Mason University, 4400 University Drive, Fairfax, Virginia 22030, USA, E-mails: <msun@gmu.edu>, <dwong2@gmu.edu>.

ping of ACS data usually ignores the data quality information. Incorporating the margin of error or related data quality information in mapping is conceptually and technically challenging. Data quality measures have to be shown together with the original ACS estimates in the mapping process. The resulting maps are likely more complex and more difficult to interpret. One of the challenges is to design maps that capture pertinent information but are comprehensible by most map readers (McGranaghan 1993).

In this article, we explore a set of methods to map the ACS estimates incorporating the associated margins of error or the derived coefficients of variation (CVs). We tend to focus our selections of method toward those that can be implemented through standard GIS software easily, partly because many census maps are produced using GIS and readers can adopt these methods without using special software. Another objective of this paper is to draw public attention to the importance of including data quality information when mapping the ACS data.

ACS Overview

Details of ACS data are available from many sources, including the Census Bureau web site[1], various reports compiled by Bureau's staff members[2] and researchers (e.g., Van Auken et al. 2004; Citro and Kalton 2007; Griffin and Waite 2006; Mather et al. 2005), and many academic papers evaluating the quality of ACS data (e.g., Scardamalia 2006). In this paper, we will limit our overview of ACS to those aspects that are relevant to the mapping of ACS estimates with margins of error and the coefficients of variation.

The ACS questionnaire is very similar to the decennial census long form, with the exceptions of a few questions (Citro and Kalton 2007, pp. 33-36, Table 2.2). Unlike the decennial census which is conducted every ten years, ACS is a continuous measurement program. Every month, the ACS questionnaire is mailed to approximately 250,000 housing unit addresses across all counties in the U.S. Over the year, the total sample size is about 3 million addresses, which is about 2.3 percent of the total 129.5 million housing addresses that existed in the U.S. in 2005. While this sample is relative large as compared to major national surveys, it is still small as compared to the approximately 18 million addresses (or one-sixth of total housing addresses) which received the census long form in 2000. The uncertainty of estimates can thus be an issue in the analysis (MacDonald 2006). Simple absolute differences between estimates may not be regarded as real differences, as they may be attributable to sampling error. In other words, the emergence of a spatial pattern based upon the differences of ACS estimates across areal units may not be real because those differences among estimates may be created by sampling errors. Therefore, when analyzing the spatial relationships or spatial distributions of ACS estimates, determining the significant differences among values is important.

The ACS sampling scheme ensures that the same housing unit will not be sampled more than once in a five-year sampling frame. The Census Bureau provides several ACS data products due to the sampling scheme specific to ACS. The products may be categorized by the length of period from which estimates are derived. Because only about 2-3 percent of housing addresses are sampled each year, data products for the one-year estimates are available only for large administrative and statistical areas with at least 65,000 people. For the three-year estimates, the reporting areas need to meet the minimum threshold of 20,000 people. The five-year estimates will be available for areas as small as census block groups. The first official one-year estimates were released in 2006. In 2008, the first three-year estimates became available. ACS will release the first five-year estimates in 2010. Therefore, when mapping ACS data, choosing a data product is partly dependent upon the census statistical or administrative units to be mapped[3].

Two types of statistical errors can be found in the ACS data: non-sampling and sampling errors. Non-sampling error refers to the variability introduced by respondents, interviewers, coders and procedures. Sampling error exists in the ACS because the sampled population may not represent the true population very well, and thus estimates are different from the parameter values in the popu-

[1] http://www.census.gov/acs/www/

[2] http://www.census.gov/acs/www/methodology/methodology_main/.

[3] Another ACS data product is the 1 percent sample file, the Public Use Microdata Sample (PUMS), which will not be discussed in this paper, as the data are different from the typical ACS estimates.

lation. The Census Bureau provides a margin of error for each estimate of a variable. In statistics, a typical measure to indicate sampling error is the standard error, which reflects the imprecision in the estimate due to sampling. The margin of error provided by the Bureau is 1.645 times of the standard error, which indicates a 90 percent confidence level. We label this MOE as 90 percent MOE, meaning that there is a 90 percent chance that the true population parameter lies within the range of (estimate) ± 90 percent MOE. This range defines the lower and upper confidence bounds[4]. From the margin of error at 90 percent confidence level, the standard error can be derived (standard error = $\frac{90\%\,MOE}{1.645}$). With the standard error, margins of error at other levels of confidence, such as 95 percent or 99 percent, can be determined. For instance, the margin of error of the more traditional 95 percent confidence level is 1.96 times of the standard error. When comparing two estimates of the same ACS variable, they are statistically different at a given confidence level if their confidence bounds do not overlap.[5]

However, the size of the margin of error cannot be used to indicate the quality of an ACS estimate, as the margin of error is relative to the scale of the estimate. Estimates with large values have larger margins of error in general, but these larger MOEs do not imply that the estimates are less reliable. A preferable measure to reflect the reliability of an ACS variable estimate is the coefficient of variation, which is the standard error (std error) divided by the estimate (sometime, it is multiplied by 100). The coefficient of variation indicates the relative amount of sampling error associated with the estimate and is independent of the scale of the estimate.

Because $CV = \frac{std\ error}{estimate}$,

and standard error can be determined by $\frac{90\%\,MOE}{1.645}$,

therefore, CV can be derived directly from MOE, i.e.,

$$CV = \left[\frac{90\%\,MOE}{1.645}\right] \Big/ estimate\,.$$

The primary goal of this paper is to incorporate the corresponding margins of error or coefficients of variation into the mapping of ACS estimates.

Some researchers using the ACS data for statistical analyses have taken into account the sampling error. For example, in studying the activities of daily living, Thomson and Gadalla (2003) and Thomson et al. (2009) consider the sampling error in a set of multilevel modeling exercises. However, maps of ACS data frequently do not include information on the uncertainty of estimates. The margins of error of estimates are often disregarded, although they are provided together with the estimates. Guidelines for the use of ACS data emphasize the importance of MOEs, but no recommendation or guideline is provided for mapping the ACS estimates (Citro and Kalton 2007, pp. 130). In reviewing certain aspects of ACS, Mather et al. (2005) include the margin of error when comparing estimates on statistical graphs. However, when estimates were displayed on maps, the MOE information was not included (Mather et al. 2005, p. 13, Figure 4). In demonstrating how the Public Participation GIS (PPGIS) can empower citizens and local communities, Merrick (2003, p. 36, Figure 1) maps the percent of Black/African American and Asian populations by census tracts using specially tabulated ACS data, but without the MOE information. Fronczek (2005, p. 4, footnote) stated that estimate differences may not be statistically significant because of sampling errors. While recognizing this issue, maps produced do not incorporate any uncertainty information (Fronczek 2005). Examples of mapping ACS estimates without error information are quite abundant in the literature (e.g., Gates 2006; Hough and Swanson 2006). The Census Bureau recognizes the importance of taking into account the error information in mapping. As a result, the thematic mapping tool in the American FactFinder web site of the U.S. Census Bureau[6] for the ACS data does include the capability to indicate if estimates of areal units are significantly different from the estimate of a selected unit.

[4] http://www.census.gov/acs/www/Downloads/data_documentation/Accuracy/accuracy2006-2008ACS3-Year.pdf.

[5] When the confidence bounds, which are related to standard errors, of any two estimates do not overlap, the two estimates are definitely different at the given confidence level. However, comparing confidence bounds is not the same as formally testing if the two estimates are different. The confidence bound approach is more conservative. Two estimates with overlapping confidence bounds may be determined to be different when they are formally tested. However, in this manuscript, we simplify the situations by assuming that when two confidence bounds overlap, the corresponding estimates are not significantly different. A formal t-test of estimate difference is generally warranted.

[6] http://factfinder.census.gov.

Mapping Data Quality

Mapping of spatial data quality has been a concern of GIS research for decades (e.g., Beard and Buttenfield 1991). The term "data quality" is rather broad and fuzzy, and other terms such as accuracy, uncertainty, reliability, and precision have been used in the literature (Thomson et al. 2005). Factors affecting spatial data uncertainty, particularly pertaining to aggregated census data, may be grouped into the three categories of temporal, spatial, and attribute (Kardos et al. 2005). According to the FGDC Content Standard for Digital Geospatial Metadata (FGDC 1998), quality of spatial data includes six items: attribute accuracy, logical consistency, completeness, positional accuracy, lineage, and cloud cover. Researchers have systematically addressed most of these data quality aspects (e.g., MacEachren 1994), and location or positional accuracy issues have been addressed frequently. Typologies of data quality information or uncertainty, some of which are intertwined with the data quality items in the FGDC metadata standards, have been proposed (e.g., Thomson et al. 2005), and some researchers have discussed frameworks for visualizing the quality of spatial data (e.g., Buttenfield 1993; MacEachren 1994). Zhang and Goodchild (2002) suggest three types of data uncertainty: error, randomness, and vagueness. For this paper, our focus is on the attribute accuracy or reliability associated with sampling error, which is a randomness issue. Particularly, users of ACS data should be concerned about the reliability of estimates, which can be reflected by the associated CV levels discussed above. Census maps are often used to identify spatial patterns, which are reflected by systematic differences of attribute values across units. Spatial patterns revealed by ACS estimates may be the result of sampling error. Therefore, mapping of ACS estimates should include information, such as the margin of error, to assist readers to discern if estimate differences are significant or not.

The cartographic literature is very rich in visualizing the reliability or uncertainty of attributes in maps, but it is less abundant on methods representing statistical differences among attribute values. MacEachren (1992) suggests different types of cartographic symbolization to represent uncertainty. His work was expanded by Leitner and Buttenfield (2000), who suggest using the visual variables of value, texture, and saturation to depict attribute uncertainty information. Among the techniques evaluated by Kardos et al. (2003), blinking of symbols seems to be the most effective. Later MacEachren et al. (2005) conclude that the extrinsic method (i.e., overlaid symbols) is more preferred by subject experts in physical sciences. However, mapping units in census maps are often polygons representing administrative or census statistical units. Graduate symbol maps may be appropriate to represent certain census variables such as counts or frequencies. But for many statistical summary variables in ratio scale, using choropleth maps is preferred, and methods focusing on symbolization may not be too effective.

As demonstrated in the literature (e.g., Leitner and Buttenfield 2000; MacEachren 1994), attribute reliability information is often displayed on a map accompanying the map of the original attribute values. According to Kardos et al. (2003), this two-map arrangement method belongs to the adjacency technique among the set of techniques of visualizing uncertainty. Attribute and the associated uncertainty information may be regarded as two variables such that they may be combined to form a bivariate map (e.g., Brewer and Pickle 2002; Olson 1981). The two variables may be represented by two types of symbols (Nelson 2000) or coloring characteristics (Nelson 1994). The bivariate map approach may be considered as the overlap method in the technique typology suggested by Kardos et al. (2003), as the spatial coincidence can be implemented using a color fill and a texture overlay (MacEachren et al. 1998). Among the two-map side-by-side comparison method, the color-fill and texture overlay method, and the method using coloring characteristics, the color fill overlaid with texture was found to be the most effective (MacEachren et al. 1998), and this bivariate overlay method was adopted in visualizing mortality statistics with data quality information (Pickle et al. 1996). MacEachren et al. (2005) also find that the method is effective for depicting the big picture and is preferred by decision makers. However, Kardos et al. (2003) conclude that the adjacency two-map comparison method and the overlay method are only moderately effective among the range of techniques they examined. Kardos et al. (2005) suggest an unconventional mapping method using hierarchical data structure based upon the quadtree to map census data quality, while preserving the census unit boundary representation. But such an approach requires a drastically different data structure and therefore may not be easily adopted.

While these cartographic and visualization techniques are instructive about the uncertainty of attribute values on the map with varying degrees

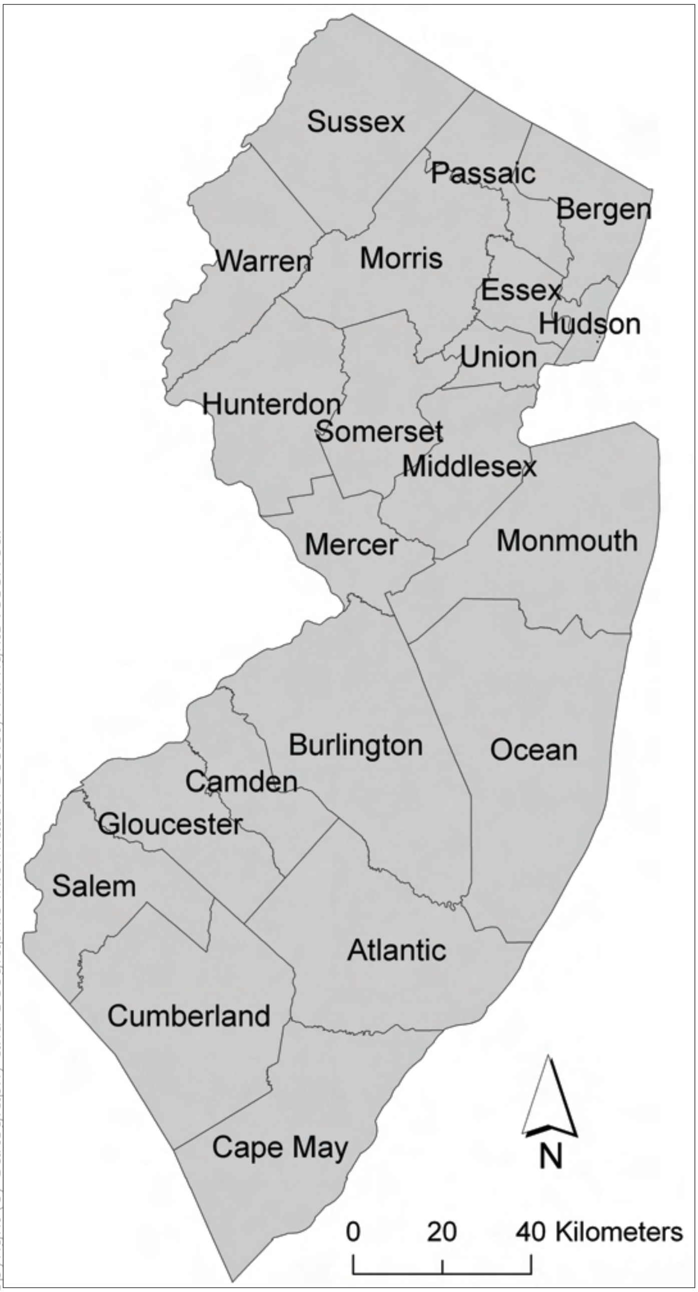

Figure 1. Counties in the State of New Jersey.

of effectiveness and may facilitate certain types of exploratory analysis and hypothesis formulation, they are not effective in helping readers to discern if attributes in various locations are significantly different or not. Discerning attribute differences statistically is especially important in interpreting maps of ACS data. Pickle et al. (1996) include choropleth maps showing mapped values significantly different from the national averages. Each map of significance accompanies a map of a specific type of mortality. Therefore, this method can be regarded as a side-by-side comparison. The map set is also accompanied by a graphic plot showing the 95-percent confidence limits of the statistic for major regions of the U.S. Providing such plots can assist readers in discerning which values are statistically different or not.

Proposed Methods of Mapping ACS Estimates

When mapping ACS estimates or a traditional census variable from a decennial census, a map offers a platform for a cross-sectional comparison. Estimates are mapped for one time frame with the intent to show if areas are different. Another common objective of mapping a census variable is to compare the variable values over time to determine if they have changed. Some existing cartographic techniques can facilitate such comparisons with the inclusion of uncertainty information, but they fall short of assisting readers to discern if the difference between any two estimates is statistically significant or not. Below, we will use the 2008 ACS data for the State of New Jersey to illustrate several methods in indicating the reliability of ACS estimates. A map of New Jersey with county labels is shown in Figure 1. This map is intended to familiarize readers with the State's county geography. The chosen variable is per capita income at the county level. We will also illustrate several methods to depict the significant differences among estimates. We tend to limit our methods to those that can be replicated using standard GIS packages, as GIS are used widely to produce census maps.

Proposed methods can be grouped into several categories. The first category of methods intends to display reliability information together with the estimates using various map layout designs. The second category provides information to assist map readers to determine if different estimates are statistically different or not. The third category of methods allows users to select estimates for comparison. We plan to develop tools to implement these methods as add-ons for GIS and will disseminate them in the future. We also recognize that the reliability of estimates may affect the robustness of choropleth map classifications, i.e., the determination of class intervals may be affected by the errors of estimates.

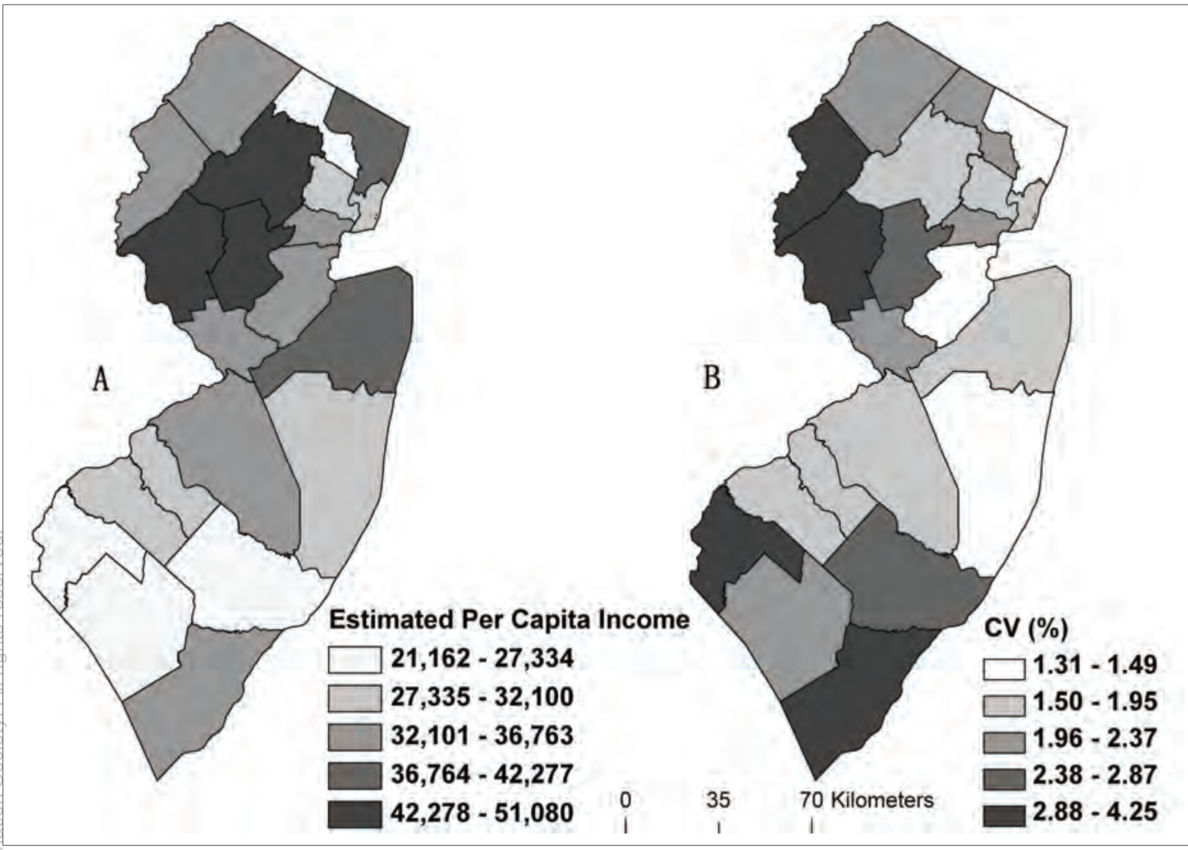

Figure 2. Per capita income estimates (A), and coefficients of variation (B) in New Jersey by counties, 2008 ACS data.

Assessing their relationships is beyond the scope of this paper, and the issue has been discussed thoroughly in Xiao et al. (2007).

Mapping the Reliability of Estimates

As mentioned before, some visualization applications have adopted a two-map approach (or the adjacency technique) where one map shows the estimate and another map shows the uncertainty information. Figure 2 shows such maps of the New Jersey data. The map of the coefficients of variation clearly indicates the reliability of estimates in the corresponding counties, and one can discern which estimates are more reliable than others. While Hunterdon County has the highest per capita income, its estimate is relatively unreliable, as indicated by the rather high CV level. The per capita income levels of Bergen, Middlesex, and Ocean counties are in the high-to-medium range, but they are relatively reliable, having the lowest CV values. However, the two-map scheme puts the burden of linking the estimates with the corresponding quality information on the map readers. Readers have to switch the focus back and forth between the two maps in order to build the connections between the estimates and their CV levels. Mapping only the CV values is not sufficient for the readers to determine if the differences between estimates of any two counties, for instance Somerset and Middlesex, are statistically different or not.

While the two-map approach puts the estimate and quality information separately on two frames of display, the bivariate legend approach, the preferred method suggested by MacEachren et al. (1998), may treat the estimate and quality level as two variables and combines the two variables onto one display frame. This specific bivariate legend design uses color fills with texture overlay. Figure 3 demonstrates this method. Conceptually, information reflected in Figure 3 is identical to the two maps shown in Figure 2, but the bivariate legend approach is more efficient as readers no longer need to focus back and forth between the maps of estimates and CVs. However, some map readers may find that the legends are somewhat complicated to interpret. Sharing the same limitation with the two-map approach, mapping CV levels in the bivariate legend cannot help determine statistical differences between estimates.

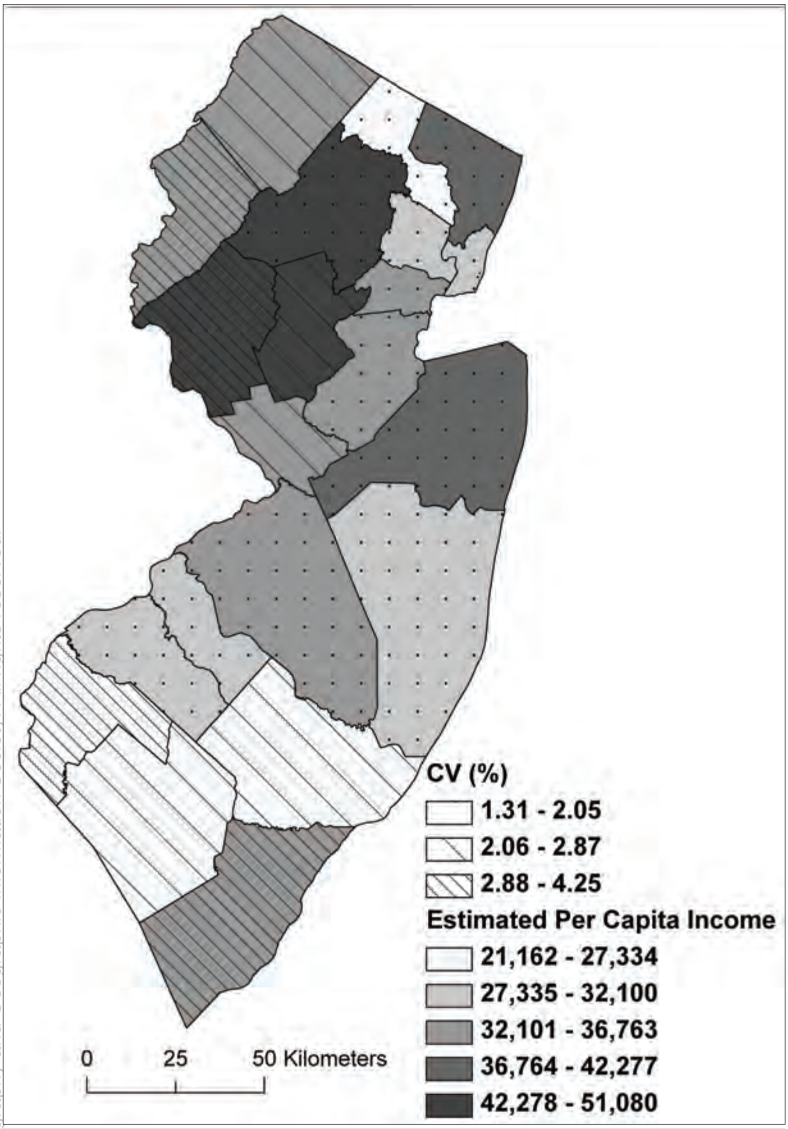

Figure 3. Per capita income estimates with coefficients of variation in New Jersey by counties, 2008 ACS data.

Mapping Significant Changes

Intent on evaluating the accuracy of ACS estimates, Gage (2006) compares ACS estimates with the corresponding variable values from the 2000 decennial census. A map showing the differences between ACS estimates and census values was first generated, and another map with a two-category legend was used to show if an area has an ACS estimate statistically different from the corresponding 2000 census value. The second map identifying areas with a significant difference is quite effective at helping readers to discern those differences and areas on the first map that are statistically meaningful. Although two maps are involved, readers likely find the set of maps quite manageable because the second map has only two categories. Nevertheless, the two maps can be consolidated into one bivariate legend map with one of the variables as a binary variable of significance. This approach is similar to the one used in Pickle et al. (1996) where hatched units have sparse data.

Using the same idea, we compare two one-year estimates of per capital income (2007 with 2008) provided by ACS for New Jersey counties. Each estimate of a given year has an associated margin of error with a 90 percent confidence interval. The range derived from (estimate ± MOE) gives the 90 percent confidence bounds of the true value of the estimate. If the confidence bounds derived from any two estimates do not overlap, then we may conclude that the two estimates are different 90 percent of the time (please refer to footnote 5). Or the difference between the two estimates is likely real but not due to a sampling error. The two estimates to be compared can be from the same location at different periods, different locations at the same period, or different locations at different periods.

Figure 4 maps the changes of estimates during the two years. The classes essentially follow the natural breaks in the data, with the exception of adjusting one break value to zero so that positive and negative changes can be distinguished easily. Figure 4 also indicates which counties experienced a significant change during the two years. When the confidence bounds of the same unit in the two years do not overlap, estimates of that areal unit in the two years are significantly different. Most New Jersey counties did not experience a significant change over the two years, except in Camden, Middlesex, Passaic, and Warren counties. The two counties that experienced a decline in income level are Atlantic and Cumberland (both in the southern part of the state). However, these declines are not statistically significant. This approach is useful for comparing estimates over time, or comparing ACS estimates with results from a census.

Identifying Significant Differences between Classes

The concept of registering differences and significance simultaneously may also be applied to comparing estimates in a cross-sectional setting. When mapping estimates for one time frame using a choropleth map, estimates are usually put into categories. In such a representation scheme, observations or units in different value classes are expected to have different attribute values. However, in mapping ACS estimates, margins of error should be considered in order to determine if the differences between estimates are real, but not due to sampling errors, as in the previous comparison between different periods. A value within the confidence bounds, (estimate ± MOE), of the estimate may be regarded as insignificantly different from the estimate. When an estimate is assigned to a class in a choropleth map, its lower and/or upper confidence bounds may be extended into other classes. Then that estimate is not significantly different from values in the lower and/or upper class(es).

Each estimate will fall into one of the four situations, and these situations are illustrated in Figure 5. In this illustration, hypothetical estimates represented by triangles are all in one class (medium), and the class breaks are at 20 and 30. Confidence bounds of each estimate are also represented by error bars with round tips. The four situations are:

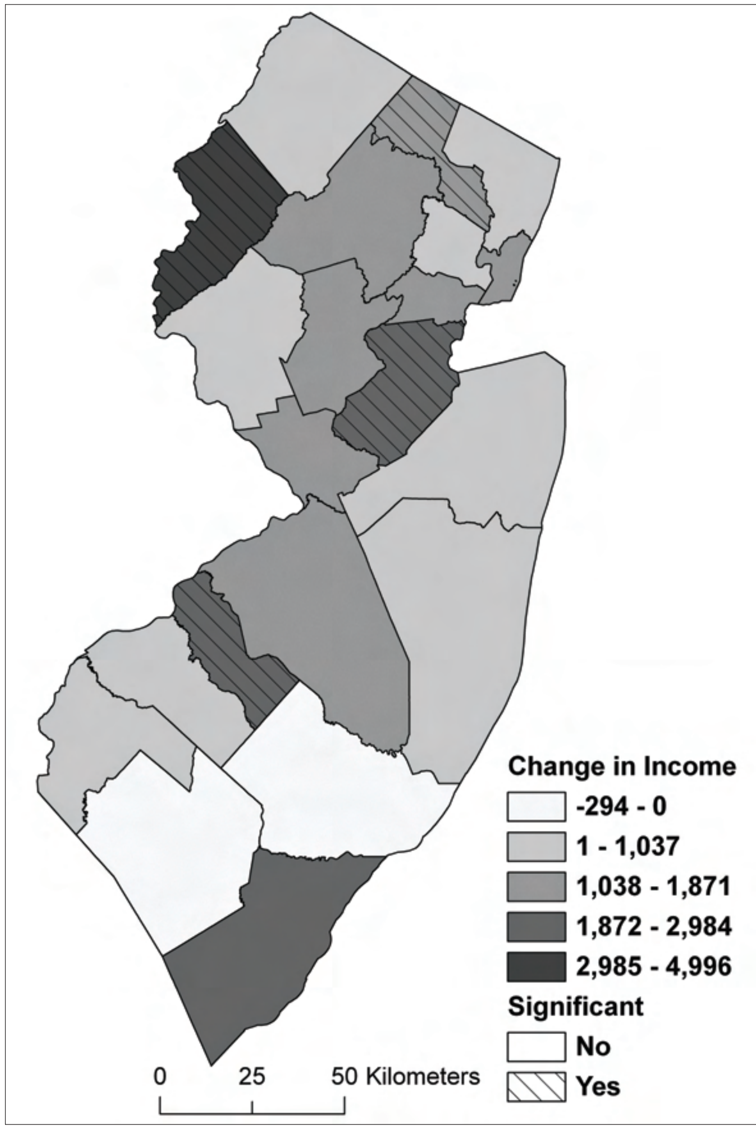

Figure 4. Change in per capita income estimates for New Jersey counties between 2007 and 2008 (2008 estimates minus 2007 estimates) using ACS data.

- The estimate is significantly different from values in both the higher and lower classes, as its confidence bounds are within the assigned class interval.
- The estimate is not significantly different from values in both the higher and lower classes; the confidence bounds of the estimate are extended beyond the interval of the assigned class into other classes.
- The estimate is not significantly different from values in the higher class, as the upper confidence bound is extended into the higher class, but the lower confidence bound stays within the assigned class interval.
- The estimate is not significantly different from values in the lower class, as the lower confidence bound is extended into the lower class, but the upper confidence bound stays within the assigned class interval.

These four types of significance may be treated as the second variable in the bivariate legend framework, and a single map can show the estimates as well as whether the estimates are statistically different from values in other classes. We call this the class comparison method. However, this method is still incapable of showing if the difference between any two estimates is statistically significant or not,

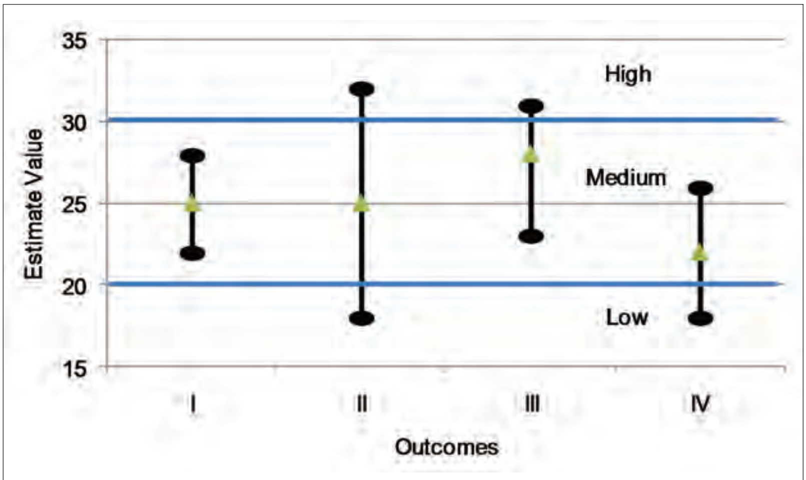

Figure 5. Categories of statistical differences when an estimate (triangle) is compared with values in other classes (high and low): (I) different from both classes; (II) not different from both classes; (III) not different from the higher class; and (IV) not different from the lower class.

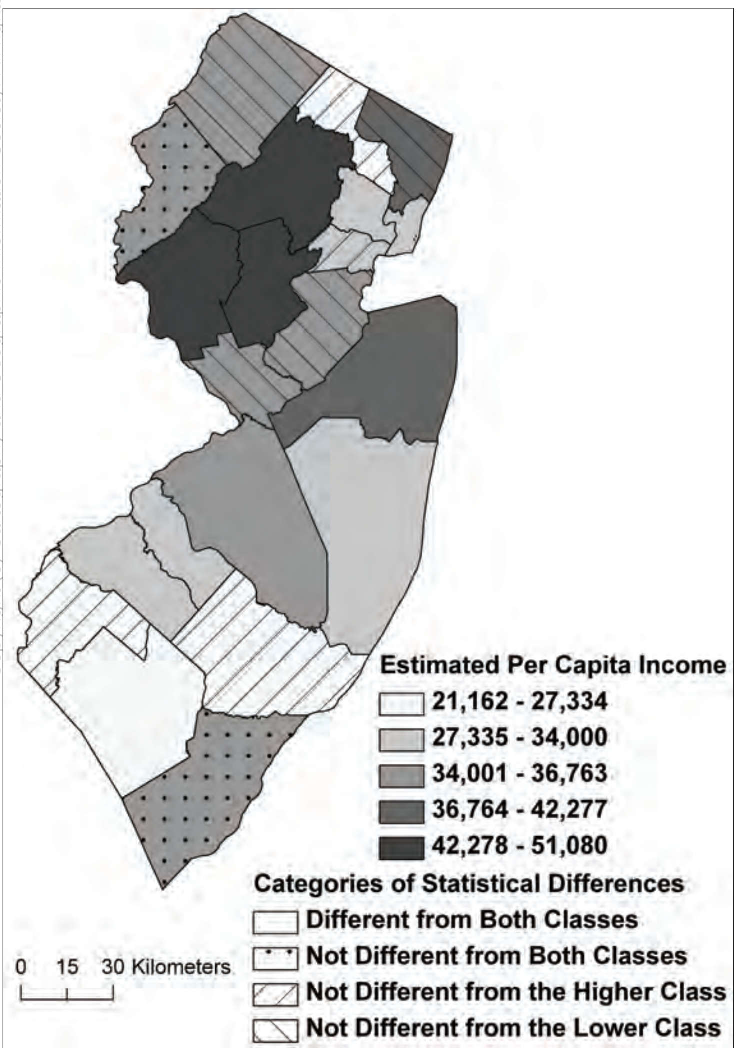

Figure 6. Per capita income estimates and categories of statistical difference from values in the nearest class(es) for New Jersey, 2008 ACS data.

as the comparison is only based upon the margin of error of one estimate, not the margins of error of both estimates.

Figure 6 is an example using the New Jersey data. The natural breaks classification is used with one minor adjustment in order to show all four categories of statistical differences. As in most classification methods, the minimum and maximum values of all observations are used to define the lower break value of the lowest class and the upper break value of the highest class, respectively. Estimates of Cumberland (minimum) and Hunterdon (maximum) define the lowest and highest break values among all classes, respectively. Cumberland, Salem, and Atlantic, all clustered around the southern part of the state, are in the lowest category of income level. For Salem and Atlantic counties, their upper confidence bounds are extended into the higher class, but their lower confidence bounds do not reach below the lower break value of the lowest class. Therefore, the per capita income levels of Salem and Atlantic can be regarded as not significantly different from values in the higher class. For the estimate of Cumberland, its upper confidence bound does not reach the higher class. Therefore, it is significantly different from values in the higher class. The estimate of Cumberland sets the lower break value of the lowest class, and its lower confidence bound is "out of range." For the sake of convenience, we treat the minimum estimate as significantly different from values in the "lower class," although a lower class does not exist. Then we may label the Cumberland estimate as significantly different from values in both classes. At the other end of the spectrum, Hunterdon County, with the highest per capita income estimate, is significantly higher than values in the lower class (fourth in the legend). Its estimate also sets the upper break value of the highest class. Similar to the Cumberland's situation, we also regard the Hunterdon estimate as significantly different from values in the "higher class." Therefore, its estimate is labeled to be different from both classes. One-third of the counties in New Jersey have estimates not statistically different from values in another class.

COUNTY	Per Capita Income	MOE	Lower Bound	Upper Bound
Cumberland	21,162	825	20,337	21,987
Atlantic	26,449	1,247	25,202	27,696
Passaic	26,588	896	25,692	27,484
Salem	27,334	1,709	25,625	29,043
Camden	29,793	903	28,890	30,696
Ocean	29,976	736	29,240	30,712
Gloucester	30,613	897	29,716	31,510
Hudson	31,330	1,004	30,326	32,334
Essex	32,100	899	31,201	32,999
Union	33,379	1,095	32,284	34,474
Middlesex	34,265	737	33,528	35,002
Cape May	34,883	2,347	32,536	37,230
Sussex	34,990	1,283	33,707	36,273
Burlington	35,392	1,103	34,289	36,495
Warren	35,432	2,479	32,953	37,911
Mercer	36,763	1,360	35,403	38,123
Monmouth	40,453	1,069	39,384	41,522
Bergen	42,277	1,007	41,270	43,284
Morris	47,075	1,390	45,685	48,465
Somerset	48,881	2,058	46,823	50,939
Hunterdon	51,080	3,004	48,076	54,084

Table 1. Sorted per capita income levels of New Jersey counties with MOEs, lower and upper bounds, using 2008 ACS data. Consecutive estimates with nonoverlapping bounds are marked by gray lines.

Modified Natural Breaks Classification

In the class comparison method described above, the probability that an estimate is significantly different from values in other classes is apparently affected not only by the size of its margin of error or confidence interval, but also the classification scheme adopted (Xiao et al. 2007). All mapping methods discussed previously are rather passive as the classification scheme is treated as given. A more "proactive" approach is to derive a classification scheme, or flexible class breaks such that interclass estimates are significantly different. In other words, after sorting estimates according to their values, consecutive estimates with overlapping confidence bounds can be grouped to the same classes and consecutive estimates with non overlapping confidence bounds are assigned to different classes.[7] To a large degree, this is a modified natural breaks classification method based upon the breaks of the confidence bounds of the ordered estimates. Depending on the distribution of the confidence bound values, this method may create classes with too many or too few observations. Also, too many or too few classes may be created. This method also fails to indicate significant differences between estimates within the same class. Nevertheless, this is an exploratory method to provide some indications of the extent that estimates across the spectrum are different from each other.

Using the New Jersey county data, estimates together with their confidence bounds are sorted to identify gaps where the bounds do not overlap (Table 1, gaps are marked with gray lines). Values selected within these gaps are used as class breaks in the classification to create a choropleth map (Figure 7). The wealthy counties in the north central section of the state have income significantly higher than the rest of the state, while Cumberland County in the southern tip has an income level significantly lower than the rest of the state. Most other counties in the state have confidence bounds overlapping each other, indicating that they are quite similarly statistically.

Interactive Visualization

The modified natural breaks classification scheme indicates that estimates in one class are statistically different from values in other classes. However, estimates within the same classes can

[7] Again, the preferred method is to test the differences of consecutive estimates. If the difference between two consecutive estimates is significant, then a class break should be inserted.

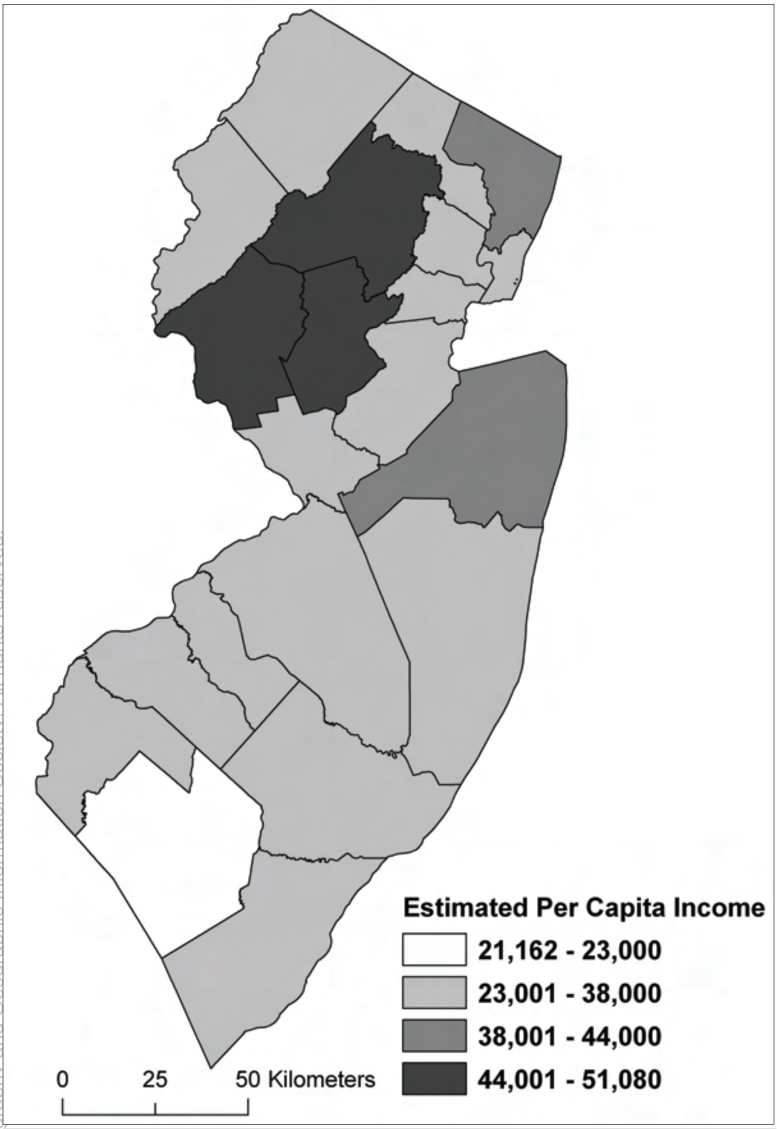

Figure 7. Per capita income estimates of counties in New Jersey; 2008 ACS data, using the modified natural breaks classification scheme.

be significantly different, and they are not identifiable on the map using the modified natural breaks method. To compare individual estimates, an interactive approach is warranted. Cliburn et al. (2002) suggest an interactive approach to allow users to select areas or regions to highlight the uncertainty characteristics of a subset. Such selected locations may be close together or far apart, but in general, they are not numerous in general. Therefore, a reader may select locations of interest for comparison first, and a bar chart can be created to compare the corresponding estimates with confidence bounds as the error bars. Plots of confidence bounds together with maps have been used to indicate the statistical properties of estimates (e.g., Pickle et al. 1996). In the current application, we intend to link the areas of interest (AOI) closer to the statistical plot. In Figure 8A, a few counties (Mercer, Middlesex, Monmouth, and Somerset) are selected for comparison. Then bar plots with estimates and confidence intervals are generated. The bars can be arranged in ascending or descending orders, such that users can determine the significance of differences easily (Figure 8B). To assist readers to associate the bars in the plot with their corresponding observations on the map, observations can first be sorted according to their coordinates, such that the bars follow a loose spatial order in the plot. This arrangement of the bars and the associated colors can minimize the reader's effort to match the bars with their corresponding locations (Figure 8C). Brushing capability can also be developed to enhance the interactive comparison process (Swayne et al., 1998; Swayne et al., 2003). In addition, a table can be generated to indicate if estimates of the chosen locations are significantly different or not, based upon the given level of confidence and the accompanied MOE information. Such a table for the selected counties in New Jersey is provided (Table 2). Coincidentally, all four selected counties have income levels significantly different from each other.[8]

A minor extension of the above interactive approach with the associated significance table (Table 2) is to map the differences between the estimate of a chosen observation and estimates of all other observations. A similar method is implemented in the Census Bureau's FactFinder web site under the thematic mapping capability[9]. An example of such a map is shown in Figure 9, where

[8] Coincidentally, the four selected estimates do not have overlapping confidence bounds. Therefore, using the more conservative confidence bound approach comes to the conclusion that they are different. Again, formal testing of differences between estimates is warranted.
[9] http://factfinder.census.gov.

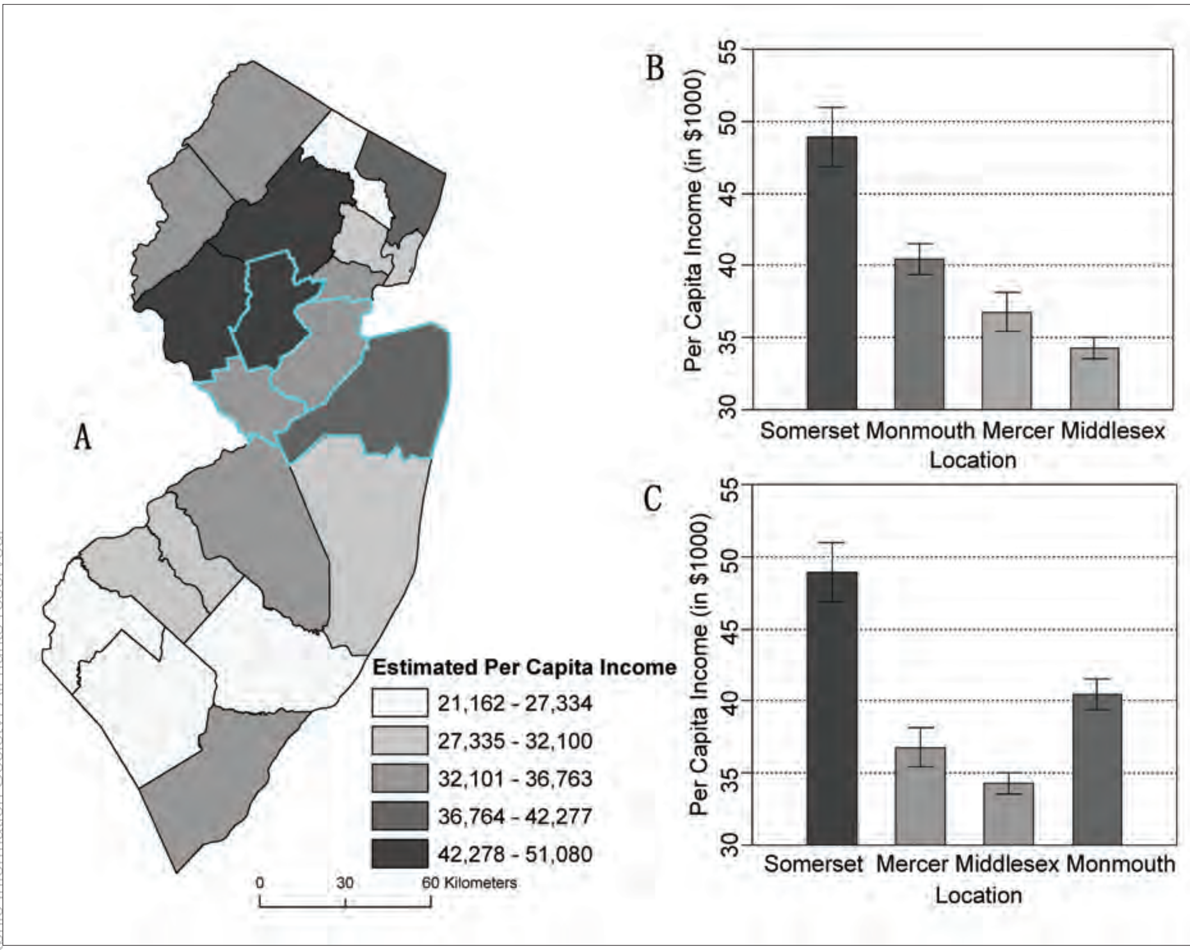

Figure 8. Comparison of per capita income estimates by selected counties in New Jersey, 2008 ACS data. Figure 8A. Selected counties with highlighted boundaries. Figure 8B. A bar chart with confidence intervals for comparing per capita income estimates, sorted in descending order. Figure 8C. A bar chart with confidence intervals for comparing per capita income estimates, sorted by their relative locations.

Middlesex County is the chosen unit. Differences between the per capita income estimate of Middlesex and other counties are mapped. Using a bivariate legend design, counties with estimates not significantly different from that of Middlesex are also indicated. With this technique, users can choose a reference observation as the basis for comparison. The results would have been captured in Table 2 if the previous method was used. However, mapping the results may reveal some pertinent spatial patterns. In this example, counties with per capita income estimates significantly higher than that of Middlesex are mostly found in the northwest of New Jersey, while those with significantly lower estimates are mostly to the south.

County	**Mercer**	**Middlesex**	**Monmouth**	**Somerset**
Mercer		Yes	Yes	Yes
Middlesex	-		Yes	Yes
Monmouth	-	-		Yes
Somerset	-	-	-	

Table 2. Significant differences in per capita income estimates between selected counties in New Jersey, 2008 ACS data.

In order to determine whether any two estimates are statistically different or not, the margins of error of both estimates have to be included in the comparison. This requirement poses a significant challenge to mapping such information together with the differences. Theoretically, a comparison involves one pair of observations, but not all observations at once. The two interactive techniques of selecting a subset of areas of interest or one areal unit as the reference for comparison discussed above limit the comparisons to selected pairs, and therefore, identifying unit pairs of significant different is rather simple. However, some features

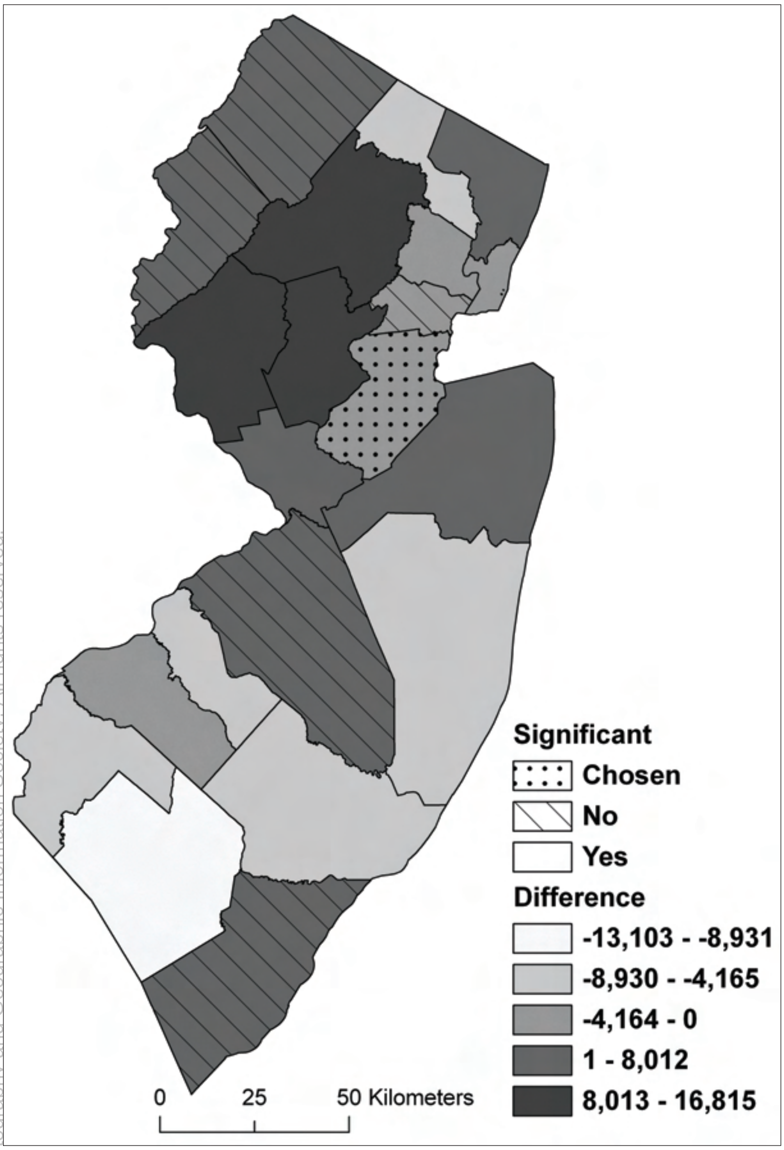

Figure 9. Comparing per capita income estimates of Middlesex County (Chosen) with other counties in New Jersey, 2008 ACS data.

of the interactive techniques, such as creating the bar charts with confidence intervals, are not supported by standard GIS functions in general.

Summary and Conclusion

Although previous discussions did not explicitly state that wrong conclusions were made based upon differences in ACS estimates when the associated CV or MOE information was not taken into account, perceived differences among many estimates are actually not statistically significant when sampling error is considered. In other words, without considering the margin of error when comparing ACS estimates, erroneous conclusions could be made. Obviously, the reliability of ACS estimates adds another level of complexity in mapping and interpreting ACS data. But as Openshaw (1989) points out, we have to live with uncertainty or error in spatial data.

In this article, we suggest several methods for mapping the ACS estimates by incorporating the associated CV or MOE information. These methods are not exhaustive but serve as the bases for future investigations to develop techniques that are more effective in incorporating the reliability information when mapping the ACS estimates. To a large degree, the manner of using the CV and MOE information in the mapping process is dependent upon the intentions of the cartographers. Some of the suggested methods are limited to revealing only the estimate reliability levels using CVs so that readers may be more aware of the unreliable estimates. Other suggested methods go as far as indicating the statistical difference of estimates or the lack thereof. As long as the ACS estimates are accompanied by the margin of error information, mapping the ACS data can and should incorporate the reliability information one way or the other. Mapping methods suggested here obviously can be applied to spatial datasets other than the ACS data if the standard errors or MOEs of the data are available.

The examples used in this paper for demonstration adopt a dataset with 21 areal units. This is a relatively small dataset, and therefore the effectiveness of our proposed methods for larger datasets has not been tested. The usability and effectiveness of these methods for larger datasets, such as the one including all counties in the U.S., are the subjects of future investigations. Our proposed methods focus on choropleth maps, which are appropriate for estimates in interval-ratio scales. Some proposed methods may be modified to suit other types of map to reflect data quality characteristics and to determine significant differences.

ACKNOWLEDGMENTS

The authors are grateful to the constructive comments provided by the two guest editors and the three anonymous referees. We are especially thankful to Professor Cynthia Brewer of The Pennsylvania State University, who encouraged us to explore a flexible classification method. The authors also thank the U.S. Census Bureau for its support of the research leading to the development of this paper. We are also indebted to Nancy K. Torrieri and Deborah H. Griffin of the Census Bureau, ACS Office, who provided insightful comments based on their expertise in ACS. However, the authors are responsible for any error in this article.

REFERENCES

Beard, M.K. and B.P. Buttenfield. 1991. *NCGIA research initiative 7: Visualization of spatial data quality*. NCGIA, Technical Paper. pp. 91-26.

Bench, K.M. 2004. *Meeting 21st century demographic data needs-implementing the American community survey. Report 7: Comparing quality measures: The American community survey's three-year averages and Census 2000's long form sample estimates.* U.S. Census Bureau. [http://www.census.gov/acs/www/AdvMeth/acs_census/creports/Report07.pdf; accessed April 30, 2010].

Brewer, C.A., and L. Pickle. 2002. Evaluation of methods for classifying epidemiological data on choropleth maps in series. *Annals of the Association of American Geographers. Association of American Geographers* 92(4): 662-81.

Broome, F.R., and D.B. Meixler. 1990. The TIGER database structure. *Cartography and Geographic Information Science* 17(1): 39-47.

Buttenfield, B.P. 1993. Representing data quality. *Cartographica* 30(2): 1-7.

Cliburn, D.C., J.J. Feddema, J.R. Miller, and T.A. Slocum. 2002. Design and evaluation of a decision support system in a water balance application. *Computers & Graphics* 26(6): 931-49.

Citro, C.F., and Kalton, G. (eds). 2007. *Using the American community survey: Benefits and challenges*. Washington, DC: The National Academies Press.

Cooke, D.F. 1998. Topology and TIGER: The Census Bureau's contribution. In: T.W. Foresman (ed), *The history of Geographic Information Systems*. UpperSaddle River, New Jersey: Prentice Hall.

FGDC. 1998. *Content Standard for Digital Geospatial Metadata* (version 2.0). [http://www.fgdc.gov/standards/projects/FGDC-standards-projects/metadata/base-metadata/v2_0698.pdf; accessed January 9, 2010].

Fronczek, P. 2005. *Income, earnings, and poverty from the 2004 American Community Survey*. American Community Survey Reports, U.S. Census Bureau. [http://www.census.gov/prod/2005pubs/acs-01.pdf; accessed on January 11, 2009].

Gage, L. 2006. Comparison of Census 2000 and American community survey 1999-2001 estimates: San Francisco and Tulare counties, California. *Population Research and Policy Review* 25: 243-56.

Gates, G.J. 2006. *Same-sex couples and the gay, lesbian, bisexual population: New estimates from the American Community Survey*. The Williams Institute on Sexual Orientation Law and Public Policy, UCLA School of Law. [http://www.law.ucla.edu/williamsinstitute/publications/SameSexCouplesandGLBpopACS.pdf; accessed January 11, 2009].

Griffin, D.H., and P.J. Waite. 2006. American community survey overview and the role of external evaluations. *Population Research and Policy Review* 25: 201-23.

Heuvelink, G.B.M., and P.A. Burrough. 2002. Developments in statistical approaches to spatial uncertainty and its propagation. *International Journal of Geographical Information Science* 16(2): 111-3.

Hough, G.C., and D.W. Swanson. 2006. An evaluation of the American community survey: Results from the Oregon test site. *Population Research and Policy Review* 25: 257-73.

Kardos, J., G.L. Benwell, and A. Moore. 2005. The visualisation of uncertainty for spatially referenced census data using hierarchical tessellations. *Transactions in GIS* 9(1): 19-34.

Kardos, J., A. Moore, and G.L. Benwell. 2003. *Visualising uncertainty in spatially-referenced attribute data using hierarchical spatial data structures*. [http://www.geocomputation.org/2003/Papers/Kardos_Paper.pdf].

Leitner, M., and B.P. Buttenfield. 2000. Guidelines for the display of attribute certainty. *Cartography and Geographic Information Science* 27(1): 3-14.

MacDonald, H. 2006. The American community survey: Warmer (more current), but fuzzier (less precise) than the decennial census. *Journal of the American Planning Association. American Planning Association* 72(4): 491-503.

MacEachren, A.M. 1992. Visualizing uncertain information. *Cartographic Perspective* 13: 10-9.

MacEachren, A.M. 1994. *Some truth with maps*. A monograph. Association of American Geographers, Washington, D.C.

MacEachren, A.M., C.A. Brewer, and L.W. Pickle. 1998. Visualizing georeferenced data: Representing reliability of health statistics. *Environment & Planning A* 30: 1547-61.

MacEachren, A.M., A. Robinson, S. Hopper, S. Gardner, R. Murray, M. Gahegan, and E. Hetzler. 2005. Visualizing geospatial information uncertainty: What we know and what we need to know. *Cartography and Geographic Information Science* 32(3): 139-60.

Mather, M., K.L. Rivers, and L.A. Jacobsen. 2005. The American community survey. *Population Bulletin* 60: 3.

McGranaghan, M. 1993. A cartographic view of spatial data quality. *Cartographica* 30(2): 8-19.

Merrick, M. 2003. Reflections on PPGIS: A view from the trenches. *Journal of the Urban and Regional Information Systems Association*. *Access and Participatory Approaches II* 15: 33-40.

Nelson, E.S. 1994. Colour detection on bivariate choropleth maps: The visual search process. *Cartographica: The International Journal for Geographic Information and Geovisualization* 31(4): 33-43.

Nelson, E.S. 2000. Designing effective bivariate symbols: The influence of perceptual grouping processes. *Cartography and Geographic Information Science* 27(4): 261-78.

Olson, J.M. 1981. Spectrally encoded two-variable maps. *Annals of the Association of American Geographers. Association of American Geographers* 71(2): 259-76.

Openshaw, S. 1989. Learning to live with errors in spatial databases. 263-276. In: M.F. Goodchild and S. Gopal (eds), *Accuracy of spatial databases*. London: Taylor & Francis.

Pickle, L.W., M. Mungiole, G.K. Jones, and A.A. White. 1996. *Atlas of United States mortality*. Hyattsville, Maryland: National Center for Health Statistics.

Scardamalia, R. 2006. The American community survey: General commentary on the findings from external evaluations. *Population Research and Policy Review* 25: 293-303.

Swayne, D.F., D. Cook, and A. Buja. 1998. XGobi: Interactive dynamic data visualization in the X window system. *Journal of Computational and Graphical Statistics* 7(1): 113-30.

Swayne, D.F., D.T. Lang, A. Buja, and D. Cook. 2003. GGobi: Evolving from XGobi into an extensible framework for interactive data visualization. *Computational Statistics & Data Analysis* 43(4): 423-44.

Thomson, E.F., and T. Gadalla. 2003. Income inequality and limitations in activities of daily living: A multilevel analysis of the 2003 American community survey. *Public Health* 122(3): 221-8.

Thomson, E.F., B. Yu, A. Nuru-Jeter, J.M. Guralnik, and M. Minkler. 2009. Basic ADL disability and functional limitation rates among older Americans from 2000-2005: The end of the decline? *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences* 64A(12): 1333-6.

Thomson, J., B. Hetzler, A. MacEachren, M. Gahegan, and M. Pavel. 2005. Typology for visualizing uncertainty. In: *Proceedings of the IS&T/SPIE Symposium on Electronic Imaging*, Conference on Visualization and Data Analysis, San Jose.

Van Auken, P.M., P.B. Hammer, P.R. Voss, and D.L. Veroff. 2004. *American community survey and Census comparison*. Final Analytical Report. Report prepared for the Bureau of the Census. [http://www.census.gov/acs/www/AdvMeth/acs_census/lreports/vossetal.pdf; accessed January 7, 2010].

Xiao, N., C.A. Calder, and M.P. Armstrong. 2007. Assessing the effect of attribute uncertainty on the robustness of choropleth map classification. *International Journal of Geographical Information Science* 21(2): 121-44.

Zhang, J., and M.F. Goodchild. 2002. *Uncertainty in geographical information*. London: Taylor & Francis.