Use of Density-Equalizing Cartograms to Visualize Trends and Disparities in State-Specific Prevalence of Obesity: 1996–2006

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Objectives. We used cartograms to visually communicate the state-specific prevalence of obesity and its association with socioeconomic variables over time to benefit and inform decisions by national health policymakers who address geographic and social inequities in health.

Methods. We generated density-equalizing maps, known as *cartograms* (in which geographic regions are sized in proportion to some variable), that illustrate indicators of population and educational attainment. We also provide an innovative presentation of the obesity choropleth map (which presents values for areas by shading).

Results. The maps depict the absolute burden of obesity, the inverse association between obesity and education, and geographic patterns in the prevalence of obesity over time.

Conclusions. The prevalence of obesity in the United States continues to increase. These cartograms can help stakeholders interpret surveillance data and their relation to demographic and socioeconomic characteristics to inform decisions. (*Am J Public Health.* 2009;99:308–312. doi:10.2105/AJPH.2008.138750)

Several national surveys have shown that prevalence rates for obesity continue to increase.[1,2] Not surprisingly, this prevalence is not uniformly distributed; obesity disproportionately affects some groups in the United States.[3,4] Among adult men, no significant differences in obesity prevalence are seen among racial/ethnic groups.[1,5,6] However, both non-Hispanic Black and Mexican American women have a higher prevalence of obesity.[1,5,6] Among adult women, poverty and low educational levels are also associated with a higher prevalence of obesity.[5]

Data from public health surveillance, often summarized in large, traditional tables, can be difficult to interpret and may not show the information in a meaningful way. One common solution is to display trends in the prevalence of obesity via maps. For instance, researchers have used choropleth maps (which present percentages for areas through the use of color, saturation, and lightness) to show changes in state-specific prevalence of obesity over time.[7] Several limitations and critiques have been noted for choropleth maps, however.[8,9] For example, large areas (often sparsely populated) tend to visually dominate smaller (often densely populated) areas,[10–14] leading to potential misinterpretation of the burden of obesity. Moreover, obesity is most highly concentrated among certain subpopulations, not only minorities but also the poor,[15] and these related factors are difficult to depict on choropleth maps.

The use of density-equalizing maps, or cartograms, minimizes such limitations by transforming the size and sometimes the shape of political areas (in this case, states) so they are proportional to another variable; traditionally, the variable is population, but other variables could be used. Cartograms are relatively new to public health but have been used successfully to map patterns of chronic disease, including the distribution of Wilms tumors in New York State,[16] mortality patterns of cerebrovascular disease in North Carolina,[17] and associations between both lung cancer and leukemia and the Rocky Flats plant site in Colorado.[10] Other successful cartograms have been developed to analyze the spatial distribution of cryptosporidiosis among AIDS patients in San Francisco, California,[18] and to characterize the spatial distribution of late-state and in situ breast cancer among women in the San Francisco Bay Area.[19] Innovative mapping applications, including cartograms, can be used in public health to improve understanding of health problems and for exploratory analysis of data.[20,21]

For our exploratory study, we used cartograms and other cartographic techniques to visually communicate the pattern of obesity prevalence and its association with socioeconomic variables over time. Our density-equalizing cartograms of population and education indicators show the prevalence of obesity, and an innovative presentation of the choropleth map shows change in obesity prevalence over time.

METHODS

Data Sources for Maps

State-specific prevalence rates of obesity for 1996 and 2006 were based on previous analyses[2] of data from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a cross-sectional telephone survey of noninstitutionalized US adults 18 years or older that relies on random-digit dialing.[22] Self-reported weight and height from the BRFSS were used to calculate body mass index (calculated as weight in kilograms divided by height in meters squared); people with a body mass index of 30.0 kg/m^2 or higher were classified as obese. To be consistent with previous analyses[7] and to permit comparisons between obesity surveillance maps, data were excluded if a person weighed 500 lbs or more or was at least 7.0 ft tall. The 10-year change in prevalence of obesity was calculated from 1996 to 2006 and was directly standardized to the distribution of the 2000 BRFSS population by gender, age, and race.

State population data were from the US Census Bureau Population Division.[23] Because the prevalence of obesity is generally lower among White and Asian people, state racial data were aggregated into 2 categories: (1) White and Asian alone and (2) African American, American Indian/Alaska Native, Native Hawaiian and other Pacific Islander, and people who identified themselves as of 2 or more races.[24] Hispanic ethnicity was not accounted for in this analysis, and those of Hispanic ethnicity were included in the White race group. Data from the US Current Population Survey included median household income by state, percentage of people 25 years or older who had at least an undergraduate degree, and percentage of people 25 years or older who had at least a high school diploma.[25]

Procedure for Making Maps

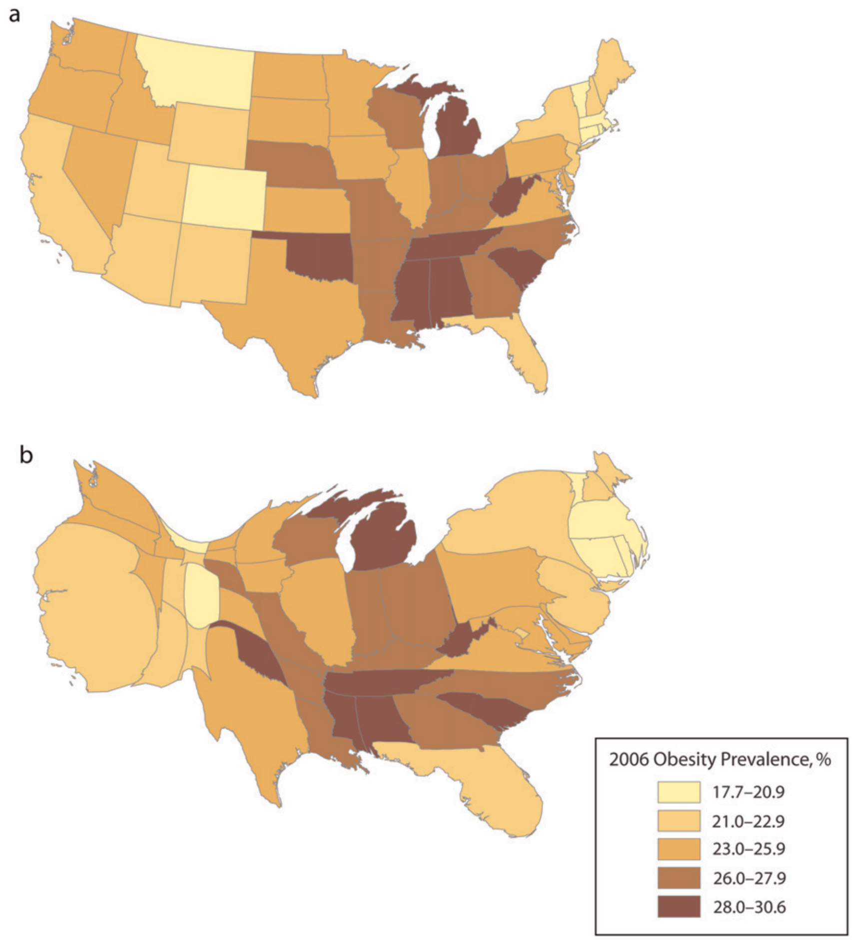
Cartograms were created via the diffusion algorithm by Gastner and Newman.[26] Although several algorithms have been developed to produce cartograms,[11,27–30] they each contain certain shortcomings. For instance, some algorithms require a long calculation time, whereas others distort or overlap the regions' shapes, making the resulting map difficult to read. We selected the Gastner–Newman algorithm for this study because of its balance between mathematical rigor, ease of implementation, and intuitive and readable results. The cartograms were generated with ArcINFO (workstation) and ArcGIS v9.2 (ESRI, Redlands, CA). Only the 48 contiguous states and the District of Columbia were included in the maps generated. Alaska and Hawaii were excluded for aesthetic reasons (their renderings were extremely distorted). The modified choropleth map was generated with ArcGIS v9.2.

RESULTS

The state-specific obesity prevalence in 2006 for adults (aged ≥ 18 years) is shown in Figure 1 by 2 methods: a choropleth map (panel a) and a population cartogram (panel b). In the choropleth map, states are shaded according to their percentage of obese adults. The population cartogram also uses shading to depict the prevalence of obesity, but each state has been resized proportional to its population. Thus, a state with twice the population of another state will appear twice as large as that state.

The impressions rendered in Figure 1 differ markedly between the 2 maps. For example, in the choropleth map (panel a), the large size of the Rocky Mountain and southwestern states combined with (in most cases) their modest or low population has the result of visually overstating the proportion of the population that has a relatively low prevalence of obesity. By contrast, when the states are resized on the basis of population (panel b), the total area of the United States perceived to have a low prevalence of obesity is much smaller. Conversely, in the choropleth map, one is given the impression that approximately one half of the United States is experiencing high rates of obesity (i.e., a prevalence of 26.0% or greater), whereas in the cartogram, the impression is conveyed that the vast majority of the United States is experiencing high rates. In another example of the different impressions given by the 2 mapping methods, California, New York, and Florida appear much larger in the cartogram than in the choropleth map because their populations are disproportionate to their actual sizes (note that this is also true for Massachusetts, Connecticut, New Jersey, and certain other smaller states).

In Figure 2, state sizes are rescaled to reflect the percentage of adults 25 years or older who attained at least an undergraduate degree; again, the prevalence of obesity (in 2006) is represented by shading. The inverse association between education and obesity was evident when the exaggerated size of the Northeastern states (because of high educational levels) was combined with their relatively low prevalence of obesity. Cartograms for median household income by state also were



Note. State sizes are proportional to state population estimate for 2006.

FIGURE 1—Percentage of obese (body mass index ≥ 30 kg/m^2) adults 18 years or older, by state in a (a) Choropleth map and (b) population cartogram: 2006.

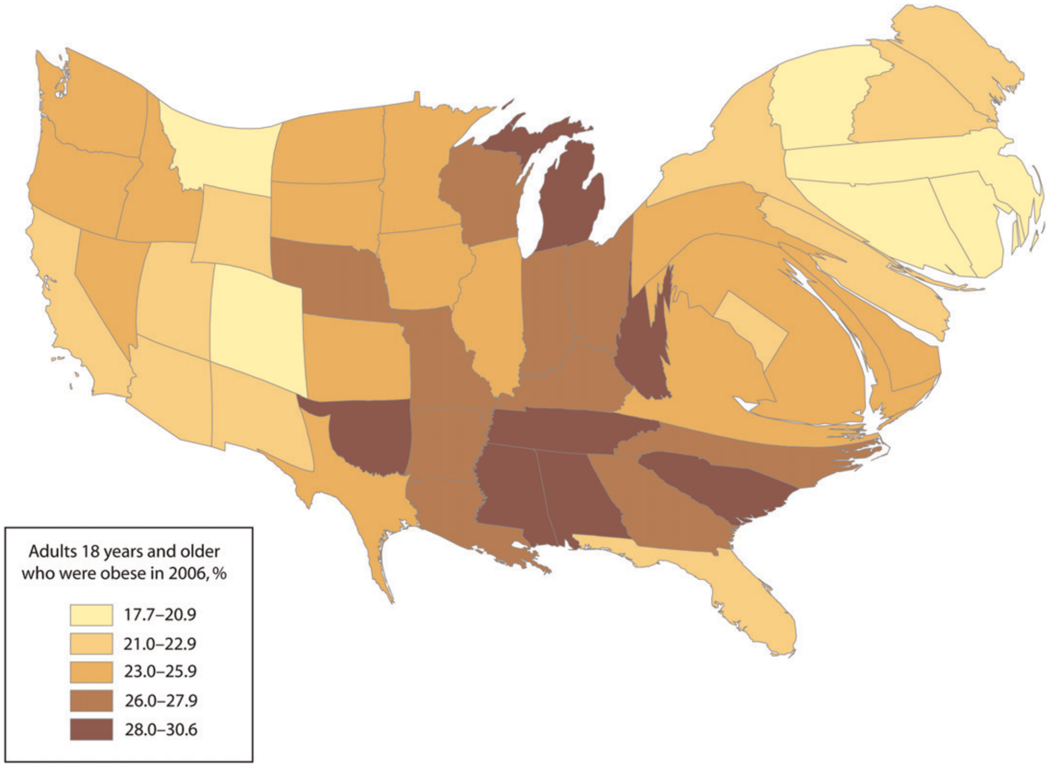


FIGURE 2—Cartogram of 2006 state-specific percentage of adults 25 years or older with at least an undergraduate degree, with shaded depiction of the percentage of obese (body mass index $\geq$30 kg/m^2) adults 18 years or older.

generated, but because median household income was highly correlated with educational attainment, the income cartograms appeared very similar to those in Figure 2 and are not presented.

In Figure 3, a choropleth map of the state-specific prevalence of obesity in 1996 rather than 2006 is presented; this map also includes a circle for each state to show the 10-year change in prevalence from 1996 to 2006. The shades used in Figures 1 and 2 are also used here, but in this case, the percentages depicted are lower than the corresponding values in the other 2 figures. The 10-year change in obesity prevalence is represented by the graduated size of the circle within each state. The states with the largest 10-year changes (in percentage points) were Georgia, Tennessee, Kansas, and South Dakota. Of these 4, Georgia was the only one to be in the lowest category for obesity prevalence in 1996. The other state in that lowest category, Colorado, had an increase in obesity prevalence of 7.75 percentage points over 10 years (the increase for Georgia was 15.20 percentage points).

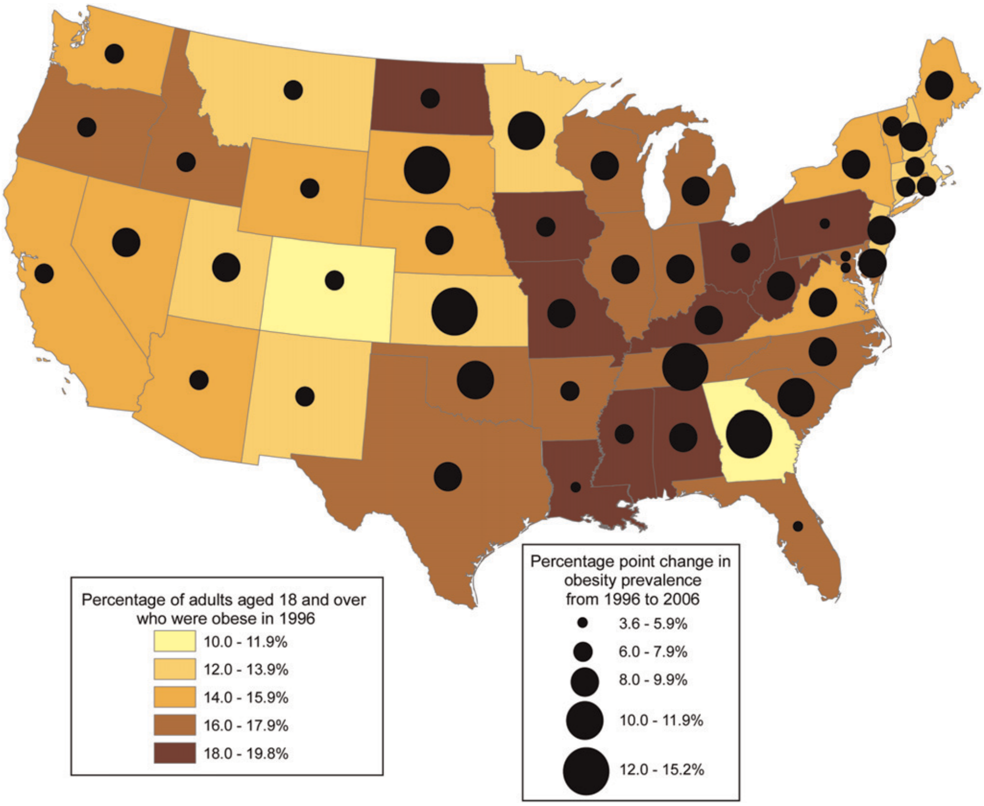
Cartograms also were generated from state-specific population density, the percentage of adults 25 years or older with at least a high school diploma, and the proportion of White and Asian people in the overall state population. These cartograms are not presented, however, because they were difficult to interpret visually. Either state sizes were too distorted (in the case of population density for the smaller states) or very little differentiation was seen among the states' sizes.

DISCUSSION

Our results suggest that cartograms that use indices of population and educational attainment and show the state-specific prevalence of obesity offer an informative representation of data on obesity. The population cartogram in Figure 1b allows the viewer to interpret the absolute obesity burden across the United States more realistically than would be the case with a typical choropleth map. The cartogram in Figure 2 allows an interpretation of the association between education and obesity burden at the state level that is more compelling than would be seen in conventional representations. Finally, the modified choropleth map of obesity prevalence in Figure 3 allows the reader to visualize simultaneously the 1996 burden of obesity in each state and the change over the next 10 years in that state (as expressed by prevalence).

Although the generation of cartograms traditionally has been a difficult task, the new diffusion-based algorithm by Gastner and Newman[26] that we implemented produces useful and interpretable maps. Even so, several cartograms we generated were difficult to interpret visually because of similar sizes among the states. A key strength of the density-equalizing cartograms is the ability to highlight disparities in multivariate associations. We found that when differences are relatively small, it becomes more difficult to interpret the cartograms visually.

We also generated cartograms that were too distorted from a combination of large differences



Note. Change from 1996 to 2006 was directly standardized to the gender, age, and race distribution of the 2000 Behavioral Risk Factor Surveillance System population.

FIGURE 3—State-specific percentage of adults 18 years or older who were obese (body mass index ≥ 30 kg/m²) in 1996 and the 10-year percentage point change from 1996 to 2006.

in population density between the larger area and less populated states and the smaller area and more populated states, coupled with the requirement to maintain the contiguity of borders of adjoining states. We found that for cartograms to be useful, the readers needed to be able to identify the states. When the distortion is low to moderate, these identifications are possible if the states retain their general shape, which users cue on for identification. However, at extremely high levels of distortion, it is difficult to identify each state correctly because these shape cues are no longer present. Therefore, we recommend that cartograms be used when the distortion is at or below the level at which the shapes of the mapped units (e.g., states) are still recognizable. Furthermore, Sui and Holt[31] have shown that readers are better at interpreting maps when they have experience with or are given a primer on cartograms. We therefore also recommend that any cartograms be accompanied by a brief description on how they were constructed and what they are meant to represent.

Limitations

This exploratory analysis had several limitations. First, the state-specific percentages for the prevalence of obesity were based on self-reported height and weight. A recent systematic review indicated that, in general, people underestimate weight and overestimate height, although the degree varies by gender and among studies.[32] Second, displays of the prevalence of obesity are necessarily simplified because all values appear evenly distributed within a state. In addition, the visual representations confer the impression that the prevalence of obesity often changes abruptly at a state border, but in reality, obesity is distributed continuously over space and does not change abruptly at an arbitrary line such as a border (e.g., the border between Colorado and Nebraska). Finally, associations observed at the state level may be inconsistent with associations observed at the individual level. Therefore, inferences that can be drawn from these maps are limited and should be interpreted with caution.

Conclusions

In conclusion, the reporting of health statistics to stakeholders, particularly the public and policymakers, can be a difficult task. Traditionally, surveillance data presented in choropleth maps have been effective in raising public concerns because these maps can depict data in a more comprehensible format than that provided by tables.[33] Therefore, these maps must convey accurate, clear, and interpretable messages for a broad audience.[34]

Combining the technique of shading geographic regions by prevalence with cartograms based on associated variables allows one to see how a given disease is distributed across various dimensions. Particularly for policymakers, the ability to visualize associations in this way can inform decisions and promote the cost-effective targeting of resources and public health interventions.[35] Cartograms based on this method recently have produced useful interpretations. For instance, the Worldmapper project, which generated cartograms of the worldwide distribution of variables such as child mortality and gross national product, identified stark inequities between different countries and regions.[36] Elsewhere, Gastner and Newman depicted the US 2000 presidential election results with a cartogram of state electoral college votes.[26] Other researchers have used density-equalized maps to explore risk of childhood cancer.[37] The current study determined that cartograms can present state-specific data on the distribution of obesity in the United States that can benefit and inform decisions by national health policymakers who address geographic and social inequities in health. ■

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***Note.** The findings and conclusions in this article are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.*

Contributors

B. Houle originated and led the study and the writing of the article. J. Holt generated the cartograms and contributed to the article. C. Gillespie analyzed the Behavioral Risk Factor Surveillance System data and contributed to the article. D.S. Freedman contributed to the study design and the article. M. Reyes supervised the study and contributed to the article.

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Human Participant Protection

No human participants were involved in this study.

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