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The geographic distribution of obesity by census tract among 59 767 insured adults in King County, WA

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Abstract

Objective—To evaluate the geographic concentration of adult obesity prevalence by census tract (CT) in King County, WA, in relation to social and economic factors.

Methods and Design—Measured heights and weights from 59 767 adult men and women enrolled in the Group Health (GH) health care system were used to estimate obesity prevalence at the CT level. CT-level measures of socioeconomic status (SES) were median home values of owner-occupied housing units, percent of residents with a college degree, and median household incomes, all drawn from the 2000 Census. Spatial regression models were used to assess the relation between CT-level obesity prevalence and socio-economic variables.

Results—Smoothed CT obesity prevalence, obtained using an Empirical Bayes tool, ranged from 16.2% to 43.7% (a 2.7-fold difference). The spatial pattern of obesity was non-random, showing a concentration in south and southeast King County. In spatial regression models, CT-level home values and college education were more strongly associated with obesity than household incomes. For each additional $100 000 in median home values, CT obesity prevalence was 2.3% lower. The three SES factors together explained 70% of the variance in CT obesity prevalence after accounting for population density, race/ethnicity, age and spatial dependence.

Conclusions—To our knowledge, this is the first report to show major social disparities in adult obesity prevalence at the CT scale that is based, moreover, on measured heights and weights. Analyses of data at sufficiently fine geographic scale are needed to guide targeted local interventions to stem the obesity epidemic.

Keywords

obesity; health status disparities; geography; socioeconomic factors; cross-sectional studies

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Conflict of interest
The authors declare no conflicts of interest.

Supplemental Information
Supplementary information is available at the journal's website.

Introduction

The social gradient in the prevalence of obesity in the US has long been a subject of debate (1). At the individual-level, obesity is more common among people with lower education and incomes, particularly women (1, 2). At the aggregate level, higher prevalence of obesity has been observed in areas with lower socioeconomic status (SES), including states (3), counties (4, 5), congressional districts (6), and zip codes (7). Given the lack of granular health data, there are fewer reports on social disparities in obesity prevalence in smaller-area studies, particularly those at census tract (CT) level.

Place-based analyses of obesity at a sufficiently fine geographic scale may offer new insights into the social, economic and environmental determinants of body weight and health (8). The well-known CDC obesity maps at state level may mask local disparities and are insufficiently detailed for local health planning purposes (2, 9). Through advances in small-area estimation, obesity estimates have been extended down to county level (10, 11). However, even county level estimates can mask dramatic local disparities, especially in highly populated and heterogeneous counties (12). Estimates of obesity prevalence at a finer geographic scale would be much more valuable for local policy making, intervention planning, and evaluation purposes.

In the New York City Community Health Survey (13) obesity prevalence was mapped at the United Hospital Fund neighborhood level (ZIP Code aggregations). Other studies used different levels of geographic aggregation, including county (5), metropolitan statistical area (14), or ZIP code (7) to demonstrate links between higher obesity prevalence ans lower area-based SES. Studies of California assembly districts (6) and Indianapolis neighborhoods (15) have likewise revealed a consistent and profound social gradient in obesity. Only two studies, including one conducted in the Seattle area, have explored childhood obesity and SES at the census tract level (15, 16).

To our knowledge, this is the first study to evaluate the geographic concentration of adult obesity prevalence by census tract (CT) in relation to social and economic factors. Importantly, the study was based on measured heights and weights of close to 60 000 insured persons, rather than on telephone self-reports. The present goal was to determine the relative influence of area-based SES measures on adult obesity prevalence at the CT level.

Methods

Participants

Group Health (GH) is a consumer-governed, nonprofit health care system that coordinates care and coverage for more than 600 000 residents in Washington (WA) State. GH coverage area includes King County, a large metropolitan county in WA State with a population of more than 1.8 million residents. Measures of height and weight are obtained routinely at primary care office visits. Clinical guidelines recommend measurement of weight and height in light street clothing without shoes. For purposes of this study, body mass index (BMI) values were calculated from the modal adult height and the most recent weight recorded between January 2005 and December 2006; respondents with a BMI of ≥30 kg/m^2 were classified as obese. BMI data were available for 61 910 GH members in King County during 2005–2006 (60% of the GH member population in King County). Of those, 96.5% (n=59 767) were geocoded to census tracts (CT), which was then used to estimate the prevalence of obesity by CT.

Socioeconomic and Environmental Variables

Area-based SES measures were the primary exposures of interest. Here, conventional CT-based measures of percent of adults with a college degree and median household income were supplemented with median home values, all from the 2000 Census. Additional covariates were percent non-Hispanic black, percent Hispanic, population density (population per square mile excluding major water features), and average age of participants within each CT. The first three covariates were from the 2000 census and the average age was from GH data. The census predictors (e.g., median home value and education) were for the entire population in order to estimate contextual effects of these factors.

Secondary analyses explored potential environmental mediators of the association between area-based SES measures and obesity, specifically related to the food environment. For the entire US at the CT scale the CDC has released data on the Modified Retail Food Environment Index (mRFEI) (17). The mRFEI is a ratio-based measure of healthful to total food retailers (e.g., healthful plus less healthful retailers), with higher values indicating a more healthful food environment. Healthful food retailers were defined as supermarkets, large grocery stores, fruit and vegetable markets and warehouse clubs and less healthful food retailers were defined as fast food restaurants or convenience stores. The CDC mRFEI data include food retailers located within each CT and within a ½ mile distance of boundary (17).

Obesity Data

Given the small sample size within some CTs, an Empirical Bayes (EB) tool was used to estimate the smoothed obesity prevalence (18). This method allowed us to include CTs with smaller sample sizes that would otherwise have to be excluded from analysis due to considerable imprecision in the estimate of obesity prevalence. This approach smooth’s the prevalence estimates with extreme values or those based on small sample sizes in the direction of the countywide prevalence. The estimated prevalence of obesity for CT with many respondents or very close to the countywide prevalence would only be marginally altered. We used a spatially naïve EB tool, which did not use information from nearby CT to smooth the obesity prevalence. While a spatially informative EB tool may result in an informative estimate, given the intent to explore spatial clustering of obesity in King County, we opted not to use a spatial EB tool; as such a tool would impose extra spatial clustering by its very nature.

To facilitate spatial analyses, it is essential to accurately specify the spatial relationships present in the data. A modified Queen’s contiguity matrix was used, which defines neighboring CTs as those sharing a border or corner, similar to how a Queen can moves during chess. We modified the default matrix by evaluating transportation patterns, with particular emphasis on CTs that may or may not be contiguous but share an important transportation artery. This is particularly important given the abundance of waterways in Seattle/King County. For example, a ship canal separates portions of Seattle, but is connected by a number of bridges. We determined that these CTs were contiguous and modified the spatial weights to reflect this. Sensitivity analyses used alternative spatial weights to determine if the choice of weights seriously influenced the results. Alternative weights included the default Queen's matrix (with no customization), 2^{nd} order Queen's matrix (i.e., includes CT bordering the CT adjacent to the referent CT), k^{th} nearest neighbor (e.g., identifies 5 nearest CT as neighbors) and inverse distance weighting with a 2-mile buffer (i.e., CT within 2-mile buffer are defined as neighbors, but more nearby CT have greater weight).

Statistical Approach

Initial analyses sought to determine if obesity in King County was randomly distributed across space. To test this, the Moran's I statistic, a global measure of spatial autocorrelation, was evaluated (19). Values of the Moran's I can range from −1.0 to 1.0 and can be interpreted in a similar manner to the correlation coefficient. A value of 1.0 indicates "perfect" spatial autocorrelation, where the variable of interest is completely clustered in space. A Moran's I statistics value near 0.0 indicates a random spatial pattern and −1.0 indicates complete spatial dispersion.

After determining the extent of spatial autocorrelation the association between smoothed obesity prevalence and each area-based SES measure was modeled individually. Each model was evaluated independently due to concerns of co-linearity and to evaluate what CT-based measures were most highly associated with obesity, before accounting for covariates. For none of the predictors of interest and their covariates did the Variance Inflation Factor (VIF) exceed 1.8, indicating that co-linearity between predictors and covariates was not a major concern (e.g., there was no indication of co-linearity between % black and % with a college degree). The covariates described above (i.e., age, gender, race/ethnicity and population density) were added after fitting an initial crude model.

After fitting ordinary least squares regression models, we evaluated spatially autoregressive linear regression models (i.e., spatial error model). The spatial error regression model accounts for spatial dependence of the measured variables and also accounts for unknown or poorly measured predictors of interest that have a spatial component. Specifically, the spatial error model partially accounts for similarities in the built environment in contiguous areas that are not fully captured by inclusion of the population density or demographic covariates. Examples of such factors may include features of the built environment, access to food or unspecified demographic factors. The Akaike Information Criteria (AIC) was used to determine the best fitting model for each of the area-based measures of interest. The final step was to determine if the models fully accounted for the spatial structures in the data by evaluating the Moran's I statistic of the residuals from each final model. A Moran's I statistic very close to zero indicates that spatial dependence was accounted for in the model. In secondary analyses, the gender-specific smoothed obesity prevalence was estimated using the same approach as described above.

The role of the food environment, as measured by the mRFEI, in potentially explaining the differences in obesity associated with area-based SES was examined using the classical mediation model (20–21). Specifically, the mRFEI may be considered a mediator of the SES-obesity association, to the extent by which it explains the influence of area-based SES to obesity. In the current setting, mediation can be said to occur if the mRFEI is associated with the area-based measures of SES, area-based SES is associated with the obesity prevalence in the absence of the mRFEI, the mRFEI has a significant and unique effect on the obesity prevalence independent of area-based SES, and the effect of area-based SES on the prevalence of obesity is reduced after adding the mRFEI to the regression model. Both crude and adjusted mediation analyses were conducted. The Stata “sgmediation” program was used which allowed us to determine if each of the components defining mediation were achieved by the mRFEI. Sobel-Goodman tests were used to evaluate whether the mRFEI explained, in part, or completely, the relation between area-based SES and obesity at the census tract scale (21).

Statistical and spatial analyses were performed using OpenGeoDa (GeoDa Center for Geospatial Analysis and Computation and Arizona Board of Regents) and Stata 12.1 (College Station, TX). Merging of data and descriptive mapping was done in ArcGIS 10.0 (ESRI Redlands, CA).

Results

The final analysis was based on 371 CTs within King County. Two CTs (total n=58 individuals), were excluded from the analysis either due to insufficient sample size (n<10) or because of missing exposure data (i.e., no information on median home value for the CT, including the University of Washington main campus and CT with small residential populations). The excluded CTs represented less than 0.3% of the county population in 2000. A total of 59 767 adults (age ≥ 18) were available for the final analysis. The number of members in each CT ranged from 22 to 413 with an average of 161. The crude prevalence of obesity in the study sample was 28.7% among men and 28.2% among women. The unsmoothed obesity prevalence ranged from 10.5% to 59.6% (a 5.7-fold difference) and the smoothed obesity prevalence ranged from 16.2% to 43.7% (a 2.7-fold difference).

Obesity prevalence in King County at the CT scale exhibited a non-random spatial pattern. The Moran’s I statistic for the smoothed obesity prevalence indicated that CTs with a high prevalence of obesity tended to be near other CTs with a high prevalence of obesity (Moran’s I = 0.67, $p < 0.001$). A geographic concentration of obesity was observed in south and southeast King County and fewer obesity clusters were observed in north Seattle and eastern suburbs (see Figure 1). See Supplemental Figures 4–6 for maps of educational attainment, median household incomes and property values by King County CT.

Given evidence for strong spatial autocorrelation, spatial methods were employed to account for the observed spatial dependence. Significant spatial autocorrelation was also observed for the predictors of interest. CTs with high median household incomes, percent college graduates, median home value, percent black, percent Hispanic and population density all tended to be located near CTs with complimentary high values for these measures. The extent of spatial clustering was particularly strong for percent of adults with college degree (Moran's I 0.81, p<0.001) and percent black (Moran's I 0.74, p<0.001) (Table 1).

In bivariate and spatially naïve analyses, each of the predictors of interest was significantly associated with the smoothed prevalence of obesity; percent with a college degree and median home value having the strongest negative association with obesity (Table 1 and Table 2). Percent non-Hispanic black and Hispanic were positively associated with obesity prevalence, and higher population density was negatively associated with the prevalence of obesity. In general, a stronger association between home value, percent college graduates and median household income was observed for women as compared to men (Table 3).

A spatial error model was used to account for spatial dependence and unspecified shared environmental factors. For each \$100 000 increase in median home values the prevalence of obesity was 2.3% lower (95% CI −2.9, −1.8) holding all other factors constant. For each 10% increase in the proportion of adults with a college degree the prevalence of obesity was 2.4% lower (95% CI −2.1, −2.7). Each \$10,000 increase in median household income resulted in a modest reduction of −0.8% (95% CI −1.2, −0.5) in obesity prevalence. Evaluating the Moran's I statistic for the residuals of the spatial error models shows that there was no longer positive spatial autocorrelation after accounting for the covariates and the spatial dependence of the data (Moran's I statistic between −0.10 and 0 for each model). The Moran's I statistic values of the model residuals indicates that spatial dependence of the data had been fully accounted for in the model.

Sensitivity analyses evaluated the use of alternative spatial weights to determine if the choice of weights influenced the results. There is no evidence that the choice of alternative spatial weights would substantially influence our interpretation, as the use of different alternative weights did not change the coefficients of interest by more than 6%. There was no evidence that the mRFEI mediated the association between low area-based SES and higher prevalence of obesity. Specifically, in neither crude nor models adjusted for age, race/ethnicity, and population-density, were the area-based SES measures associated with the mRFEI score. In addition, there was no evidence that the mRFEI score was associated with the prevalence of obesity, either independently or after accounting for demographic covariates. The proportion of the association between area-based measures of SES and obesity was never greater than 0.7% (for crude model with median household income as the independent variable of interest) and the p-values from the Sobel and Goodman tests for mediation showed that the p-value for mediation was never less than 0.59. From the established framework of mediation, there was no evidence that the mRFEI explained differences in obesity associated with area-based SES.

The available data suggest that in the bivariate setting, 43% of the variation in area-level obesity prevalence can be explained by median home values. Accounting for population density, race/ethnicity and age increases the proportion of variance explained to 53%, while an additional accounting for spatial dependence raises the variance explained to 67%. A similar trend was observed for the proportion with of the adult population with a college degree, with the variance increasing from 62% in the bivariate setting to 70% after accounting for population density, race/ethnicity, age and spatial dependence. An examination of crude and adjusted linear regression models with standardized β-coefficients confirmed to account for the different scales of the area-based SES variables confirmed that percent with a college education had the strongest association with obesity, followed by property values and median household income.

Discussion

The present analyses are the first-ever demonstration of sharp disparities in obesity prevalence at the CT level in relation to the underlying social and economic factors. Even though King County is generally regarded as one of the healthier counties in WA State, the uncorrected prevalence of obesity by CT ranged from 10.5% to 59.6% (a 5.7-fold difference), whereas the corrected prevalence by CT ranged from 16.2% to 43.7% (a 2.7-fold difference). In some CTs, the prevalence of obesity among GH members approached 50%. The geographic distribution of obesity prevalence was non-random, showing a concentration in south and southeast King County. Though limited data were available on built environment factors that may influence obesity, adjustment for a measure of healthy food availability and population density, did not account for the observed association between area-based SES and obesity prevalence at the CT scale.

These data support and extend previous studies on the geographic distribution of obesity and its health consequences in the US. Given the general lack of health data at fine geographic scales, including the CT level, most studies are unable to go below the county level. Slack et al observed that county level prevalence of adult obesity was both regionally concentrated and associated to such county-level SES factors as low education and unemployment (22). Similarly, CDC studies have identified a diagnosed diabetes belt, consisting of 644 counties in 15 states, located mostly in the southern US (23). Both studies made the point that local-level data were important for identifying vulnerable areas and for driving geographically targeted interventions to prevent obesity and diabetes. The data presented here is one step in identifying and evaluating such local data.

In those studies, local-level factors were identified as those at county- as opposed to state-level. However, even county-level CDC data, often based on self-report from the Behavioral Risk Factor Surveillance System (BRFSS), may be inadequate for local policy planning, implementation, and program evaluation purposes. The present analyses offer a paradigm shift by focusing on local factors at the much finer CT level. Such fine-grain data analyses are made possible through access to aggregated BMI data obtained from a health insurer.

Unlike the self-reported heights and weights in BRFSS, the data used here were based on measured heights and weights taken during routine clinic visits. A recent study commented that the reported regional differences in the geographic distribution of obesity in the US appeared to vary depending on whether the data were obtained through direct measures or through self-report (24). In that study, the geographic distribution of obesity was assessed across US Census divisions (spanning several states), and showed that the geographic concentration of obesity at this scale was influenced by use of self-report versus measured data. Such assessments have not been conducted for sub-county areas, but clearly measured heights/weights area preferable over self-report data should they be available.

The present ecological analyses at CT level support and extend previous studies conducted in King County and elsewhere, particularly with regards to the non-random spatial concentration of obesity and the ecologic association between lower area-based measures of SES and a higher prevalence of obesity (6, 7, 16). Our studies on obesity prevalence by ZIP Code, based on BRFSS data from multiple years for King County, observed similar concentration of obesity and a significant association between obesity and residential property values at the ZIP Code scale (7). The observed geographic disparities by ZIP Code or CT were much higher than those traditionally linked to incomes or race/ethnicity as one would expect in an ecologic study.

Although substantial disparities in obesity rates within King County have been observed before (7), this is the first report based on a large population, measured heights and weights, and at the CT level. The local public health deparment in King County (Public Health Seattle King County) routinely presents sub-county data based on BRFSS data for 21 Health Planning Areas (HPA), which are ZIP Code aggregations (25). Future work should explore how use of data from 371 CTs may paint a truer picture of the distribution of obesity compared to geographic aggregations routinely used by public health agencies.

This study demonstrates that the use of granular insurer data to map geographic distribution of obesity can be a potentially valuable tool in public health. The present disparities at CT level stand in contrast to the well-known CDC maps, where the differences in obesity between the richer and the poorer states are only modestly apparent (2, 26). Whereas national maps tend to mask local disparities in both SES and health status, the present data clearly show that obesity was most concentrated in economically disadvantaged areas, and that the association was not explained by differences in the food environment or population density.

The refinement and development of small-area estimation techniques will most likely lead to more sub-state and community-specific analyses (10, 11, 27). Mapping disease prevalence by neighborhood may also provide unique insights into the social and environmental determinants of obesity and health. Demonstrating such relations is beyond the scope of the present ecological study. However, the present results are consistent with past research linking composite CT level measures of deprivation derived from the Census such as the Singh index with individual level health (28). However, composite Census-based measures, including those derived from *a priori* and data driven approaches, can be difficult to interpret because of multiple constructs and variables included (28–32). At the individual level also, obesity rates among women were inversely linked to residential property values after adjusting for numerous socio-demographic covariates (33).

The potential importance of residential property values as a measure of area SES deserves some discussion. Socio-economic variables can affect long-term health and body weight through different causal pathways and at the individual, household, and neighborhood levels. Most individual-level health research has reduced SES to only two variables education and income (34). Previous studies conducted in King County point to the usefulness of residential property values as a wealth metric for health research (28). Whereas past studies have identified CT poverty as a promising area-based predictor of health outcomes (35, 36), in the Seattle area both individual and ecologic studies have pointed to residential property values as being most strongly associated with increased obesity and poor self-rated health (7, 28, 33). In the present analyses, median incomes at the census tract level were associated with the prevalence of obesity, but much less so than either are area-based education or home values.

The limitations of income-based measures of SES have been widely discussed (37, 38). Wealth, as opposed to income, may better reflect both resource availability and social prestige. Wealth-based measures have been shown to be positively associated with obesity in individual-level studies (33, 39). Area-based home values could be considered a proxy for accumulated wealth, since home values are among the most important components of accumulated wealth (40). One conclusion of the present study is that incomes may have limited utility in examining social disparities in obesity, especially at the aggregate level.

The present study had numerous strengths. First, heights and weights were measured in the course of a clinic visit and were not collected through telephone self-report allowing us to estimate the unbiased obesity prevalence, side stepping potential problems using self-reported heights and weights. Second, the large and geographically diverse sample size of nearly 60 000 allowed us to estimate the prevalence of obesity for almost every CT in King County, WA.

This study also had a number of limitations. First, this was an insured population, which may have better health than the general population. Despite this, we observed dramatic disparities in obesity, which may suggest that the true disparities are more profound than observed here. Second, there may have been biases in who provided BMI data. GH members contributing a valid BMI measure tended to be older, have a higher RxRisk score (41), and were more likely to be female. Additionally, the use of aggregated CT data and an ecologic analysis approach does not allow us to generalize the effect of SES on obesity risk at the individual-level, nor does it allow for examination of cross-level effects. For example, from these data we cannot evaluate whether living in a lower value home in an area with low home values has a greater impact on obesity than living in a lower value home in an area with higher home values. Furthermore, the paucity of individual-level measures of SES, race/ethnicity or other factors is an additional limitation and precluded a multi-level analysis from being conducted. Due to privacy concerns, in the present analysis, only age and gender were available as individual-level measures. Lastly, the use of data from the modified Retail Food Environment Index (mRFEI) to account for differences in the food environment may not be the best summary measure reflecting the availability of healthy or unhealthy food.

Nonetheless, the present data show that the prevalence of obesity can be reliably predicted by small area SES, particularly education levels and home values. Together, the area-based measures of median household income, median home value and percent with college education accounted for 68% of the variance in the prevalence of obesity at the census tract level. Further evaluations should explicitly evaluate the value of these measures in formally predicting area-level obesity, which may result in a powerful new tool in policy making and assessment for public health. In particular, the use of insurer health data to map the geographic distribution of obesity can be a potentially valuable tool in public health.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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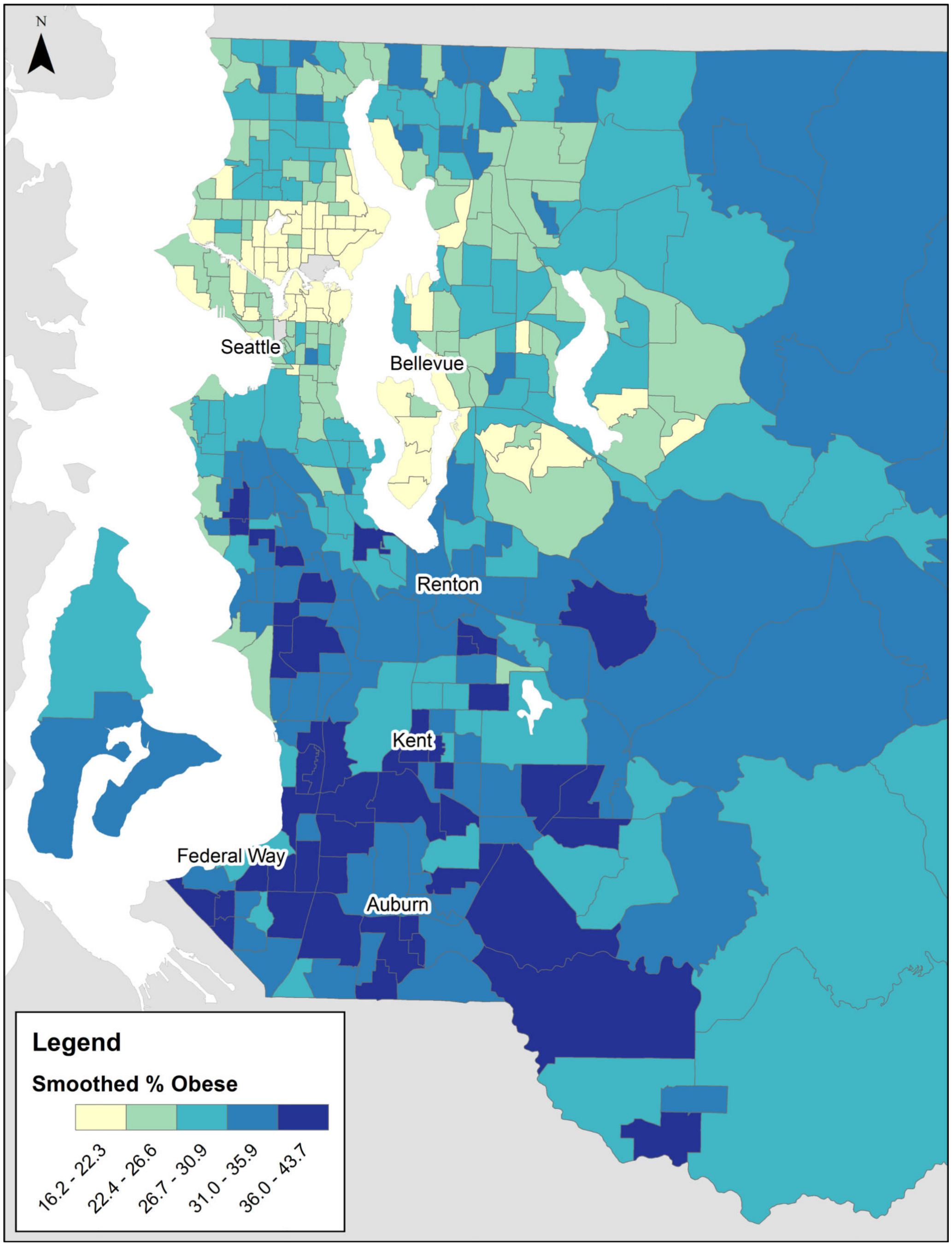

Figure 1.
Map of obesity in adult Group Health members by Census Tract in King County, WA (2005–2006)

Table 1

Univariate Moran's I statistic and bivariate association of socio-demographic variables with smoothed obesity prevalence

	Univariate Spatial Autocorrleation		Bivariate correlation with smoothed % obese
	Moran's I Statistic[1]	**P-value**	**Correlation Coefficient (r)**
Obesity (smoothed)	0.67	<0.001	-
Obesity (crude)	0.65	<0.001	-
Obesity (smoothed, women)	0.61	<0.001	-
Obesity (smoothed, men)	0.50	<0.001	-
Median Household Income	0.61	<0.001	−0.28
% College Graduates	0.81	<0.001	−0.79
Median Home Value	0.63	<0.001	−0.65
Black (%)	0.74	<0.001	0.19
Hispanic (%)	0.43	<0.001	0.38
Population per square mile	0.58	<0.001	−0.28

[1]Higher values of the Moran's I statistics indicate greater extent of spatial clustering for that individual variable. A value of 0 indicates a random spatial pattern, a value of −1 indicates perfect dispersion and a value of 1 indicates perfect clustering.

Table 2

Results of ordinary least squares and spatial regression models for area-based measures of socioeconomic status

	Median Home Value (per $100,000 increase)			% College Graduate (per 10% increase)			Median Household Income (per $10,000 increase)		
	B (95% CI)	AIC[1]	Moran's I of residuals	β (95% CI)	AIC[1]	Moran's I of residuals	β (95% CI)	AIC[1]	Moran's I of residuals
Crude OLS Model	−3.9 (−4.3, −3.4)	2161.2	0.45	−2.6 (−2.8, −2.4)	2007.5	0.27	−0.8 (−1.1, 0.6)	2336.7	0.68
Adjusted OLS Model[2]	−3.3 (−3.8, −2.9)	2098	0.32	−2.6 (−2.9, −2.3)	1969.9	0.17	−1.1 (−1.4, −0.7)	2214.3	0.43
Spatial Error Model[2]	−2.3 (−2.9, −1.8)	2004.1	−0.06	−2.4 (−2.7, −2.1)	1944.5	−0.01	−0.8 (−1.2, −0.5)	2034.5	−0.09

[1] AIC is Akaike's Information Criteria, lower values indicating better model fit

[2] Adjusted for mean age, population density, percent Hispanic and percent non-Hispanic black

Table 3

Results of Gender-specific OLS and Spatial Regression Models

	Median Home Value (per $100,000 increase)			% College Graduate (per 10% increase)			Median Household Income (per $10,000 increase)		
	β (95% CI)	AIC[1]	Moran's I of residuals	β (95% CI)	AIC[1]	Moran's I of residuals	β (95% CI)	AIC[1]	Moran's I of residuals
Men									
Crude OLS Model	−2.0 (−2.3, −1.6)	1944.9	0.31	−1.4 (−1.6, −1.2)	1860.2	0.19	−0.3 (−0.5, −0.1)	2046.8	0.49
Adjusted OLS Model[2]	−1.9 (−2.2, −1.5)	1913.9	0.19	−1.5 (−1.7, −1.3)	1831.6	0.08	−0.5 (−0.7, −0.2)	1985.6	0.29
Spatial Error Model[2]	−1.5 (−1.9, −1.0)	1880.6	−0.04	−1.5 (−1.7, −1.3)	1825.9	0.00	−0.3 (−0.6, −0.1)	1907.2	−0.07
Women									
Crude OLS Model	−3.5 (−3.9, −3.1)	2100.3	0.38	−2.3 (−2.5, −2.1)	1967.7	0.19	−0.9 (−1.2, −0.6)	2264.0	0.61
Adjusted OLS Model[2]	−2.9 (−3.4, −2.5)	2040.4	0.27	−2.2 (−2.5, −2.0)	1950.7	0.14	−1.0 (−1.3, −0.7)	2143.9	0.38
Spatial Error Model[2]	−2.4 (−2.9, −1.9)	1979.5	−0.03	−2.1 (−2.4, −1.8)	1934.0	0.00	−0.9 (−1.2, −0.6)	2014.4	−0.06

[1] AIC is Akaike's Information Criteria, lower values indicating better model fit

[2] Adjusted for mean age, population density, percent Hispanic and percent non-Hispanic black