Using GIS and Secondary Data to Target Diabetes-Related Public Health Efforts

AMY B. CURTIS, PhD, MPH^a

CATHERINE KOTHARI, MA^a

RAJIB PAUL, PhD^b

ELYSE CONNORS, MA^a

ABSTRACT

Objectives. To efficiently help communities prevent and manage diabetes, health departments need to be able to target populations with high risk but low resources. To aid in this process, we mapped county-level diabetes-related rates and resources/use using publicly available secondary data to identify Michigan counties with high diabetes prevalence and low or no medical and/or community resources.

Methods. We collected county-level diabetes-related rates and resources from Web-based sources and mapped them using geographic information systems (GIS) software. Data included age-adjusted county diabetes rates, diabetes-related medical resource and resource use (i.e., the number of endocrinologists and percentage of Medicare patients with diabetes who received hemoglobin A1c testing in the past year), community resources (i.e., the number of certified diabetes self-management education and diabetes support groups), as well as population estimates and demographics (e.g., rural residence, education, poverty, and race/ethnicity). We created GIS maps highlighting areas that had higher-than-median rates of disease and lower-than-median resources. We also conducted linear, logistic, and Poisson regression analyses to confirm GIS findings.

Results. There were clear regional trends in resource distribution across Michigan. The 15 counties in the Upper Peninsula were lacking in medical resources but higher in community resources compared with the 68 counties in the Lower Peninsula. There was little apparent association between need (diabetes prevalence) and diabetes-related resources/use. Specific counties with high diabetes prevalence and low resources were easily identified using GIS mapping.

Conclusion. Using public data and mapping tools identified diabetes health-service shortage areas for targeted public health programming.

^aWestern Michigan University, College of Health & Human Services, Interdisciplinary Health Sciences, Kalamazoo, MI

^bWestern Michigan University Statistics Department, Kalamazoo, MI

Address correspondence to: Amy B. Curtis, PhD, MPH, Western Michigan University, College of Health & Human Services, Interdisciplinary Health Sciences, 1903 W. Michigan Ave., MS-5379, Kalamazoo, MI 49008; tel. 269-387-8447; fax 269-387-8912; e-mail <amy.curtis@wmich.edu>.

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Diabetes is endemic in the United States and its prevalence is increasing. From 2004 to 2010, the age-adjusted rate of diabetes among adults rose from 7.3% to 8.4%, and annual incidence rates continue to rise.^{1,2} Type 2 diabetes accounts for approximately 95% of diabetes cases,³ and this increased prevalence has been attributed primarily to lifestyle changes and the increasing rates of obesity in the U.S.⁴⁻⁶

Diabetes is a chronic condition that involves a considerable amount of medical care as well as careful disease self-management.⁷ In addition to regularly scheduled primary care visits and endocrinology visits for complicated cases,⁸ those with diabetes must adhere to appropriate self-management practices, including glucose monitoring; foot self-examinations; and regimens for nutrition, exercise, and prescribed medications.^{9,10} These lifestyle changes can be confusing, especially regarding nutrition, and adherence is difficult.^{11,12} However, public health strategies, such as individual and group health education within clinic and community settings, have proven effective in facilitating these changes.¹³⁻¹⁶ As a result, diabetes self-management education (DSME) programs are recommended by the American Diabetes Association (ADA) for all people diagnosed with diabetes.^{17,18} Diabetes support groups have also emerged as a popular community resource for diabetes management.¹⁹

Unfortunately, demand for these services is rising at a time that public health budgets are shrinking.^{20,21} In the face of limited public health funds, developing strategies to accurately target services is crucial. Historically, public health data have played a key role, frequently through large-scale surveillance efforts and longitudinal survey studies.^{22,23} However, the expense of collecting these data places them outside the reach of most state and local public health efforts. The increased availability of electronically, publicly accessible health-related information^{24,25} can allow state and local systems to more efficiently target diabetes programming.²⁶ This study describes one such method that was conducted using county-level Michigan data coupled with geographic information systems (GIS), a powerful tool for identifying and communicating problem areas. The purpose of this study was to demonstrate the utility of secondary data analysis and GIS in determining if diabetes rates were associated with diabetes-related resources and resource use, as well as to identify diabetes-related high need/low resource counties within Michigan.

METHODS

Design

We conducted a secondary data analysis using GIS and electronically available published county-level Michigan data. We collected data through two methods: exporting existing datasets and abstracting information published on various websites. Three types of data were collected for each of the 83 counties: diabetes-related health information, population demographics, and diabetes resources and their use. The study region, the state of Michigan, reflects the national trend of increased diabetes, with age-adjusted prevalence growing from 7.7% in 2004 to 9.2% in 2010.²⁷

County attribute dataset compilation

Diabetes-related health data. Due to the positive association between obesity and diabetes,^{5,6} county-level age-adjusted diabetes (2005–2009) and obesity (2009) rates were exported from the Centers for Disease Control and Prevention (CDC) website.²⁸ CDC prevalence estimates were derived from survey responses collected in the Behavioral Risk Factor Surveillance System²⁹ and combined with annual population estimates from the U.S. Census Bureau's Population Estimates Program.³⁰ Diabetes rates were based on the percentage of adult survey respondents who replied “yes” when asked, “Has a doctor ever told you that you have diabetes?” Age-adjusted rates were used to account for the different age distributions within each county. To illustrate the increase in counties meeting the 2009 highest quartile cutoff for diabetes prevalence in Michigan during 2005–2009 (i.e., a rate of 9.5 per 100,000 population), counties were categorized into four groups based on 2009 diabetes prevalence quartiles. Obesity rates were based on the self-reported height and weight of these same respondents; the body mass index (BMI) category was subsequently calculated from these data. The percentage of county adults with an obese BMI were categorized into low obesity counties (i.e., an obesity rate at or below the state median) and high obesity counties (i.e., obesity rates above the state median).

Population size and demographics. Because of the positive association between diabetes and lower socioeconomic status,³¹ rural geography,³² and minority race/ethnicity,³³ we also collected information regarding demographics. The 2009 county population and demographic estimates (race/ethnicity, living in a rural setting, and education) were exported from the County Health Rankings website³⁴ and based upon the Dartmouth Atlas of Health Care,³⁵ which drew the population, rural residence, and race/ethnicity figures from 2009 U.S. Census Bureau data. For the education-level

variable, the County Health Rankings used data from 2006–2010 to determine high school graduation rates (i.e., the percentage of county adults aged 25 years or older with a high school degree or general equivalency diploma). The remaining demographic variable, poverty rate, was defined by the percentage of households with incomes lower than the federally defined poverty rate in 2009 and was manually abstracted from the U.S. Census Bureau website.³⁶

Diabetes resource availability and use. Data on medical resource use (hemoglobin A1c [A1c] testing) and availability (endocrinologists) and community-based resources (DSME programs and support groups) were collected and summarized for each county. A1c testing, exported from the County Health Rankings website³⁴ and based upon the Dartmouth Atlas of Health Care,³⁵ was measured as the percentage of Medicare patients with diabetes who received at least one A1c test in the previous year, and reflected rates from 2009. The number of endocrinologists practicing in each county in 2010 was abstracted from the Ucompare Healthcare website³⁷ and expressed as a rate by dividing this number by 100,000. If an endocrinologist practiced in more than one county, that person was counted in both counties.

The number of DSMEs within each county was manually abstracted from the ADA website,³⁸ and the number of diabetes support groups was abstracted from the Michigan Diabetes Outreach Network website in 2010.³⁹ Similar to the endocrinologist variable, both community resource variables were depicted as rate per 100,000 residents.

For mapping purposes, a county was considered low in a resource when the rate was either at or below the statewide median rate for that resource. Conversely, a county was defined as high in a resource when the county resource rate was above the state median rate.

Developing study maps. Study maps were created using ArcGIS® version 10.2.⁴⁰ A shapefile for the state of Michigan containing county boundaries was imported from the Michigan Center for Geographic Information website.⁴¹ The state map layer was then joined to the county attribute dataset using the five-digit Federal Information Processing Standard county code.

Spatial and statistical analyses. The maps were examined visually to identify low resource/high diabetes counties. Following visual analysis, we used multivariate regression analyses to determine if age-adjusted diabetes rates were predictive of A1c testing after controlling for percentage rural, percentage of population of minority race, percentage of population living below the federal poverty level (FPL), and percentage of the popula-

tion that are high school graduates. The same four covariates were controlled for in modeling whether age-adjusted diabetes rates predicted endocrinologists, DSMEs, and support groups. Due to zero-inflated data, endocrinologists, DSMEs, and support groups were modeled using a two-part regression.⁴² First, we modeled the chances of observing zero using binary logistic regression, where each resource was defined as “yes” (having at least one resource in the county) or “no.” This modeling was followed by a Poisson regression in which the logarithms of the mean of the nonzero responses were modeled. Regression coefficients were estimated using the Expectation-Maximization algorithm.⁴³ We considered the same sets of county-level covariates for both; however, the choice of covariates in the final Poisson models was impacted by the requirement for the zero-inflated Poisson regression that the design matrix of the covariates for the nonzero part be of full rank. This requirement led to different sets of covariates for DSMEs and support groups vs. endocrinologists (Table) to satisfy this criterion.

The alpha level was set at 5% while performing two-sided hypotheses. Statistical analyses were conducted using R software⁴⁴ along with the Political Science Computational Laboratory package contributed by Simon Jackman (Stanford University), Alex Takh, Achim Zeileis, Christina Maimone, and Jim Fearon.⁴⁵

RESULTS

Diabetes prevalence

The series of maps displayed in Figure 1, created for the years 2005–2009 and categorized using 2009 quartiles, demonstrates the increasing prevalence of diabetes across the state overall. However, this increasing trend appears to have slowed in the Upper Peninsula compared with the Lower Peninsula, where the percentage of counties in the highest quartile (as defined by 2009 state numbers, $\geq 9.5\%$) decreased from 27% in 2008 (four counties) to 13% in 2009 (two counties). In the Lower Peninsula, during the same time period, 9% of counties ($n=6$) were in the highest state quartile in 2008 compared with 25% of counties ($n=17$) in 2009.

Medical resources/resource use

Testing levels for A1c ranged from 67% to 95%, with a median of 86%. Twenty-nine percent of Michigan's 83 counties had one or more endocrinology practices, with a median rate of 0 per 100,000 residents (rates ranged from 0.0 to 10.9). When these medical resources and resource use factors were examined against diabetes rates, there appeared to be no relationship between the rates and the availability of these factors. There were

Table. Association between age-adjusted diabetes rates and resource availability and use in Michigan counties (n=83), 2009–2010

Variable	Medical		Community	
	A1c ^{a,b} Beta SE (p-value)	Endocrinologist ^{a,b} Beta SE (p-value)	DSME ^{a,c} Beta SE (p-value)	Support group ^{a,c} Beta SE (p-value)
	Linear regression	Logistic regression	Logistic regression	Logistic regression
County-level age-adjusted diabetes rate	−0.793 0.66 (0.231)	1.508 0.84 (0.072)	10.630 5,218.57 (0.998)	17.974 20.49 (0.380)
		Poisson regression	Poisson regression	Poisson regression
County-level age-adjusted diabetes rate	NA	−0.213 0.19 (0.271)	−0.220 0.17 (0.197)	0.013 0.15 (0.933)

^aA1c = percentage of Medicare patients receiving an A1c test in the previous year, 2009. For endocrinologist, DSME, and support group outcome variables, each was modeled as having the resource in the county, yes or no, for binary logistic regression and then nonzero counts were modeled using Poisson regression.

^bModel controlled for percentage rural, percentage nonwhite minority, percentage below poverty level, and percentage of high school graduates.

^cModel controlled for percentage rural, percentage nonwhite minority, and percentage below poverty level.

A1c = hemoglobin A1c

DSME = diabetes self-management education

SE = standard error

NA = not applicable

clusters of higher A1c testing rates in the Western and Northeastern part of the Lower Peninsula as well as the mid-portion of the Upper Peninsula. There was a lack of endocrinologists in all but Southeast Michigan and in a couple of counties in Northern Michigan.

Twenty-nine of Michigan's 83 counties were low in both medical resources and use. In the Upper Peninsula, the two counties with the highest diabetes rates in 2009 had lower-than-median medical resources/use in 2009. In the Lower Peninsula, less than one-third

(four of 14) of low medical resource/use counties were also high in diabetes (Figure 2).

Community resources

Similar numbers of counties had DSMEs and support groups: 68.7% had one or more DSMEs and 69.9% had one or more support groups in operation. The median rates of these resources were 1.0 per 100,000 population for DSMEs and 1.4 per 100,000 population for support groups. The rate of DSMEs ranged from

Figure 1. Five-year trend of age-adjusted diabetes prevalence for Michigan counties using 2009 quartile categorization^a

^aData were categorized in quartiles by 2009 prevalence rates (percentage of adult population).

Figure 2. Maps of Michigan age-adjusted diabetes prevalence and medical resource availability and utilization (2009–2010)

A1c = hemoglobin A1c

0.0 to 14.9 per 100,000 population, and the rate of support groups ranged from 0.0 to 29.7 per 100,000 population. When examining diabetes rates overlaid by diabetes-related community resources, there again appeared to be no association between rates and resources. Higher rates of both DSMEs and diabetes support groups were clustered in the Upper Peninsula regardless of diabetes rates (Figure 3).

Low resources/use and high diabetes rates

Taken together, three counties in Michigan were identified as higher than the median on diabetes rates and lower than the median on all four measures of resources and their use: Berrien, Ionia, and Van Buren counties. All three counties are located in the southern part of the Lower Peninsula; Berrien and Van Buren counties are in the southwest corner of the state and Ionia is in the central, southern part of the state.

Target population illustration

Two example maps were created to illustrate the potential of such maps to highlight pockets of high need or regions with a particular target population for diabetes-related interventions. The first map in Figure 4 highlights counties with higher than state median diabetes and poverty rates as well as a higher-

than-median percentage of minority populations (nonwhite) for interventions targeting low-income minority populations with diabetes, with clusters noted in West Michigan, in the Bay county region, in Chippewa county in the Upper Peninsula, and in Wayne County (Detroit). The second map shows 16 high diabetes/high obesity/low high school graduation rate counties; the counties are similar to the first map, with notable differences in the Upper Peninsula and the most southern portion of the Lower Peninsula, where the target areas shifted east.

Regression analysis

Similar to the GIS findings, the multivariate regression results indicated that diabetes rates were not associated with any of the county resource/use measures after controlling for other factors (Table). A multivariate linear regression model of those with diabetes in Medicare receiving at least one A1c test in the previous year found no association with age-adjusted county diabetes rates ($\beta = -0.793$, $p = 0.231$).

For each of the zero-inflated outcome variables (endocrinologist, DSMEs, and support group), two sets of regression (logistic and Poisson) results are shown for the age-adjusted diabetes rates. Age-adjusted diabetes rates were not statistically significantly related

Figure 3. Maps of Michigan age-adjusted diabetes prevalence (2009) and community resources (2010)

DSME = diabetes self-management education

to any of the resources in either the logistic or Poisson models ($p > 0.05$).

DISCUSSION

This study illustrates the utility of accessing publicly available secondary data combined with GIS maps to examine resource gaps and target interventions. Policy-relevant findings were obtained quickly, on a relatively low budget, with no threats to human subjects, and with exemption from the Western Michigan University Institutional Review Board. By geographically examining the entire state at the county level, this study demonstrated the wide variation in medical and community resources across the state, a variation that had little apparent link to the severity of a county's diabetes problems, but did show regional and temporal trends. Geographically, the Upper Peninsula was found to be lower in medical-related resources/use and higher in community-based resources, particularly support groups, compared with the rest of the state. Three counties in southern Michigan (Berrien, Ionia, and Van Buren counties) were also identified as being high in diabetes rates and lower than the median on all resources/use. The overall lack of a disease rate-

resource relationship was confirmed with regression modeling; however, the regional trends were identified through the visual analysis of the maps, an interpretation that can be completed without any statistical expertise.

The study findings highlight several health-service shortage areas across medical and community resources. The median percentage of Michigan Medicare recipients receiving at least one A1c test in the previous year, a primary medical management tool, was 86% in 2009, far below the ADA-recommended 100% testing twice a year.⁹ While increased work is needed in this area across the state, it is especially needed in the cluster of lower testing counties seen in the east and south of the Lower Peninsula and east and west ends of the Upper Peninsula. Also related to medical resources, there was one endocrinology practice for every 3,774 patients with diabetes in Michigan; this shortage is typical across the U.S.⁴⁶ However, the finding that the availability of endocrinologists per diabetes patient was unevenly spread throughout the state is important to note. Those in the northern part of the state will likely have to travel much farther, and may have to wait much longer, to access this resource.

A key component of diabetes self-management is

health education. Diabetes education is recommended for all diabetes patients upon diagnosis and as needed thereafter.^{8,9} However, less than 70% of counties had at least one ADA-certified DSME program per 100,000 population with diabetes. Also, the rate of DSMEs was actually lower in a number of high prevalence areas, such as Detroit. Although there is less evidence regarding the effectiveness of support groups, they are a tool that can be used to help those with diabetes self-manage their disease.⁴⁷ The pattern of support groups was somewhat similar to the pattern for DSMEs; the rate was highest in the Upper Peninsula. This finding is different from the medical-related resources/use that were generally more plentiful in the Lower Peninsula compared with the Upper Peninsula.

While this study was one of the first to combine geographic and secondary data to examine an entire state for the county-level distribution of resources relative to the diabetes problem, GIS and public health data have multiple applications in health policy. For example, they can be used to model the spread of infectious diseases to identify vectors, pinpoint spatial clustering of health events, and investigate health disparities.⁴⁸

In a diabetes-related example, one study used national data at the ZIP Code level to determine the impact of disease management programs on geographic regions with high diabetes rates and high densities of minority populations. It found that individuals from high minority areas benefited most from the programs, with a greater increase in A1c testing rates.⁴⁹ Mapping study figures clearly communicates the results to a range of audiences, from community groups to policy makers and administrators, showing statistical relationships through a medium that is commonly understood. When linked with publicly available health information, which is becoming more and more plentiful,⁵⁰ this method has tremendous potential to inform health administration and community advocacy.^{48,51}

The types of spatial and health data used in this study are widely available, an important factor in policy-relevant research.⁵² Spatial shapefiles and community-level demographic data, such as that used in the current study, are obtainable online through U.S. Census TIGER/Line® Shapefiles and associated aggregated U.S. Census data. Summary public health data are available through federal and state surveillance

Figure 4. Identifying target populations for diabetes intervention in Michigan counties^a

^a“High” denotes greater than the state median. All data are from 2009, except percentage of county residents who were high school graduates, which was calculated using County Health Rankings data from 2006–2010. Diabetes rates are age-adjusted.

systems, disease registries, and posted health survey data such as the County Health Rankings, which were used in this study. Health utilization data are available in geographic units, such as ZIP Codes, through hospital discharge data, and in a multitude of proprietary databases maintained by health systems and insurance companies.⁵³ Health-care resource and provider information, as with all of the resource data for this study, can be obtained through Internet searches for specific locations and through directories of professional organizations, such as the ADA, the American Hospital Association, and the American Medical Association.

The potential of GIS and health data can be further extended when supplemented with primary data, such as that collected through surveys and interviews. Typically, as is the case with diabetes, these data can be implemented in smaller geographic units. For instance, a study was conducted that used GIS data collected from interviews regarding places that individuals most frequently visited to aid in targeting a culturally sensitive diabetes prevention program in one rural, southern community.⁵⁴ This mixed-methods GIS approach has been used in other diabetes-related public health assessments to examine the effectiveness of programming,⁴⁷ the health outcomes of a community,^{55,56} the relationship of socio-environmental factors to disease outcomes,⁵⁷ and the association of social network and health knowledge.⁵⁸ Another survey study in Genesee County, Michigan, identified an important problem-resource gap: those living in ZIP Codes with the highest risk for diabetes were the least likely to receive diabetes screening.⁵⁹ This finding is consistent with the lack of association between resources and rates in the current study.

Limitations

Although all counties were included in the analysis, several methodological limitations should be noted. This was a cross-sectional, ecological study that used publicly available data with only one year of data for each of the resources and A1c testing. It cannot be determined if these medical factors and community resources have affected diabetes rates or even if those with diabetes are accessing these resources in their county of residence. Additionally, we were not able to determine if higher resources have led to a decline in diabetes rates. Finally, the dates for the resources and rates were collected from several different sources and included both 2009 and 2010. However, these data can be used to target counties for further examination and to identify geographic areas of potentially high risk/low resources.

CONCLUSION

Using publicly available secondary data with GIS analysis, several regional diabetes-related resource shortages were identified, as was a statewide disconnect between county-level diabetes rates and diabetes resources and use, including A1c testing, endocrinologists, DSME programs, and diabetes support groups. This approach provided policy-relevant information that is useful for public health planning and evaluation.

The Western Michigan University Human Subjects Institutional Review Board (IRB) reviewed the study and deemed it exempt from IRB oversight.

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