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American Indians in the Great Plains Region have the highest diabetes mortality rates in the nation compared with other racial or ethnic groups or American Indians in other regions. Public health officials, Tribal leaders, and community members are calling diabetes an epidemic and serious public health issue. Strategies to prevent and control early mortality from diabetes in this population have not been as effective as needed. Effective prevention and intervention programs require that Tribal leaders and policy makers better understand the epidemic. This requires an investigation into the social determinants of health, and conditions from which differences in diabetes emerge. Examining the risk conditions that result in differential vulnerability in Tribal and county specific environments may provide guidance for public health initiatives aimed at reaching high risk populations. This dissertation uses Tribally-recommended methods for describing diabetes mortality in Great Plains Tribes and county-level diabetes prevalence data within a social determinants of health framework to examine associations between risk conditions and diabetes.

Diabetes mortality data from 2002-2010 were examined to assess differences in mortality among American Indians and whites in the GPR. Diabetes prevalence data and select risk conditions were also assessed through multiple regression analysis. Results show significant regional and Tribal specific differences in diabetes mortality. The social determinants of health were useful in predicting diabetes in the GPR.

DIABETES PREVALENCE AND MORTALITY IN THE GREAT PLAINS REGION AND DIFFERENCES BASED ON THE SOCIAL DETERMINANTS OF HEALTH

by

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CHAPTER I

PROPOSAL

Introduction

Diabetes is a serious public health problem. Diabetes diagnoses have increased significantly in the last two decades, impacting every age group, sex, State, racial and ethnic group in the US (CDC, 2012). In the Great Plains Region (GPR), (Montana, Wyoming, South Dakota, North Dakota, Iowa, and Nebraska) diabetes prevalence has increased sharply since 1995 with South Dakota reporting a 121.4 percent increase compared with just 8 percent in some states (CDC, 2012). American Indians (AIs) are a high risk group and experience disproportionate prevalence, more complications, and premature mortality from diabetes. Mortality from diabetes in the GPR ranges from 80.8 to 119.3 per 100,000 population compared with 25.2 in the US all races population and 64.9 for all American Indians (AI)/ Alaska Natives (AN) based on age adjusted rates (IHS, 2011). Diabetes was the second leading cause of death for AIs in the GPR in 2010 (Giroux & Maschino, 2013) and in the US, AIs die from diabetes at a rate that is 3.3 times higher than non-Hispanic whites (NHWs) (IHS, 2009). Diabetes prevalence and mortality varies among AI populations despite similar geographies, cultures, and histories. For example between 2002 and 2010, the Confederated Salish and Kootenai Tribes in Montana had the lowest mortality rate from diabetes among AIANs in the GPR, 32.5 per 100,000 (SEER, 2013). However, the Omaha Tribe of Nebraska had the highest mortality of all AIANs in the GPR, 179.3 per 100,000 population based on age adjusted rates (SEER, 2013).

Attempts to describe differences between AIANs and NHWs and address diabetes disparities in AIANs have been met with limited success. Previous efforts by the medical community focused on the etiology, biology, prevalence of diabetes in segments of a given population, and on health care delivery standards (Dixon and Roubideaux, 2001; Moy et al., 2006). The majority of published literature on diabetes in AIANs focuses on lifestyle and behavior modification grounded in various individual theories (e.g., Bandura, 1998). However, most of these approaches fail to address the underlying reasons for behaviors that lead to diabetes and premature mortality, namely the social and environmental conditions that influence health behaviors or risk conditions. Risk conditions often include issues of race, poverty, income and low employment, lack of education, rural vs. urban geographies, housing stress, medically underserved areas and persons. Clinical interventions (e.g., hypoglycemic medications) by providers are common and seek to reduce complications in AIANs with diabetes (Gilliland et al., 2002); however, among AIANs non-adherence is common (Keim et al., 2004). The most recent approach to address the diabetes epidemic in AIANs is the Special Diabetes Program for Indians. Reports from this program are not favorable, and show that during the SDPI program period the number of people with diabetes increased, and the number of people receiving specialized diabetes care decreased (Ramesh et.al, 2008). These previous efforts failed to address the risk conditions and the environment from which diabetes may emerge, therefore, immediate actions and new strategies to intervene must be examined. Successful strategies must begin with an understanding the epidemiology of diabetes (O'Connell, et.al, 2010).

Epidemiology of Diabetes. By 2050, 1 in 3 adults could have diabetes (CDC, 2011) and in 2008, 7.8 percent of the US population had diabetes and 57 million had pre-diabetes (Atlas, 2010). Drastic increases in diabetes prevalence nation-wide are already documented. In 1995 only three states reported age-adjusted diabetes prevalence of greater than six percent; however, by 2010, every state in the US reported diabetes prevalence greater than six percent (CDC, 2012). Also, data from the 1995, 2000, 2005, and 2010 Behavioral Risk Factor Surveillance System (BRFSS) show consistent and alarming increases in diabetes prevalence ranging from 8.5% to more than 225% in some states (CDC, 2012). With such increases, it is not surprising that diabetes was the 7th leading cause of death based on US death certificates in 2007 (Atlas, 2010). However, it is likely that deaths from diabetes are much higher than estimated and account for more deaths in AIAN populations than reported due to misclassification of race and underreporting of diabetes. Previous reports indicate that only 10 to 15 percent of death certificates reported diabetes as the underlying cause of death when actually 35 to 40 percent were caused by diabetes (NIDDK, 2011).

Prevalence of Diabetes. In 2010, prevalent cases of diabetes increased to 8.3 percent of the US population or 25.8 million people (CDC, 2011). In AIANs, the prevalence of diabetes is a serious issue and differences in prevalence among AIANs and NHWs require careful investigation to determine why AIANs experience higher prevalence. For example, AIAN youth are 9 times more likely to be diagnosed with diabetes than non-AIAN youth (IHS, 2011a) and between 1990-2009 there was a 110 percent increase in type 2 diabetes diagnoses in AIAN communities (IHS, 2011a). In fact, some AIAN communities report diabetes cases in more than one-third of their population (IHS, 2011b). In the GPR, diabetes prevalence increased from 1995-2010 in every state, with the increases ranging from 36 percent to 121.4 percent (CDC, 2012) (See Figure 1.)

Estimating the prevalence of diabetes among AIANs is difficult because of insufficient tribal specific data (CDC, 2012). For example, in 2010 approximately 15.7 million NHWs reported diabetes cases, and for non-Hispanic blacks there were 4.9 million (CDC, 2012). AIAN specific data are grouped and reported with other minority groups, and in this case made up the remaining 5.2 million cases (CDC, 2012). Higher prevalence results in increased mortality (Smith et.al, 2013) and often mortality is the result of comorbidities.

Comorbidities. People with diabetes often experience comorbidities such as, heart disease, stroke, kidney failure, and many experience increased mortality from pneumonia and influenza (NIDDK, 2013). AIANs experience more comorbidities and more severe complications from diabetes that diminish their quality of life and lead to premature mortality. A recent study compared AI adults with diabetes and the US adult population with diabetes and found higher prevalence of hypertension, cerebrovascular disease, lower-extremity amputations, mental health disorders, and liver disease (O'Connell et al., 2010).

Age. Older age is a predictor of all cause mortality (McEwen et al., 2007) and rates of diabetes increase with age in the US population (Morewitz, 2006). Between the ages of 25-44, death from diabetes occurs in about 7 percent of individuals; however after the age of 75, death from diabetes increases to 13.5 percent (Geiss et al., 2011). For middle-aged individuals with diabetes their life expectancy decreases by 5 to 10 years (Geiss et al., 2011).

Age increases the likelihood of other risk factors. In one study in the GPR, AIs over the age of 45 years were more likely to report hypertension, obesity, and smoking than NHWs or AIs between 18-44 years. This same study reported that AIs over 45 years had higher rates of diabetes (24% vs. 9%), obesity, and smoking (Harwell et al., 2001) than NHWs.

Lifestyles and Behaviors. An extensive body of literature confirms the importance of maintaining healthy lifestyles and behaviors to prevent and control diabetes (Mokdad, et al, 2003; Kumari et.al, 2004). National initiatives such as Healthy People 2020 aim to promote healthy behaviors and decrease lifestyle risk factors associated with diabetes (Lloyd-Jones, et.al, 2010; Koh, 2010). Combined, previous studies and reports confirm that smoking (USDHHS, 2004), obesity (NIH, 2006), physical inactivity (USDHHS, 2005), and unhealthy diets (USDHHS and USDA, 2005) increase the risk of diabetes and death from diabetes.

In sum, diabetes morbidity and mortality is influenced by multiple factors including comorbidities, age, lifestyles, and behaviors. The use of social determinants of health (SDH) framework may provide new insight and understanding about the epidemiology of diabetes as it relates to risk conditions. With new insight about the interplay of these factors, prevention and intervention strategies can be developed to intervene on county-specific conditions that increase diabetes prevalence and mortality.

Justification and Significance of the Research. The proposed study will examine differences in diabetes mortality in AI populations and NHWs by tribal CHSDA region in the GPR. This study will also examine whether differences in risk conditions may explain differences in diabetes prevalence by GPR county. The researcher is not aware of any study that has used county-level data to compare diabetes prevalence and risk conditions in this region using a SDH approach. Importantly, the SDH approach serves as the basis and vision for Healthy People 2020 where the health of the individual is directly linked to the health of the larger community, and the health of communities determines the health status of the Nations (Koh, 2010; USDHHS, 2000).

The goal of the proposed study is to use existing county-level data to describe diabetes related mortality among AIs and NHWs and examine associations between risk conditions (eg., race, poverty, income and low employment, lack of education, rural vs. urban geographies, housing stress, medically underserved areas and persons) and diabetes prevalence in the GPR. Results from this study will provide critical guidance for public health programs and policies to address the diabetes epidemic in this region. This study also supports the Healthy People 2020 goal to reduce diabetes mortality (Barker & Garfield, 2012), congressional demands to address the 'diabetes crisis in Indian Country' (United States, 2010), and the Health and Human Services (HHS) 2012 call to eliminate minority health disparities through integrated approaches in research. Achieving the aims of this study will result in new knowledge about differences in diabetes mortality in AIs, America's highest risk population. This study will also result in new knowledge about the risk conditions, regional differences and social deprivation (i.e., SDH) as a predictor of diabetes prevalence.

Social Determinants of Health (SDH) and Risk Conditions. Risk conditions are based on the SDH's (Halfon, 2012; Marmot, 2005; Mitchell, 2012; Wanless, Mitchell, & Wister, 2010). The SDH paradigm considers the influence of certain risk conditions on a health outcome in a community or population. For example, the SDH's may include: poverty, income, gender, race, culture, stressful environments, inadequate housing and living conditions, urbanization, lack of education, and food insecurity (Malcolm King, 2009; M. King, Smith, & Gracey, 2009; Mitchell, 2012). The SDH framework asserts that health differences stem from social causes and therefore require social solutions (Mitchell, 2012). This differs from a traditional socio ecological approach (Stokols, 1996), where solutions are based on individual risk factors, such as: diet, body weight, physical inactivity, income, healthcare, and age. This study will focus on poverty, persistent childhood poverty, housing stress, low education, medical underservice, percent AIAN, and geographic designation as rural or urban. This focus will provide a deeper understanding of how social deprivation, as defined by the SDH, relates to diabetes prevalence in the GPR. Due to the unique focus of this study, the next section describes the AIAN population, diabetes, tribal regions, risk conditions, medical services and designation.

Study Terms Used

American Indian Alaska Native (AIAN) Populations. AIANs are tribal groups in the United States. The 2010 census reported that 2.9 million people identified their race as AIAN along with another racial category, a 39 percent increase from 2000, and 2.3 million people identified their sole racial classification as AI or AN (Census, 2010). The Bureau of Indian Affairs (BIA) recognizes 562 different tribal groups and of these, 28 reside in the GPR (2012). Preferred identifiers vary by geographical and tribal group and most often, the terms American Indian, Native American, or Alaska Native are used. The National Congress of the American Indian has supported the use of American Indian and Alaska Native as the recognized reference term for the indigenous peoples of the United States. In this proposal AI refers to the indigenous peoples of the GPR; this is mainly because generally ANs do not reside in this region. However, most of the literature and data refer to AIs and ANs by using the term AIAN. AIANs in this study are identified in the data based on self-report status.

Diabetes. Diabetes is a term used to describe two different types of diabetes: 1) Type 1 diabetes also known as insulin dependent diabetes mellitus (IDDM) or juvenile-onset diabetes, and 2) Type 2 diabetes (T2DM) also known as non-insulin dependent diabetes (NIDDM). Type 1 diabetes is marked by "processes of beta-cell destruction that leads to diabetes mellitus in which insulin is required for survival"… (Alberti & Zimmet, 1998, p 545). T2DM includes insulin "disorders or inaction"..(Alberti & Zimmet, 1998, p.545) and is the most common form of diabetes in the US population and among AIANs. T2DM accounts for approximately 95 percent of all diabetes cases (CDC, 2011).

When diabetes is listed as the underlying cause of death, records do not differentiate between Type 1 and T2DM; however, the conditions from which T2DM emerge are significantly different than Type 1. This study focuses on the risk conditions and literature related to T2DM (diabetes).

Death from Diabetes. Physicians, coroners, and others identify the underlying cause of death and report it to the National Center for Health Care Statistics. Death certificates are then coded using the International Classification of Diseases, 10^{th} Revision (ICD-10) standards. This study uses ICD- E10-E14 cause of death codes to examine mortality from diabetes.

Reservation Counties. A county is a geographic area of a state. Federal American Indian reservations are geographic areas with boundaries established by treaties, statutes, or other federal process. Reservations are comprised of counties and may include more than one state (US Census, 2000).

Tribal Contract Health Service Delivery Area (CHSDA) Regions. Tribal CHSDA regions are comprised of counties located on or bordering federally recognized tribal lands (eg.§42 CFR 136.22). Approximately 57 percent of the AIAN population resides in 624 tribal CHSDA counties throughout the US (Espey, et al, 2008) and in the GPR, 110 of the counties have CHSDA status (SEER, 2013). Within these geographic areas health services are provided from public or private medical or hospital facilities at the expense of the Indian Health Service (IHS, 2012). CHSDA counties are used by researchers and federal programs like the US National Institutes of Health to identify AIAN populations and subsequent county-based mortality rates by racial classification

(AIAN vs. NHW). For example, the Surveillance Epidemiology and End Results (SEER) program uses CHSDA status to classify segments of the US population by county, race, region, and disease specific mortality (2013). The use of tribal CHSDA regions is a preferred approach for describing health disparities in AIANs because these areas have higher AIAN populations and often report less misclassification of AIAN status when compared with non-CHSDA counties (Maschino, et al, 2013; Espey, et al, 2008;Cobb & Paisano, 1998). However, the use of tribal CHSDA counties must be approached with caution because tribes do not always feel that federally designated tribal CHSDA regions accurately represent their tribe(s) and tribal members (Giroux, personal communication, January 13, 2013). In this study, the researcher consulted with the Great Plains Tribal Chairman's Epidemiology Center to determine which counties should be included in tribal specific analyses (Maschino, 2013). For example, some tribes in the GPR prefer that reservation counties are used instead of CHSDA counties (Maschino, 2013; Maschino et al, 2012). Also, tribal CHSDA counties may overlap and therefore tribal specific mortality rates must be interpreted with caution. Of the 118 counties included in the GPR, 20 counties overlap and are shared by more than one tribal CHSDA region. In this study, diabetes mortality data is based on 110 CHSDA counties, 8 additional reservation counties. Combined this area makes up 25 tribal CHSDA regions.

Housing Stress. Housing stress occurs when individuals do not have complete plumbing, kitchen facilities, rent and owner costs consume more than 30 percent of income, or homes with more than 1 person per room (ERS, 2003).

Indian Health Service (IHS). The IHS provides health service delivery to more than 2.1 million AIANs in the US (IHS, 2013) and more than 300,000 have diabetes (IHS, 2009). In 2007 IHS and Tribes operated 46 hospitals, 33 ambulatory facilities, 304 health centers, 20 school health centers, and 143 health stations across the US (IHS, 2011). The 2013 IHS budget appropriation was $4.1 billion, equating to $2,741 per capita for health care expenditures compared with the total US population expenditure of $7,239 per capita (IHS, 2013). This shortage often results in medically underserved areas and persons.

Medically Underserved Areas/Persons (MUA/Ps). The Health Resources and Services Administration (HRSA) classifies counties or a group of contiguous counties as medically underserved areas (MUAs) based on the shortage of personal health services (see Appendix A). These areas and this designation includes individuals with economic, cultural, and linguistic barriers to health services (USDHHS, 2013). HRSA uses an index of medical underservice (IMU) to designate MUA/Ps based on the ratio of primary medical care physicians per 1,000 population, infant mortality rate, percentage of incomes below the poverty level, and percentage of population age 65 or older (USDHHS, 1995).

Obesity or Overweight. Obesity or overweight is defined as having a body mass index of $30 kg/m^2$ or abdominal obesity greater than 102cm in men or 88 cm in women (Morewitz, 2006). This study uses self-report height and weight from the BRFSS telephone survey. Individuals with a BMI ≥ 30 (weight [kg] / height $[m]^2$) are considered obese.

Poverty and Persistent Child Poverty. Poverty is defined by the US Census as having an income less than what is needed to purchase basic supplies and shelter to survive (US Census, 2010). The Office of Management and Budget (OMB) establishes a poverty threshold each year and in 2009 the poverty line for individuals under 65 year was $11,161. This amount varies based on age and family composition. This study defines persistent poverty as counties where the poverty rate of residents was 20 percent or more in 1970, 1980, 1990, and 2000. Similarly, persistent child poverty is defined as counties where the poverty rate of children under the age of 18 was more than 20 percent or more in 1970, 1980, 1990, and 2000 (ERS, 2004).

Food Access. Limited access to healthy foods is defined as the proportion of a county population who do not live close to a grocery store and who are low income. In rural areas, this includes populations who live less than 10 miles from a grocery store. In non-rural areas, this includes populations who live less than 1 mile from a grocery store. Low income is defined as having an annual family income of less than or equal to 200 percent of the federal poverty threshold for the family size (RWJF, 2013)

Rural and Urban Classification. More than 20 percent of the US population resides in rural areas, and more than 75 percent of the nation's counties are rural (Hart et.al, 2005). Definitions of rural and urban differ, but often this designation is based on population size, density, proximity, degree of urbanization, adjacency and relationship to a metropolitan area, principal economic activity, economic and trade relationships, and work commutes (see Tables 2 and 3). In this study, the Economic Research Service (ERS) Urban Index Codes (UIC) are used to measure the impact of rurality on diabetes prevalence. The UIC codes were selected based on the following guidelines: 1) measure something explicit and meaningful; (2) be replicable; (3) be derived from available, high-quality data; (4) be quantifiable and not subjective, and (5) have on-the-ground validity (Hart et.al, 2005; ERS, 2004).While beyond the scope of this study, additional information and methodologies for rural and urban designation are available (see Hart et.al, 2005). With this study focus in mind, the next section reviews the literature related to the SDH's and diabetes among AIANs.

Literature Review

Social Determinants of Health. Diabetes prevention efforts tend to focus on individual level factors and behaviors that contribute to diabetes. These efforts may help an individual, but they have had limited impact on the incidence of diabetes in communities or populations. It is in this context that the term 'risk conditions' emerges. Risk conditions in this study focus on issues of race, poverty, income and low employment, lack of education, rural vs. urban geographies, housing stress, medically underserved areas and persons.

Race. In the US, racial and ethnic minorities have poorer health than NHWs (CDC, 2004; Marmot, 2005; Morewitz, 2006). These groups report higher mortality from diabetes and experience more risk conditions (Mitchell, 2012). As a population, AIANs are one of the smallest racial and ethnic minority groups in the US but experience more health disparities (Geiger & Borchelt, 2003) than NHWs and other minority groups (i.e., African American). Factors such as colonization in the form of segregation, oppression, and discrimination are pervasive among AIAN communities (King et al., 2009; Wilson and Yellow Bird, 2005) and may contribute to elevated risk conditions. The predominant racial classification in the GPR is NHW and AIs are the largest minority race in this region (US Census, 2000;2010). As a racial minority, AIs may experience racial oppressions that contribute to health differences (Krieger, 1999;2001). For example, AIs may receive differential treatment because of their race, and Zuckerman and colleagues reported that AIANs perceptions of care interactions with providers were poor when compared with NHWs (2004). AIs with diabetes may experience more discrimination from health care providers than NHWs (Gonzales, et.al, 2013) 2013). These and other studies suggest that race and discrimination in the health care setting may influence how AIs seek care, manage diabetes, and cope with complications from diabetes.

Poverty. The link between poverty and diabetes is not completely clear (Morewitz, 2006), although some studies show that persistent poverty is a condition from which diabetes and obesity emerge (Atlas, 2010). Individuals who live in persistent poverty areas may have higher adult obesity rates, fewer educational opportunities, less access to healthy foods, and lower physical activity (Atlas, 2010). Previous studies report that when individuals live in federally designated poverty areas they have higher rates of all-cause mortality (Waitzman & Smith, 1998). Among AIANs in the US, 28 percent live at or below the poverty level compared with 10.6 percent of NHWs (US Census, 2010). Rates of poverty vary by county in the GPR; however, the GPR includes three counties with the highest poverty rates in the US, where over 47 percent of residents live in poverty compared to the national county average of 15 percent (SAIPE, 2012). Understanding how poverty is associated with diabetes prevalence is important because

AIs and NHWs living in the same counties often experience poverty conditions differently.

Income and Low Employment. AIANs report significantly lower income than NHWs and in 2010 the median income for AIANs in the US was $39,664 compared with $67,892 for NHWs (USDHHS, 2013). Differences in employment status often predict income potential. For example, among AIANs and NHWs over the age of 16 years, 26 percent of AIANs work in management or professional occupations compared with 40 percent of NHWs (US Census, 2010). Low income and low employment are linked with persistent poverty conditions. Both are associated with higher mortality from all causes in the general US population (Castor et al., 2006; Saydah, Imperatore, & Beckles, 2013). In AIs, the link between income, low employment, and diabetes prevalence and mortality is less clear. For example in one recent study, income was a predictor of diabetes mortality in the US population, but not in AIs (Saydah et al., 2013). Also, there are differences in how income and employment impact individuals based on age and gender. In populations under 65 years, premature mortality may be more associated with low income and low employment more than in populations over 65 years (Ali et al., 2011; Backlund et al., 2007). Reasons for this are not clear and this study will examine low income and employment in relation to other SDH's for a more comprehensive understanding of the interplay between income, employment, and health outcomes, like diabetes.

Lack of Education. Lower educational attainment contributes to premature mortality from diabetes. In a previous US population based study, individuals with less than a high school diploma were four times more likely to die from diabetes than individuals with a college degree (Saydah et al., 2013).

Individuals with lower educational attainment also tend to be less healthy and experience more comorbidities from diabetes (McEwen et al., 2007). In 2010, 77 percent of AIANs over the age of 25 had a high school diploma compared with 91 percent of NHWs (USDHHS, 2013). In the US population, diabetes incidence is higher in low education groups and these groups are less likely to be diagnosed or adhere to care (Lopez et.al, 2007). However, data from the 2005-2006 BRFSS reported that AIANs with less than a 12th grade education had the lowest rates of diabetes and rates of diabetes among AIANs increased as education increased (CDC, 2012). In fact, the 2005-2006 BRFSS reported the highest prevalence of diabetes in AIANs with a bachelor's degree or higher and this was also reported in the 1995-1996 BRFSS (CDC, 2012). Although previous studies reported the highest level of education is a stronger predictor of diabetes prevalence compared with household income or occupation (Williams et al., 2010), no study has examined the association between education and other SDH's on diabetes prevalence in the GPR.

Rural vs. Urban Geography. Differences in rural vs. urban locations must be considered to fully understand risk conditions related to diabetes. Rural counties often have more elderly people and children, higher unemployment, higher poverty, and report more chronic diseases (Hart et.al, 2005). Individuals living in rural areas often travel longer distances for medical services. Rural medical services areas are often underfunded, understaffed, and have limited advanced technologies and treatments.

However, despite these barriers, previous studies in the US population report that rates of obesity and diabetes increase when populations move from rural environments to more urban environments (Jernigan, Duran, Ahn, & Winkleby, 2010). Among AIANs, the impact of geography on diabetes and other health outcomes is not completely understood. Unlike most NHWs, AIANs (tribes) are inextricably linked to their native homelands; however, reservation relocation acts forced tribes to adapt to different geographies and many abandoned their traditional diets (Wendorf and Goldfine, 1991) and cultural practices. Importantly, among AIs, urbanization and the loss of ceremonial plants and land base prevent some AIs from engaging in cultural practices that protect against diabetes and other health disparities.

The impact of industrialization, technology, mass media, and migration to urban areas, contribute to obesity, and ultimately diabetes (Candib, 2007; Healy et al., 2008). These impacts contribute to obesogenic environments, where poverty, decreased physical activity, fast food, low and high calorie fetal environments contribute to obesity, diabetes, and death (Candib, 2007). One report published by the State of Montana found diabetes mortality was associated with frontier counties but not with small urban counties (MTDPHHS, 2013). In addition to this, the State reported that when a county contains a reservation (or tribal CHSDA region), prevalent cases of diabetes increases (Gohdes et al., 2004). Combined, this body of literature shows that differences in geography (Isserman, 2005; Bender et.al, 1985) may create risk conditions that increase diabetes prevalence.

Medically Underserved Areas/Persons (MUA/Ps.) Primary prevention and health care are essential for addressing the diabetes epidemic and mortality from diabetes. Health care access and quality contribute to differences in health status and outcomes. Several counties in the GPR are considered MUA/Ps. County-level designation as an MUA/P is a risk condition for diabetes, often compounded in AIs by structural barriers, geographic distance, access to transportation, and reported differential treatment by health care providers. AIANs report less access to hospitals; health clinics or contract health services implemented by the IHS and tribal health programs (IHS, 2013) when compared with the US population. Several studies report access to care as a barrier in seeking treatment for AIANs with diabetes (McEwen et al., 2007; Moy, Smith, Johansson, & Andrews, 2006; Saydah et al., 2013).

The costs of diabetes burdens medically underserved areas and health care systems. On average, people with diabetes have medical costs that are 2.3 times more than individuals without diabetes (American Diabetes, 2008). Nationally and within the GPR, AIs navigate the IHS, a healthcare system that is funded at less than 50 percent of need (IHS, 2013; Zuckerman et al., 2004). In sum, poor quality health care, disparate insurance coverage, incomplete access and under utilization of health care services increase rates of diabetes and complications from diabetes (Roubideaux, 2005; Zuckerman et al., 2004; Stokols, 1992).

Housing Stress. Housing stress has been linked to poor health, reduced physical functioning and increased child mortality (Jacob, Ludwig, & Miller, 2013). Housing stress, part of the built environment, is emerging in the literature as a key risk condition for obesity and diabetes (Jacob et al., 2013). This study uses housing stress as an indicator of the built environment at the county-level. A recent study reported that unaffordable housing may harm health, but no association was found between housing affordability and diabetes (Pollack, Griffin, & Lynch, 2010). The interplay of housing stress on diabetes and subsequent mortality is not understood, but remains a critical issue for the public's health and particularly high risk populations like AIs. This study will examine housing stress' impact on diabetes prevalence and its association with other risk conditions.

Food Access. Poor food access may lead to lead to obesity, a risk factor for diabetes. Disparities in food access have been documented among low-income, minority, and rural populations (Wing et al., 2001). Access to supermarkets with healthy foods promote healthier diets in residents and reduce obesity (Larson, Story & Nelson, 2009). While beyond the scope of this study, food insecurity (Seligman et.al, 200&), fast-food establishments and high-fat content fast-food are associated with increased BMI, a risk factor for diabetes (Block, Scribner, & DeSalvo, 2004). Combined, previous research suggests the SDH framework is appropriate for examining risk conditions and disparities that emerge from food access (Drewnowski & Darmon, 2005).

Combined, AIs living in the GPR navigate stressful environments that ultimately determine health, where inadequate health care (Dixon & Roubideaux, 2001), inferior housing, lack of education, and other conditions create the context from which health disparities like those experienced by AIs with regard to diabetes emerge. Unfortunately, strategies to address these disparities have not been successful (Daniel et al., 1999;

Gilliland, Azen, Perez, & Carter, 2002; Gohdes et al., 2004; Kattelmann, Conti, & Ren, 2010; Knowler et al., 2009) and new approaches that test the SDH framework are desperately needed (Gittelsohn & Rowan, 2011). The SDH approach will support future prevention, policy, and advocacy efforts while taking into account the influence of critical risk conditions and lifestyle and behavior factors.

Lifestyles and Behaviors. Smoking and obesity are the leading cause of preventable mortality in all populations and are associated with higher use of health care services and chronic diseases (Morewitz, 2006). Combined, these contribute to increased diabetes mortality in the US population (McEwen et al., 2007). In this study, smoking, obesity, and physical activity are used as covariates because previous studies have identified these as correlates of elevated diabetes prevalence.

Smoking. Smoking causes up to 50 percent of all preventable deaths in the US (Gohlke, 2004) and is associated with diabetes (Foy et.al, 2005). Rates of smoking in AIs vary by age, gender, education, and region—among the GPR AIs, rates are among the highest in the US with more than 43.7 percent current smokers (CDC, 2010). Data from the 2005-2006 BRFSS report that AIANs between the ages of 18-24 report the highest percentage of current smoking across all age groups (46.2%) and men smoke more than women. Also, AIANs with less than a 12th grade education report the highest levels of current smoking (47.1%) (CDC, 2010).

Obesity. Obesity and overweight are cardiometabolic risk factors associated with diabetes and other chronic diseases (Denny et.al, 2005).In the GPR, rates of obesity among AIANs are increasing, BRFSS data reported 27.3 percent prevalence in 1996 and

34 percent in 2006 (CDC, 2012). One study reported that up to 75 percent of diabetes risk is due to obesity (Costacou and Mayer-Davis, 2003) and obesity combined with other factors like smoking, physical inactivity, alcohol use, and diet have a synergistic effect

Physical Activity. Sedentary lifestyles contribute to diabetes; however, moderate to vigorous physical activity protects against diabetes by reducing obesity and hypertension (Morewitz, 2006). Physical inactivity is a risk factor for diabetes (Michimi & Wimberly, 2010).

Examining SDH's and diabetes in the GPR will test the SDH framework and result in new knowledge about the associations between SDH's and diabetes mortality and prevalence.

Methodology

This study utilizes a cross-sectional ecologic study design to compare diabetes mortality by tribal CHSDA and diabetes prevalence by county in the GPR. The overall goal of this study is to increase understanding and awareness of differences in diabetes prevalence and mortality in the GPR among AIs and NHWs based on a SDH framework. This study will use existing data from SEER which includes cause of death by race, county and year to describe differences in cause specific mortality rates from diabetes among 28 tribal CHSDA regions in the GPR. Diabetes prevalence data, lifestyle, and behavior risk factors for 390 counties in the GPR will come from the 2004 BRFSS (CDC, 2013). Risk conditions based on the SDH framework will come from the USDA's 2004 Economic Resource County Typology Codes (ERS) database and the Health Research Service Administration (HRSA).The specific aims of this proposal are:

1) Compare AIAN and NHW mortality rates from diabetes among tribal CHSDA regions in the GPR and describe disparities observed; and

2) Examine associations between SDH and diabetes prevalence in the GPR.

Description of Study Area. The GPR as defined for the study encompasses six states and 28 tribal CHSDA regions: Montana, Wyoming, North Dakota, South Dakota, Nebraska, and Iowa. This does not include MN, which is sometimes defined as part of the GPR because the Great Plains Tribal Chairman's Health Board does not serve tribes in MN, and the researcher was unfamiliar with these tribes and tribal CHSDA designation. Combined, the GPR includes six states, 390 counties, 7,641,494 persons, of whom 74.6 percent were NHW and 4.17 percent AIAN based on data from 2005 (ACS, 2005). This study focuses on 78.8 percent of the population who are AIAN or NHW, other racial groups in the region include Hispanic/Latino, Black, two or more races, and other (Census, 2010). Because the predominant racial classification in the GPR is NHW and AIAN this study will focus on these groups and observed differences.

Secondary Data. The Surveillance, Epidemiology, and End Results (SEER) Program provides US mortality data from 1969-2010 from the National Center for Health Statistics (SEER, 2013). The Economic Research Service (ERS) classifies counties into 9 groups, 2 metropolitan and 7 nonmetropolitan based on the 2000 Census (Hart et.al, 2005). BRFSS data includes information on select health behaviors and conditions collected through a state-based, ongoing, and random-digit–dialed telephone survey for noninstitutionalized U.S. civilian adults aged ≥18 years (CDC, 2013). The American

Community Survey (ACS) data comes from a nationwide survey that collects population and housing characteristics on an ongoing sample basis (ACS, 2007). The Health Resources Services Administration (HRSA) uses an index of medical underservice to designate medically underserved areas and persons (MUA/P) throughout the US. The US County Health Rankings estimates limited access to healthy foods using data from the USDA Food Environment Atlas (RWJF, 2013).

Aim 1. Compare AIAN and NHW mortality rates from diabetes among tribal CHSDA regions in the GPR and describe disparities observed

Aim 1 Data. SEER*Stat data will be used to examine diabetes as the underlying cause of death by AI vs. NHW status for from 2002-2010. Multi-year data will be aggregated from 2002-2010 to limit potential instability of county rates (Espey, et.al, 2008). Aim 1 will compare differences in age-adjusted diabetes mortality rates of AIANs to NHWs by tribal CHSDA region in the GPR using the 2000 US standard population (SEER, 2013). National vital statistics provide coverage of deaths within the GPR by county and the National Center for Health Statistics data includes county of residence and underlying cause of death for each decedent in the United States by year. Deaths are coded according to International Classification of Disease, 10th Revision (ICD-10) standards and only underlying causes of death (ICD 10 E10-E14) will be used to calculate mortality rates from SEER 2002-2010 US mortality registry (SEER, 2013). Tribes, reservations, and counties have been identified and defined previously (Giroux & Maschino, 2013). Tribal CHSDA region data will be used because it provides the most comprehensive measure of mortality between AIANs and NHWs in the GPR. In order to calculate tribal CHSDA region death rates from diabetes between AIANs and NHWs living in the same county, Aim 1 will combine multiple counties that make up a tribal CHSDA region to calculate deaths rates from diabetes from 2002-2010. This approach follows previous research, and was recommended by the Great Plains Tribal Chairman's Health Board Epidemiology Center (Maschino,et. al, 2013; Espey, et.al, 2008). Table 1 describes the proposed variables that will be used and the dataset complied on each county in the GPR (see Table 1).

Aim 1 Analysis. Aim 1 will use descriptive epidemiology to examine observed differences in diabetes mortality in the GPR among AIANs and NHWs by tribal CHSDA region. Diabetes mortality rates will be expressed per 100,000 persons and age-adjusted to eliminate the effect of differences in age composition among AIANs and NHWs (Espey, et.al, 2008). Data are suppressed by SEER when <10 deaths occurred during the time period of interest (SEER, 2013). Available mortality data will be abstracted and aggregated for AIs and NHWs for twenty-eight tribal CHSDA regions in the GPR to describe diabetes mortality rates and rate ratios. Aim 1 will compare mortality rates between AIANs and NHW populations by rate ratios (RR) with 95% confidence intervals (CI). For this comparison when the rates differ significantly from 1.0 (p<.05) the terms higher and lower will be used. SEER*Stat 8.0.4 software will be used to calculate age-adjusted diabetes mortality rates (2013). Microsoft Excel and SPSS version 20.0 will be used to create charts, figures, and other graphs as needed.

Aim 2. Examine associations between SDH, lifestyle and behavior risk conditions and diabetes prevalence in the GPR.

Aim 2 primary research question:

What is the effect of social deprivation on diabetes prevalence in the GPR?

Aim 2 sub questions:

1. What condition(s) appear most useful in predicting diabetes prevalence?

2. Is there an association between percentage AIAN by county and diabetes prevalence?

3. Is there a difference in diabetes prevalence between tribal CHSDA region county designation and non tribal CHSDA region designation?

4. Is there a difference in diabetes prevalence between rural and urban areas?

5. Is there a difference in diabetes prevalence between counties with housing stress and without housing stress?

6. Is there a difference in diabetes prevalence between counties with low education and regular education designation?

7. Is there a difference in diabetes prevalence between counties with persistent poverty designation and counties without persistent poverty designation?

8. Is there a difference in diabetes prevalence between counties with persistent child poverty designation and non-persistent child poverty designation?

9. Is there a difference between MUA/P designation and non MUA/P designation in diabetes prevalence rates?

10. Is there an association between percentage food access by county and diabetes prevalence?

11. Is there an association between percentage college degree by county and diabetes prevalence?

Covariates for Aim 2 include smoking, physical inactivity, and obesity.

Aim 2 Data. U.S. Department of Agriculture (USDA) Food Environment Atlas provides county-level data on a variety of risk conditions (see Table 2). Data from the 2004 Economic Research Service (ERS) will be used to assess counties (see Table 3) for housing stress, low education, low employment, persistent poverty, and persistent child poverty. The data in the Atlas are sourced from different government entities for all 3141 U.S. counties and provide extensive coverage for the GPR counties (n=390). Diabetes prevalence, obesity, smoking and physical inactivity will be extracted from the Centers for Disease Control (CDC) BRFSS. BRFSS is a national random digit dial telephone survey representative of the total non-institutionalized population over 18 years of age living in households with a land line telephone. All data from the BRFSS are weighted by population and measures are age-adjusted (Nelson et.al, 2001). Also, HRSA designates counties as Medically Underserved Areas/Populations (MUA/P) based on a composite index score (0-100) which represents the best and least served areas in the US (see Appendix A). Table 4 lists all the variables for Aim 2 and the definitions and data sources.

Aim 2 Analyses. There is not a standard approach for measuring the SDH's in the GPR; however, guidelines for measuring what Krieger and colleagues call *social class* have been used as a reference in the design of Aim 2 (1997). Also, in the development of this proposal there were extensive discussions about the use of a social deprivation index to examine predictors of diabetes prevalence in the GPR. However, based on expert advice (Richter, personal communication, September 15, 2013), these variables will not be combined into an SDH index. In the event that preliminary analyses of Aim 2 data suggest an index or combined score would be helpful in answering the primary research question, "What is the effect of social deprivation on diabetes prevalence in the GPR?" a social deprivation index score will be calculated from the SDH risk conditions based on recommended guidelines (Krieger et.al, 1997). Analyses will be conducted to examine associations of select SDH risk conditions with diabetes prevalence rates (dependent variable) for 390 counties in the GPR. Risk conditions will be examined based on county-level diabetes prevalence rates only because AI and NHW diabetes prevalence are not available.

The first step in the analysis process will include running descriptive statistics (e.g., mean, median, standard deviations) on each of the independent variables (e.g., percent AIAN, age, rural/urban, housing stress, education, poverty, MUA/P). Scatter plots will be used to examine bivariate relationships between these variables and diabetes prevalence. Outliers will be assessed. A correlation matrix will be used to get a better sense of how independent variables relate to diabetes prevalence and to each other. Once complete, a multiple regression model will be used to fit each independent variable (predictor) separately with covariates of smoking, obesity, and physical activity. In the initial multiple regression model only those that are statistically significant by themselves will be included. The significance level of $p<.20$ will be the criterion at this stage of the analysis (Richter, personal communication, October 12, 2013). Results from each regression model will be examined and counties with higher prevalence of diabetes will be compared with counties that have lower prevalence of diabetes.

This process will begin with graphing the data and reviewing the correlation coefficient for each explanatory variable. R^2 values will determine the amount of variation around the regression line. The regression results from SPSS will be used to determine if the slope is significantly different from zero at the .20 % level. Significant relationships will be explored for each explanatory variable and diabetes prevalence. Residuals from the regression model will be examined. Covariates include smoking, obesity, and physical activity. Results for each regression model will be examined and counties with higher prevalence of diabetes will be compared with counties that have lower prevalence of diabetes.

Multiple linear regression will examine explanatory variables and diabetes prevalence where Y is the prevalence of diabetes or dependent variable, the Xs represent the explanatory (predictor) variables, and bs are regression coefficients. Covariates are also included in this model but based on results of model fitting, some of these variables may not be included (see Figure 2.).

The results of this model will increase understanding about the conditions most useful for predicting diabetes prevalence. This process will include entering diabetes prevalence by county as the dependent variable in the linear regression model and the risk conditions as independent variables. A purposeful selection method will be used to examine independent variables in the order of their explanatory power. Missing values will be omitted with the multiple regression fitting. In the event several values are missing, a multiple imputation method will be used to impute missing values. Additional statistics to assess the validity of the linear regression analysis will be examined. Residual plots will be used to assess the validity of assumptions.

Specifically, question 1 will combine questions 2-10 into a multiple regression model to determine which conditions best predict diabetes. Questions 2, 4, 10, and 11 are continuous variables and data for 390 counties will be used. Questions 3, 5, 6, 7, 8 and 9 are dichotomous variables reported by "0"= no and "1"=yes. For question 2, "Is there an association between percentage AIAN by county and diabetes prevalence?" 2004 age-adjusted BRFSS prevalence data by county all races will be used. For question 4, "Is there a difference between rural and urban areas and diabetes prevalence?" ERS UIC codes will be used. The UIC index ranges from 1-9, with 1 being the least rural and 9 being the most urban. In this study no county was designated as a metro area of 1 million population or more (n=0), therefore, for this study, the index will range from 2-9.

For question 9, "Is there a difference in diabetes prevalence between counties with MUA/P designation and non MUA/P designation?" the MUA/P indexed score for each county will be used, ranging from 0-100. The individual scores for MUA/P counties will be used to dichotomize MUA/P status, this will be done by calculating the number of counties with scores>62 as "0"= No MUA/P and < 61.9 as "1"= Yes MUA/P status. For question 10, “Is there an association between percentage limited food access by county and diabetes prevalence?” data from the 2005 County Health Rankings will be used.

This overall approach is warranted because previous literature in other populations show that rural areas, housing stress, low education and low employment are associated with mortality and in some cases diabetes prevalence; however, these studies have not been conducted with this population or region and therefore it is not clear how these will be associated with the outcome of interest.

Missing data. Due to the nature of this study, data will not be excluded from analysis when they are missing or are greater than two standard deviations (SD) from the group mean (Donders, van der Heijden, Stijnen, & Moons, 2006).

Data cleaning and transformation. The process of data cleaning and transformation has begun because it was impossible to propose a study without knowing which data would be available. Data cleaning and transformation will continue to ensure all variables can be analyzed. In the event that recoding is necessary, data will be computed and appropriate transformations will be conducted and documented in a data log book (Donders et al., 2006). Variables will be extracted from aggregate data sources, and the proposed research will follow all data specific terms. This study will report power post-hoc, based on the analyses and variables included above. However, it is known that for Aim 1, data for 26 of the 28 tribal CHSDA regions are available, and for Aim 2 data coverage for all GPR counties (n=390) are available. Combined, this coverage will answer the research questions.

Research Validity. Accurately reporting and assessing diabetes mortality in all populations including AIs can be challenging, where death certificates are often not completed, inaccurate, or underreport American Indian status (Geiss, Herman, & Smith, 2011; Gohdes et al., 2004). Another challenge with reporting and estimating diabetes deaths stems from the complications and comorbidities associated with diabetes (Morewitz, 2006). For example, the majority of diabetes-related deaths report the underlying cause of death as cardiovascular disease and a contributing cause of death as diabetes. However, once the underlying cause of death is identified, it is reported to the National Center for Health Care Statistics. Death certificates are then coded using the International Classification of Diseases, 10th Revision (ICD-10) standards. These data are used by Surveillance Epidemiology End Results (SEER) and other government databases to examine mortality rates and trends in the US population.

Another threat to validity relates to the BRFSS prevalence data reported. AIANs may not be represented in the BRFSS adequately because until 2011, the survey relied on landline telephones to reach participants and many AIAN households do not have them. In one study, 76.4 percent of AIAN households had landlines compared with 95 percent of NHWs (US Department of Commerce, 1999) and therefore surveys such as the BRFSS may not reach AIAN households. Also, self-report data from the BRFSS is subject to recall bias; however, previous studies report the survey findings are both reliable and valid (CDC, 2012).

The validity of this study is largely based on the use of national datasets that attempt to account for representation of AIAN status and diabetes mortality and county-level diabetes prevalence. Measures of risk conditions are defined through complex sampling, expert extrapolation and statistical transformation of missing or skewed data.

Limitations. This study has several strengths, and some methodological limitations. First, it is an ecological study and therefore is subject to ecological fallacy, meaning the risk conditions in counties may not apply to individuals within these counties (Morgenstein, 1995). However, several studies and public health policies stress the importance of ecologic studies in determining population-level factors related to health disparities. Second, this study uses secondary data sources and while these data sources use the best available statistical methods and methodological designs, there are limitations within each of these data sets. Third, this study does not address or have access to genetic information related to diabetes mortality or prevalence. Genetic or family traits are likely influenced by environmental factors and therefore, race in conjunction with other conditions (age, poverty, unemployment, housing, education) should be considered to fully understand reasons for differences in diabetes mortality among AIANs and NHWs. Future studies should examine gene-environment interactions and risk conditions for a more comprehensive assessment of risk conditions and linkages. Fourth, the racial classification of NHW or AIAN within the study population for mortality is based on descriptions of race in the medical record that may have been coded differently by the national datasets. When a deceased person is biracial, interracial, mixed, multiethnic, multinational, multiracial these individuals are coded as unknown. This study does not include Hispanic mortality rates because most data are unreliable due to small numbers, and the recommended comparison group for the GPR is AIANs and NHWs (Maschino, et.al, 2013).

These limitations are balanced by several strengths including these: tribally-recommended design, increased secondary data source is efficient, and ultimately this study will lead to improved understanding about the associations of diabetes and risk conditions by county in the GPR.

Ethical Issues. There are no foreseeable ethical issues that would be manifested as a result of this study.

Data Storage. All data comes from publically available data sources in aggregate form with no individual identifiers. However, precautions to protect and maintain the highest level of data quality will be taken. Data will be downloaded from public sources and saved on a Drop Box file that allows committee members to review and access data. A data log will also be saved in this location and include comments about the data, challenges, and possible issues. All files will be date stamped and saved on an external, password protected external hard drive. Once the dissertation is completed, the student will maintain these files until a future time when they are no longer needed.

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CHAPTER II

DIFFERENCES IN DIABETES MORTALITY AMONG AIANS AND WHITES IN THE GPR

Abstract

To compare American Indian and white mortality rates from diabetes among Tribal Contract Health Service Delivery Areas (CHSDAs) in the Great Plains Region (GPR) and describe disparities observed. Mortality data from the National Center for Vital Statistics and Seer*STAT were used to identify diabetes as the underlying cause of death for each decedent in the GPR from 2002-2010. Mortality data were abstracted and aggregated for American Indians and whites for twenty-five reservation CHSDAs in the GPR. Rate ratios with 95% confidence intervals were used and SEER*Stat 8.0.4 software calculated age-adjusted diabetes mortality rates. Age adjusted mortality rates for American Indians were significantly higher than whites during the 8-year period. In the GPR, American Indians were 3.44 times more likely to die from diabetes than whites. South Dakota had the largest rate ratio (5.47 times that of whites), and Iowa had the lowest rate ratio, (1.1). Reservation CHSDA rate ratios ranged from 1.78 to 10.25. American Indians in the GPR have higher diabetes mortality rates than whites in the

GPR. Mortality rates among American Indians persist despite special programs and initiatives aimed at reducing diabetes in these populations. Effective and immediate

efforts are needed to address premature diabetes mortality among American Indians in the GPR.

Introduction

Deaths from diabetes have increased significantly in the last two decades, impacting every state, age group, sex, and racial and ethnic group in the US (CDC, 2014). However, some regions and populations carry a disproportionate burden of diabetes. Diabetes was the 4th leading cause of death among American Indians and Alaska Natives between 1999-2010 and the 7th leading cause of death in the US population (IHS, 2011). Diabetes was the second leading cause of death for AIs in North Dakota, South Dakota, Iowa and Nebraska in 2010 (Giroux & Maschino, 2013); however, these rates may be 15 to 25 percent higher because death certificates often underreport diabetes as the underlying cause of death. To address mortality differences, public health officials, Tribes, and policy makers must first document Tribal specific disparities. However, this task is often difficult to complete due to the lack of Tribal specific data, small populations, and confidentiality issues. In addition, there is a lack of substantial data and poor surveillance infrastructure in Tribal communities. No known published study has examined mortality rate differences in diabetes among AIs and whites residing in the same reservation areas in the Great Plains Region (GPR), (Montana, Wyoming, South Dakota, North Dakota, Iowa, and Nebraska).

Persons with diabetes often experience comorbidities such as heart disease, stroke, and kidney failure. Many diabetics s experience increased mortality from pneumonia and influenza (O’Connell et.al, 2010). American Indians experience more comorbidities and more severe complications from diabetes that lead to premature mortality. A recent study in South Dakota compared American Indian adults with diabetes and the US adult population with diabetes and found higher prevalence of hypertension, cerebrovascular disease, lower-extremity amputations, mental health disorders, and liver disease among the AI adults (Christensen & Kightlinger, 2013).

Often American Indians experience more risk factors for diabetes complications than other racial and ethnic groups. American Indians over the age of 25 are less likely to have a college degree or high school diploma and among AIs, 77 percent have a high school diploma compared with 91 percent of whites (Census, 2012). American Indians report higher rates of smoking, obesity, and unhealthy diets, all of which increase the risk of diabetes and death from diabetes (NHLBI, 2010; Jernigan, et.al, 2010). American Indians report significantly lower income than whites. In 2010, the median income for AIs in the US was $39,664 compared with $67,892 for whites (Census, 2012). Low income is linked with persistent poverty conditions. Both lower income and persistent poverty are associated with higher mortality from all causes in the general US population (Saydah, Imperatore, & Beckles, 2013).

American Indian communities experience segregation, oppression, and discrimination often linked to colonization (King & Gracey, 2009;Wilson & Yellow Bird, 2005) and these factors may contribute to differences in diabetes mortality and inequalities in health outcomes across Tribal nations. As a racial minority, American Indians may experience racial oppressions that contribute to health differences (Krieger, 2001). American Indians may experience more discrimination from health care providers than whites (Gonzales, et.al, 2013) and this may influence how they seek care, prevent or manage diabetes, and cope with complications from diabetes. Health care service and delivery for AIs are often described by geographic region. One unique contribution of this study is the use of a tribally recommended approach for calculating reservation specific mortality rates (Maschino, 2013).

In the GPR, AIs represent a relatively small percent of the population as a racial minority. However, AI are an important group to study because of mounting evidence that they experience extreme health disparities and premature mortality (Gohdes, et.al, 2004; Christensen & Kightlinger, 2013;Geiger & Borchelt, 2003). Similarly, in the US, racial and ethnic minorities have poorer health than whites (Marmot, 2005; Morewitz, 2006; CDC, 2004) and report higher mortality from diabetes.

The purpose of this study is to document diabetes mortality among AIs and whites in the Great Plains Region and describe disparities observed.

Research Design and Methods

Description of Study Area. The GPR as defined for the study encompasses six states and 25 Tribal CHSDA regions: Montana, Wyoming, North Dakota, South Dakota, Nebraska, and Iowa. This does not include Minnesota or Wisconsin, which are sometimes defined as part of the GPR because the Great Plains Tribal Chairman's Health Board and the Montana Wyoming Tribal Leaders Council were partners in this study, and they do not serve tribes in Minnesota or Wisconsin areas. Combined, the GPR includes six states, 390 counties, 7,641,494 persons, of whom 74.6 percent were white and 4.17 percent AI (Census, 2010). This study focuses on 78.8 percent of the population who are

AI alone or white alone. Other populations in the GPR include Hispanic/Latino, Asian Pacific Islander, African American, Native Hawaiian, and two or more races; however, the predominant racial classification in Montana, South Dakota, and North Dakota is white alone and AI alone. This study will focus on these groups and observed differences.

American Indians. American Indians and Alaska Natives (AI/AN) are Tribal groups in the United States therefore are not truly ethnic minorities. The 2010 census reported that 5.2 million people identified their race as AI/AN alone or in addition to another racial category. Of these, 2.9 million identified AI/AN alone and 2.3 million people identified as AI/AN in combination with another race. The AI/AN population has increased 39% since 2000 (Census, 2012). The Bureau of Indian Affairs recognizes 566 different Tribal groups and of these, 25 reservations are located in the GPR (DOI, 2013). In this study, AI refers to the indigenous peoples of the GPR. Few ANs reside in this region. American Indians in this study were identified in the data based for death certificates.

Reservation CHSDA Regions. Contract Health Service Delivery Areas (CHSDA) regions are comprised of counties located on or bordering federally recognized Tribal lands (e.g. §42 CFR 136.22). Approximately 57 percent of the AI population resides in 624 Tribal CHSDA counties throughout the US (Espey, et.al, 2008). In the GPR, 110 of the counties have CHSDA status. Within these CHSDA areas health services are provided from public or private medical or hospital facilities at the expense of the Indian Health Service if funding is available. CHSDA counties are often used by researchers and federal programs to identify AI populations and subsequent county-based mortality rates by racial classification (AI vs. white). For example, the Surveillance Epidemiology and End Results (SEER) program uses CHSDA status to classify segments of the US population by county, race, region, and disease specific mortality (SEER, 2014). Reservation CHSDA regions have higher AI populations and often report less misclassification of AI status when compared with non-CHSDA counties (Giroux & Maschino, 2013; Espey et.al, 2008). However, the use of reservation CHSDA counties must be approached with caution because Tribes do not always feel that federally designated reservation CHSDA regions accurately represent their Tribe(s) and Tribal members (Giroux, personal communication, January 13, 2013). In this study, the researcher consulted with two Tribal Health Boards in the GPR, the Northern Plains Tribal Epidemiology Center and the Montana Wyoming Tribal Leaders Council, to determine which counties should be included in Tribal specific analyses. For example, some Tribes in the GPR prefer that reservation counties are used instead of CHSDA counties (Giroux & Maschino, 2013). Also, reservation CHSDA counties may overlap and therefore Tribal specific mortality rates must be interpreted with caution. Of the 118 counties included in the GPR, 20 counties overlap and are shared by more than one reservation CHSDA region. In this study, diabetes mortality data is based on 110 CHSDA counties, and 8 additional reservation counties. Combined this area makes up 25 reservation CHSDA regions.

The reservations, and counties linked to Tribes in the current study were identified and defined based on previous work with Tribal leaders in the area (Giroux & Maschino, 2013) and county designations from the 2000 US Census. Reservation

CHSDA region data were used because Tribal registries are not available in these areas, and reservation CHSDAs provide the most comprehensive area to measure of mortality between AIs and whites in the GPR. In order to calculate reservation CHSDA region diabetes mortality rate ratios between AIs and whites living in the same county, this study combined multiple counties that make up reservation CHSDAs. Tribes and reservations were designated based on federal recognition and the counties that made up reservation boundaries (Census, 2010).

Data. SEER*Stat data were used to examine diabetes as the underlying cause of death by AI vs. white status from 2002-2010. Multi-year data were aggregated from 2002-2010 to limit potential instability of county rates, as suggested by a previous research report (Espey et.al, 2008). The National Center for Vital Statistics National Statistics System in the U.S. provides coverage of deaths within the GPR by county and includes county of residence, race/ethnicity, and underlying cause of death for each decedent by year. Only individuals who self-reported one race, American Indian (or Alaska Native), were counted as decedents in the numerator. Population characteristics from the 2000 Census were used to calculate rates and only individuals who self-report as exclusively American Indian (or Alaska Native) were included in the denominator. We do not anticipate there were many miscoded AIs, as very few ANs (<.01%) reside in this geographic area. Deaths coded according to the International Classification of Disease, 10th Revision (ICD-10) standards and only underlying causes of death “Diabetes Mellitus” (ICD 10 E10-E14) were used to calculate mortality rates from the SEER 2002-2010 US mortality registry (NCI, 2014).

Diabetes mortality rates were expressed per 100,000 persons and age-adjusted to eliminate the effect of differences in age composition among AIs and whites. SEER*Stat 8.0.4 software calculated age-adjusted diabetes mortality rates using the 2000 US standard population. Data were suppressed by SEER when <10 deaths occurred during the time period of interest. Mortality rates between AIs and white populations were compared by rate ratios (RR) with 95% confidence intervals (CI).

Results

The age-adjusted diabetes mortality rates among AIs residing in reservation CHSDA areas were significantly higher, 71 per 100,000, than whites residing in the same areas, compared with 20.6 per 100,000. In the GPR, this mortality rate ratio is 3.44 times higher than whites. This is significantly higher than the US mortality rate for AI/ANs of 20.5 per 100,000 (NCI, 2013). Table 5 shows differences in mortality rates by state in the GPR, with South Dakota having the highest mortality rate ratio of any state in the region. In all GPR states, the mortality rates for AIs were significantly higher than each state than whites except Iowa.

There was variation in mortality rates from diabetes by reservation CHSDA region. The Confederated Salish and Kootenai Tribes of Montana had the lowest rate ratio, 1.78 times higher for AIs than whites in the same reservation CHSDA counties. While the Sac and Fox Tribes of Iowa had the highest rate ratio, 10.25 times higher for AIs than whites in the same reservation CHSDA counties. This was surprising based on the state-specific rate ratios in Table 5, where Iowa had the lowest rate ratio (1.1) between AIs and whites aggregated at the state level. However, the mortality rate for the

Sac and Fox Tribes of Iowa includes only those CHSDA counties within or bordering the reservation. American Indians living off the reservation experience lower diabetes mortality than those living on the reservation. The Omaha Tribe of Nebraska had the highest rate, 181.9 per 100,000 population followed by the Sac and Fox Tribes of Iowa. South Dakota had more reservations with rates higher than North Dakota, Montana, or Wyoming, (see Table 6).

There was substantial variation between AIs and whites in the same geographies. There was also variation between Tribes and by geographies. For example two Tribes in Montana shared one county; however, one Tribe's diabetes mortality rate ratio was 5.91 compared with the other Tribe's rate ratio of 3.84. Both rate ratios were higher than the Montana rate ratio of 3.36; however, one Tribe was significantly higher than both. In South Dakota, two Tribes shared one county and their mortality rate ratios were 5.3 and 5.8. These rates were similar to the South Dakota state ratio of 5.47.

Conclusions

American Indians experience higher mortality from diabetes than whites living in the same geographic areas, in this case reservation CHSDAs and specific states. This may be related to several risk factors and conditions described in previous reports, including low income, low education, obesity, smoking, genetic predisposition, westernization, loss of traditional foods, barriers to seeking treatment, discrimination, severe complications related to diabetes, high rates of cardiovascular disease and other comorbidities, cultural differences in diabetes based on how it is perceived and treated, and others (Cobb & Paisano, 1998; Whiting, Unwin & Roglic, 2010; Moy, et.al, 2006). These individual risk factors may be magnified in certain AI populations and geographies where diabetes mortality rates are the highest.

Possible explanations for increased mortality among American Indians in the GPR may be related to higher prevalence of diabetes in the GPR and the presence of more risk factors associated with diabetes and premature mortality often found in reservation CHSDA areas. For example, the estimated prevalence of diabetes among all residents living in reservation CHSDAs in the GPR is 8.20 percent compared with 7.46 percent of non-CHSDAs in the GPR (CDC, 2004). Among reservation CHSDAs in the GPR, 20.73 percent report limited food access compared with 14.76 percent of non-CHSDAs (USDA, 2006). Smoking is a behavioral risk factor that contributes to premature mortality and among Tribal CHSDAs, rates are higher, 21.07 percent compared with 18.4 percent (CDC, 2005). Persistent poverty and persistent child poverty is less than 1 percent in non-CHSDAs, but 18.35 percent of Tribal CHSDAs experience persistent poverty and 24.77 percent of Tribal CHSDAs have persistent child poverty (USDA, 1990), (see Figure 3).

To address these differences based on Tribe and geography, future studies could examine Tribal specific factors and geographies associated with lower diabetes mortality. This line of research could examine diabetes disparities using a strength-based approach, where Tribes with lower mortality rates are involved in assessing the individual and population-level characteristics that may be protective against diabetes and subsequent mortality. Examining differences using a social determinants of health framework might provide insight about the environment, conditions, and modifiable risk factors associated with diabetes disparities (Mitchell, 2012; Marmot, 2005).

By documenting mortality rate differences based on state, regional, and Tribal area, this study underscores the need for effective, Tribe-specific public health initiatives, policies and interventions. First, immediate efforts might focus on communicating and describing the extent of disparities with Tribal leaders and community members. Knowledge of documented great disparities in diabetes mortality might compel federal funding agencies, community health programs, the Indian Health Service, and families to take action. Second, Tribes in the GPR might consider sharing best practices and lesson learned from previous diabetes prevention and interventions. For example, the variation of diabetes mortality in the GPR among AIs shows that some Tribes have significantly lower mortality rates than others. Last, because every Tribe has a unique culture, history, language, and geography—differences in diabetes mortality must be addressed through the lens of the Tribal population experiencing them, with assistance from public health professionals, policy makers, and Tribal leaders (Giroux & Maschino, 2013;Gonzales et.al, 2013; Christensen & Kightlinger, 2013). Higher rates of diabetes mortality among American Indians living in reservation CHSDAs may be related to oppression and discrimination (Krieger, 2001; Wilson & Yellow Bird, 2005). Documenting and understanding risk factors as they relate to diabetes mortality may inform future interventions aimed at alleviating disparities reported in this study.

This study has some limitations and several strengths. Accurately reporting and assessing diabetes mortality in all populations including AIs can be challenging given that death certificates may be incomplete, inaccurate, or underreport AI status (Gohdes et.al, 2004)). Another challenge with reporting and estimating diabetes deaths stems from the complications and comorbidities associated with diabetes (Morewitz, 2006). For example, the majority of diabetes-related deaths report the underlying cause of death as cardiovascular disease and a contributing cause of death as diabetes. In this study, only the underlying cause of death of diabetes was examined, and contributing cause of death was not. These limitations are balanced by several strengths including these: Tribally-recommended design, secondary data source used provides an efficient approach to improved understanding about disparities in diabetes mortality by Tribe and region. The Tribally-recommended design used to identify reservation CHSDA regions was shared with the lead author by the Northern Plains Tribal Epidemiology Center, informed by Tribal leaders and Tribal health directors. Next, the lead author extracted the data and compiled the results. Results were shared with the Tribal consortiums as a first step in documenting diabetes disparities. In the coming months, the lead author will present results of this study to Tribes in the GPR while supporting future efforts and programs aimed at eliminating differences in diabetes mortality. Tribes and public health officials agree that documenting disparities to show they exist is the first of many steps in achieving health equity for all, including AIs.

In summary, this study adds to the literature, a clear picture of the geographic and Tribal-specific disparities in the GPR that have not been published previously. Researchers, public health professionals, clinicians, community members, and policy makers working in partnership with and in communities must take immediate action through multifaceted strategies to reduce disparities that lead to early mortality among AIs. The time to do this is now. These results are a call to further action to address these severe Tribal disparities.

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CHAPTER III

TYPE 2 DIABETES AND THE SOCIAL DETERMINANTS OF HEALTH IN THE GREAT PLAINS REGION

Abstract

The purpose of this study was to examine associations between social determinants of health (SDH) and type 2 diabetes (T2D) prevalence in the Great Plains Region (GPR), where many American Indians reside. Social determinants included issues of race, poverty, income, low employment, lack of education, rural vs. urban geographies, housing stress, medically underserved areas, and limited food access. A cross-sectional ecologic study design was used to compare SDH and diabetes prevalence by county in the GPR. Data from the 2004 and 2005 BRFSS, 2006 USDA Environmental Food Atlas, and 2004 Economic Research Service were used. SDH explained 24% of the variance in diabetes prevalence, even after consideration of the known risk factors of obesity, smoking, and inactivity. Rural location and absence of college degree were strong predictors of diabetes prevalence. Low employment, persistent poverty, and limited food access were positively associated with diabetes prevalence rates. To achieve health equity for all, public health professionals and policy makers must focus on the addressing population-level conditions that create differences in health status; that is, the social determinants of health.

Introduction

Diabetes is a public health epidemic. Type 2 diabetes (T2D) is preventable yet rates continue to climb and by 2050, 1 in 3 adults could have diabetes (CDC, 2011). In 1995 only three states reported an age-adjusted diabetes prevalence rate of greater than six percent. In 2010, every state in the US reported prevalence rate of greater than six percent (CDC, 2012). Data from the 1995, 2000, 2005, and 2010 Behavioral Risk Factor Surveillance System (BRFSS) show consistent and alarming increases in diabetes prevalence ranging from 8.5 percent to more than 225 percent in some states (CDC, 2004). Individuals living in rural areas experience higher rates of diabetes than those living in urban areas (O'Connor & Wellenius, 2012). Racial and ethnic minorities are disproportionately impacted by diabetes (Liao et.al, 2011) and among American Indians, diabetes prevalence continues to increase (Roberts et.al, 2009).

Efforts to address diabetes have focused on the etiology, biology, prevalence of diabetes in segments of a given population, and on health care delivery standards (Albright & Gregg, 2013; Dixon & Roubideaux, 2001; Moy, et.al, 2006). Often these efforts focus on lifestyle and behavior modification grounded in various individual theories such as social cognitive theory or the health belief model (Bandura, 1998; Rosenstock, 1974; Rosenstock, Strecher, & Becker, 1988; Marinik, et.al, 2013). For example, low levels of physical activity and consumption of energy dense foods lead to obesity, a key risk factor associated with diabetes (Artinian, et.al, 2010). Theories and efforts have led to numerous initiatives to increase physical activity and promote healthy eating. However, most initiatives have not been successful in reducing the incidence of diabetes at the individual or population level. In some initiatives, the number of people with diabetes increased, and the number of people receiving specialized diabetes care decreased (Ramesh et.al, 2008). Previous studies have confirmed the importance of additional risk factors associated with diabetes, including: older age (Chew, et.al, 2013), rural geographies (O'Connor & Wellenius, 2012), racial and ethnic group status, and socioeconomic status (Sims et.al, 2011). Yet initiatives rarely address the underlying reasons for diabetes; namely, the social and environmental conditions, or social determinants of health (SDH) that influence the modifiable risk factors.

The SDH framework is emerging as a key conceptual tool for understanding the causes of diabetes and potential solutions to reverse the diabetes epidemic, especially among American Indians and groups living in rural areas. In recent years, the SDH framework has been promoted by the 2008 World Health Organization Commission (Koh, 2010), global public health leaders, multiple disciplines (Mitchell, 2012), and researchers from various nations (Marmot, 2005). Importantly, the SDH framework provides new insight about the reasons why individuals with lower socioeconomic position experience higher incidence of diabetes than individuals with higher socioeconomic status. This is critical for increasing understanding about determinants of health at the population level. Only a limited number of studies have applied the SDH framework to population-level characteristics with the aim of better understanding the risk conditions associated with diabetes (Sims et.al, 2011;Gary-Webb, Suglia, &Tehranifar, 2013; Chang et.al, 2013). Therefore, the purpose of this study was to determine if indicators of the SDH are useful predictors of diabetes prevalence in the

Great Plains Region (GPR) of the United States. The GPR was selected because of the significant disparities in health, economic and social conditions, and a high American Indian population. The SDH in this study were selected based on the Healthy People 2020 SDH framework (Krieger, 1999) and categorized based on education, economic stability, neighborhood and built environment, health and health care, and social and community context (see Figure 4.) This study focused on the risk conditions related to diabetes in the GPR and groups living in rural areas near or on American Indian reservations.

Methods

Study Design. A cross-sectional ecologic study design was used to compare diabetes prevalence by county in the GPR. The SDH approach was warranted because previous literature in other populations show that selected SDH were associated with health disparities (Koh, 2010; Gracey & King, 2009; Nelson, et.al, 2000); however, these studies were not conducted in the GPR and therefore it is not clear how SDH indicators are associated with diabetes prevalence in this specific region. Social determinants were assessed in relation to diabetes prevalence by county

Study Area. The GPR was selected as the area of interest for this study. This area was selected because of the major American Indian and rural populations. The GPR was defined for the study encompasses six states: Montana, Wyoming, North Dakota, South Dakota, Nebraska, and Iowa. The population of the 390 GPR counties was 7,641,494 with 74.6 percent NHW and 4.17 percent AIAN based on data from 2005 census data (ACS, 2005).

Data Sources and Variables. Publically available data from multiple databases were used to examine the SDH and diabetes prevalence by county. In order to closely match available data sets with diabetes prevalence, the outcome of interest, 2004 was selected as the reference point. Diabetes prevalence, obesity, smoking, and physical inactivity data were extracted from the 2004 BRFSS (Centers for Disease Control (CDC) based on county level estimates. BRFSS is a national random digit dial telephone survey representative of the total non-institutionalized population over 18 years of age living in households with a land line telephone. County estimates were calculated based on Bayesian multi-level modeling techniques where data from 2003-2005 were combined to estimate diabetes prevalence by county for 2004 (NCI, 2012). All data from the BRFSS are weighted by population and measures were age-adjusted (CDC, 2004).

Diabetes prevalence was the estimated age-adjusted proportion of persons >20 years with diabetes based on self-report data from the 2004 BRFSS (CDC, 2004).

Data from the 2005 American Community Survey were used for percent American Indian Alaska Native and percent of persons with college degrees. Tribal Contract Health Service Delivery Area (CHSDA) data came from the 2006 CHSDA Region Summary (§42 CFR 136.22) (NCI, 2013). Data from the 2004 Economic Research Service (ERS) were used to designate counties with housing stress, low education, low employment, persistent poverty, and persistent child poverty. ERS data are sourced from different government entities for all 3141 U.S. counties and provide extensive coverage for the GPR counties (n=390) (USDA, 2004).

Rural and urban county designation codes were used from the 2004 ERS rural urban continuum codes (USDA, 2004). Rural-urban designations differentiate metropolitan counties by the population size and nonmetropolitan counties by the degree of urbanization and adjacency to a metro area. Each county in the U.S. is designated with a code ranging from 1-9, where 1 represents the most urban and 9 the most rural (USDA, 2004).

Data from the US Department of Agriculture (USDA) Food Environment Atlas 2006 were used to assess percent of county population with limited food access (USDA, 2006). Data for Medically Underserved Areas (MUA) came from the Health Research Services Administration (HRSA) based on an Index of Medical Underservice (IMU) score derived from the ratio of primary medical care physicians, infant mortality rates, poverty, and percent of the population over age 65 (HRSA, ND; HRSA, 1995). Service areas, in this case counties, with an IMU of $\leq$ 62.0 qualify as a MUA's, based on a composite index score (0-100) with 0 representing the lowest served area possible, and 100 representing the highest served area possible.

Analysis. Analysis consisted of several steps. First, descriptives and measures of central tendency were calculated and compiled for each SDH indicator and the behavioral indicators. Then a correlation matrix was constructed for the SDH indicators, behavioral indicators and the outcome of diabetes prevalence. The next step was modeling individual level SDH and behavioral indicators with diabetes prevalence. Findings from the individual level modeling were used to build the combined models. This study controlled for known diabetes behavioral risk factors (smoking, obesity, and inactivity) in the subsequent modeling.

Multiple regression analyses were used to assess the most useful SDH predictors of diabetes prevalence in the GPR in preliminary models. Predictors were selected based on existing literature (Marmot, 2005; Gracey, 2009) and the degree to which the predictor variables explained additional variance in diabetes prevalence in the single linear regression. A multiple regression model was used to fit each independent SDH variable (predictor) separately with covariates of smoking, obesity, and physical inactivity, for the outcome diabetes prevalence. The statistical significance of each predictor was derived from the 95 percent confidence intervals of the regression coefficients in a single summary model. Multicollinearity was assessed using the variance inflation factor for each predictor in the regression model and was not problematic. Results from each regression model were examined.

Missing values were omitted from the multiple linear regression model. Residual plots were used to confirm the validity of assumptions that there was a linear relationship between the predictors and diabetes prevalence. The overall regression included all predictor variables except percent American Indian by county and low education by county because better measures of these two variables were identified, CHSDA status and college degree. Counties designated as low education (USDA, 2004) were not included in the full model and not significantly associated with diabetes; however, this may be related to the lack of variation in the sample, as only 1 percent were designated as low education counties.

Results

The original sample included 390 counties in the Great Plains Region, Montana, Wyoming, North Dakota, South Dakota, Nebraska, and Iowa. Table 7 provides a summary of SDH and characteristics of the study sample. A total of 360 counties were included in the model and 30 counties were omitted because of missing data.

Overall, diabetes prevalence in the GPR ranged from 4.2 percent to 14.6 percent in counties, with a mean of 7.6 percent. This rate is slightly higher than the 7.1 percent of the US overall population average (CDC, 2004). The proportion of American Indians in the sample varied, with some counties reporting no American Indian population, and others reporting high levels. Current smoking rates, averaged of 19.5 percent, which is slightly lower than the US overall population average of 20.2 percent (CDC, 2004). Obesity was 25.1 percent in the GPR with some counties reporting rates as high as37.2 percent. The obesity rate for this study sample was higher than the US overall population rate of 23.3 percent (CDC, 2004). Physical inactivity ranged from 11.2 percent to 32.3 percent of the population (CDC, 2004). Limited food access ranged from 0 to 71 percent in some counties with an average of 16 percent (CDC, 2004; USDA, 2006) compared with 5.7 percent of the US overall population average (ACS, 2005). Thus, many counties experienced limited food access. More than 17.1 percent of the population in the GPR had a 4-year degree or higher, which is comparable to 17.2 percent in the US overall population (ACS, 2005). More than 7 percent of GPR counties experience housing stress and 11 percent of these counties have persistent child poverty. More than 75 percent of these counties are classified as medically underserved. Of the 390 counties in the GPR, 109 were CHSDAs (NCI, 2012).

Individual simple linear regression models demonstrated that all of the SDH and predictors alone were associated with diabetes prevalence, which was consistent with previous literature (Wilcox, et.al, 2000; McEwen, et.al, 2007; Williams et.al, 2010). However, when the predictors were entered into the model with covariates, the results remained significant but resulted in lower predictive abilities of diabetes prevalence.

The main purpose of this study was to determine if the SDH were useful in predicting county level diabetes prevalence in the GPR. This study controlled for known diabetes risk factors (smoking, obesity, and inactivity) and found that SDH were statistically significant and predicted diabetes prevalence at the county level. The overall regression was statistically significant and produced an R square of .738 [$F (9, 348) = 35.623$, $p<.0001$]. Approximately 49 percent of the variance in diabetes prevalence was explained by the covariates and the full model explained 74 percent of the variance, meaning that approximately 24 percent of the additional variance in diabetes was due to the SDH predictors and this was significant at the $p<.0001$ level. Results from the multiple regression model show that college degree and rurality were the important predictors of diabetes in the GPR. Rurality was associated with a 0.129 increase in diabetes prevalence ($t=6.44$; $p<.001$). As rural index score increased one point on the rural index scale (1-9 scale), diabetes prevalence increased. Absence of a college degree was a significant predictor of diabetes. For every one percentage point increase in the percent population with a college degree there was a .054 decrease in diabetes prevalence (t=-6.63; p<.001). For example, if diabetes prevalence was 3 percent in all counties, and the percent of the population with a 4-year college degree was 20 percent in one county, and 21 percent in another county- the model predicts that diabetes prevalence would be 2.46 percent or 0.054 less in the county with 21 percent college degree compared with the county with 20 percent college degree. Limited food access accounted for a slight increase in diabetes prevalence where for every one percentage point increase in limited food access, a 0.008 increase in diabetes was predicted (t=2.51;p<.013).

Across variables with dichotomous response options in the regression model, the increase in diabetes prevalence was measured by the mean difference in diabetes prevalence by county for each variable. Low employment was associated with a 0.872 increase in diabetes prevalence (t=3.12;p<.002). Persistent poverty was associated with a 0.834 increase in diabetes prevalence (t=3.35;p<.001). Other variables were not statistically significant (p<.05) predictors of diabetes in the full model. Obesity was the only covariate in the full model that was statistically significant (t=.286;p<.001); however, the other covariates, inactivity and smoking were retained in the full model because they were statistically important in explaining the variation in diabetes prevalence (see Table 8.)

All SDH and covariates were statistically significant in explaining diabetes prevalence in the GPR (p<.05). For example, in the simple linear regression obesity accounted for more than 51 percent of the variance in diabetes prevalence by county (r^2=.509;p<.01), college degree accounted for 33 percent of the variance (r^2=.329;p<.01), and low employment accounted for more than 36 percent of the variance (r^2=.362;p<.01).

However, when the SDH indicators were combined with covariates some of their predictive power was lost due to the interdependence across variables. For example, obesity was positively correlated with diabetes prevalence (r=.713; p<.001), and inactivity (r=.427;p<.001). College degree was negatively correlated with diabetes (r=-.570;p<.001), obesity (r=-.398;p<.001), inactivity (r=-.455;p<.001), and rural location (r=-.424;p<.001).

Discussion

This study found that SDH are useful and significant predictors of diabetes in the GPR.

The selected SDH indicators were predictive of diabetes prevalence in the GPR. Each SDH had differing contribution to explaining the county diabetes prevalence rate, with rurality and education having the highest contribution when all variables and indicators were considered.

The social context, environment, and differential vulnerability of populations often relate to diabetes prevalence yet these are often difficult to conceptualize or measure. An emerging body of literature points to the need for diabetes prevention efforts that focus on modifying environments (McEwen et.al, 2007; Williams et.al, 2010; Gittelsohn & Rowan, 2011) where decreased physical activity, increased access to energy dense foods and globalization lead to diabetes. These statistically significant findings underscore the importance of prevention efforts that consider SDH.

A report by the World Health Organization found the underlying factors driving the diabetes epidemic in populations are most devastating for disadvantaged populations

(IDF, ND). In this study an additional 24 percent of the diabetes variance was explained by SDH and further examining the predictive ability of SDH in different populations and contexts may lead to more effective diabetes prevention efforts. Expanded prevention efforts that consider differential vulnerability of populations based on circumstances might better address the underlying reasons for increases in diabetes other chronic diseases. In this study, rural residence was associated with higher levels of diabetes prevalence in the GPR and this contributes to the increasing literature that show residents in rural counties often experience poorer health outcomes than non-rural counties due to differences in economic and social conditions, for example limited food access (Whiting, Unwin & Roglic, 2010; O'Connor &Wellenius, 2012).

Education is a fundamental social determinant of health (McEwen et.al, 2007). Counties in the GPR with populations over the age of 25 years with a 4-year degree or higher had significantly lower diabetes prevalence rates. It is well known that education, and college degrees in particular, have the ability to change the social and economic context, where income, employment, access to healthy foods, housing increase and behavioral risk factors like smoking and inactivity decrease (Williams et.al, 2010). Thus, educational attainment remains a useful predictor of diabetes. This finding builds on previous study where the highest level of education was a better predictor of diabetes than household income or occupation (Williams et.al, 2010).

Secondary findings that link SDH with modifiable risk factors are important. Limited food access is a strong predictor of obesity (Drewnowski & Darmon, 2005;Wing et.al, 2001). In this study obesity and limited food access accounted for 56 percent of the variance in diabetes prevalence by county (r^2=.562;p<.001). Counties in the GPR are three times more likely than the US overall population to experience limited food access. This is not surprising given the high rates of poverty in the GPR. The GPR includes three counties with the highest poverty rates in the nation (Christensen & Kightlinger, 2013) and 5.6 percent of counties in the GPR were classified as persistent poverty counties (USDA, 2006). Low employment and persistent poverty were significantly associated with increased diabetes prevalence in the GPR. This finding was consistent with previous studies in other areas that report low employment and poverty are associated with adult obesity, less access to healthy foods, and lower physical activity (Seligman et.al, 2007; Williams et.al, 2010).

After adjusting for covariates of obesity, smoking, and physical inactivity, the other SDH were not significant in the full model, but remain essential predictors for understanding diabetes. The fact that some of the SDH were not significant and others were somewhat surprising given previous literature on risk conditions associated with diabetes including persistent child poverty, CHSDA's, and medically underserviced areas. However, this reinforces the need for population based studies and interventions that target the unique aspects of a population and geography. For example, previous studies reported that when counties were designated as CHSDAs, they were associated with greater health disparities because of the high percent AIAN residing in these counties (Espey, et.al, 2008; Harwell, 2001). However, in this study, counties designated at CHSDAs were associated with diabetes alone and with covariates (0.74), but in the full model CHSDA designation was not significantly associated with diabetes prevalence.

This may be related to the unique predictive ability of CHSDA status alone, and its predictive ability in the full model, where other SDH such as MUA or rural urban status account for the variance in diabetes prevalence that would be explained by CHSDA status.

This study has several strengths, and some methodological limitations. First, it is an ecological study and therefore is subject to ecological fallacy, meaning the associations between risk conditions at the county level and the prevalence of diabetes at the county level may not apply to individual characteristics and their association to diabetes prevalence within these counties (Morgenstern, 1995). However, several studies and public health policies stress the importance of ecologic studies in determining population-level factors related to health disparities, including diabetes (Schwartz, 1994; Richard, Gauvin, & Raine, 2011). Second, this study does not address or have access to genetic information related to diabetes prevalence. Genetic or family traits are linked to diabetes (Schulz et.al, 2008) and therefore should be considered to fully understand increasing diabetes prevalence in the GPR. Genetic factors interact with both SDH and behavioral determinants in their influence on diabetes prevalence. Future studies should examine these gene-environment interactions and risk conditions for a more comprehensive assessment of SDH.

These limitations are balanced by several strengths. The SDH framework allows for focus on population-level risk conditions rather limiting the focus to only individual risk factors. A more comprehensive approach is critical for increasing understanding about the conditions associated with increasing diabetes prevalence, and the multifaceted interventions to slow down or decrease prevalence. This study used multiple publically available population-based data sets derived from the best available statistical methods to conceptualize the SDH and diabetes. Also, the study design was informed by researchers and clinicians with extensive experience in the GPR and with diabetes. Therefore the approach and selection of SDH were tailored to the geographical context, culture, and history and health status of the GPR population.

Global efforts are needed that focus on changing the social context and differential vulnerability, exposure, and health care associated with diabetes. The World Health Organization reports the underlying determinants of diabetes are consistent throughout the world and increasingly associated with economic development that creates obesogenic environments (IDF, ND). However, economic development opportunities might improve the social context for GPR populations by improving their access to health care, healthy foods, educational and employment opportunities. Underlying determinants of diabetes in the GPR may be more closely linked to the environmental context, characterized by rural areas and limited food access.

The social determinants of diabetes are complex, and this complexity leads to a lack of understanding about the SDH. Also, lack of understanding may result in flawed public health initiatives and policies aimed at achieving health equity for all. To extend understanding of SDH there is a need for multi-level approaches that address individual and population-level determinants of diabetes (Gittelsohn & Rowan, 2011; Candib, 2007). Existing research has not fully examined how population-level risk conditions impact individual behaviors that create increased diabetes prevalence. For example, in this study low employment was a significant predictor of diabetes; however, to further understanding about the impact of low employment on diabetes, one must consider individual factors like education level, skills, access to jobs, and existing health conditions. One possible public health measure that may address these indicators and improve health is increased employment opportunities and college degree programs in the rural areas. This may include policies and programs that increase the skills, educational attainment, and capacity of groups who are socially disadvantaged and marginalized, populations disproportionately impacted by diabetes. Such programs and policies would address income, poverty, limited food access, and housing stress—all of which are associated with diabetes.

Another prevention approach worth considering is the life course framework (Braveman & Barclay, 2009; Halfon, 2012) where the differential vulnerability of diabetes in populations is based on their early life experiences and could include SDH. For example, women may experience limited food access or live in medically underserved areas during pregnancy and this leads to increased risk for diabetes later in life, for both mother and child.[41] Policies and programs aimed at addressing the SDH throughout the life course might result in dramatic decreases in diabetes while building an evidence base that informs national diabetes policies and legislation (CDC, 2011).

The impact of SDH on diabetes has been established (Walker et.al, 2014) and verified in this study However, this is not sufficient to change how diabetes and other chronic diseases are perceived, treated, and documented. In order to reverse the diabetes epidemic, existing policies, care delivery systems, legislation, and structures must acknowledge the social and economic conditions that determine health in populations. Failure to recognize and improve these conditions may result in further health disparities. Approaches limited to Individual risks often result in programs and policies that perpetuate individual pathologies, deficit models, blaming, and victimization.

Existing diabetes prevention efforts must target SDH rather than limiting interventions and changes to lifestyle, clinical, or behavioral approaches. Such efforts could apply the Healthy People 2020 SDH framework designed to create objectives and measure progress associated with eliminating health disparities like diabetes. Funding for research that establishes causal pathways of SDH and diabetes must include the communities and populations for which prevention programs and interventions are intended to reach. Importantly, SDH may be defined differently by communities who possess an intimate knowledge, history, culture, and insight about the structural barriers to achieving health. The evidence gained through SDH research must be applied to national policies, funding decisions, and clinical care decisions.

What seems to be clear is that the SDH framework shows that current approaches based on individual risk factors alone will not change population-level risk conditions that increase diabetes prevalence. Ultimately findings from this study have the potential to increase understanding about the associations of SDH and diabetes prevalence in the GPR.

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CHAPTER IV

CONCLUSION

Increasing prevalence and high rates of mortality from diabetes in the GPR are a major public health problem. In the last year I have learned a great deal about the underlying causes of diabetes in populations and among American Indians--unfortunately, I learned less about the solutions. My fear at the beginning of this study was writing about the extreme health disparities among disadvantaged and often marginalized populations without offering a solution.

I do not have a solution. However, this process taught me more about the underlying causes of diabetes and the differential vulnerability of populations simply because of where they live. These obesogenic environments have limited access to healthy foods, residents living in these areas often have limited access to exercise or physical activity opportunities, and these areas are often extremely urban or extremely rural. In this study, I found that as rurality increased, diabetes prevalence increased. I have thought a lot about next steps for public health efforts aimed at addressing the diabetes epidemic. I think we as public health professionals, must first consider that people cannot simply change where they live. However, it is possible to change environments to be less obesogenic through systems and policies change. For example, rural communities often do not have sidewalks or safe places to exercise and policies aimed at creating these places might increase the percent of the population who exercise regularly and decrease diabetes risk.

People who live in rural areas with jobs, college degrees, and houses seem to fare much better with regard to diabetes than individuals without these. I found that college degree was a significant predictor associated with decreased diabetes prevalence. This is undoubtedly linked to low employment, poverty, persistent poverty, and rural location. If the solution to the diabetes epidemic was as simple as ensuring everyone had a college degree it would be easy to focus public health efforts in these areas—but college degrees alone are not the solution. We live complex lives. We are complex beings. What our mothers ate during pregnancy makes us less or more vulnerable to diabetes. The genes we were born with are not socially determined, yet they still matter with regard to increased vulnerability and diabetes risk. Our relationships, interactions, and health are linked to so many things, many of which we have limited or no control over.

In some ways this lack of control is similar to the theoretical aspects and impossible assumptions of the multiple regression model. The multiple regression model I used in this study is based on an assumption that all of the other variables in the model are constant and do not change. In my study, predictors and their significance changed based on the addition or removal of SDH in the multiple regression model. Our lives, the social context, vulnerability, relationships, income, housing status, health care access and college degree change throughout our life course. One of these SDH alone will not result in increased diabetes risk, but combined they will.

What needs to change, that has not is the way that we approach prevention and wellness as public health professionals. By this I mean that we need to begin with upstream approaches that help people and communities stay healthy by emphasizing the SDH rather than focusing on interventions for those who are already unhealthy. This is not to say that individuals with diabetes do not deserve of the best public health interventions around- no, it is just that we have focused so much of our research and health care dollars on prevention strategies that simply do not work or often fail to reach those for which the outreach or intervention is intended.

My work reinforces the need for increased understanding about what determines health and how it varies based on where we live, who we are, and who our ancestors were. I know this much, I will continue to work toward a solution. This dissertation process has opened my eyes to great disparities that exist among populations and between American Indians and Whites residing in the same areas. It has also helped me think in a new way about the possibilities of health in the GPR.

APPENDIX A

MEDICAL SERVICE AREAS/PERSONS

HRSA applies the Index of Medical Underservice (IMU) to data on a service area to obtain a score for the area. The IMU scale is from 0 to 100, where 0 represents completely underserved and 100 represents best served or least underserved. Under the established criteria, each service area found to have an IMU of 62.0 or less qualifies for designation as an MUA.

The IMU involves four variables, the ratio of primary medical care physicians per 1,000 population, infant mortality rate, percentage of the population with incomes below the poverty level, and percentage of the population age 65 or over. The value of each of these variables for the service area is converted to a weighted value, according to established criteria. The four values are summed to obtain the area's IMU score (USDHHS, 1995). According to HRSA, the MUA designation includes the following information (1995):

(1) Definition of the service area being requested for designation.

(2) The latest available data on:

(a) the resident civilian, non-institutional population of the service area (aggregated from individual county, MCD/CCD or C.T. population data)

(b) the percent of the service area's population with incomes below the poverty level

(c) the percent of the service area's population age 65 and over

(d) the infant mortality rate (IMR) for the service area, or for the county or subcounty area which includes it.

(e) the current number of full-time-equivalent (FTE) primary care physicians providing patient care in the service area, and their locations of practice.

(3) The computed ratio of FTE primary care physicians per thousand population for the service area (from items 2a and 2e above).

(4) The IMU for the service area is then computed and translated into values of each of the four indicators (2b, 2c, 2d, and 3) into a score. The IMU is the sum of the four scores.

APPENDIX B

TABLES AND FIGURES

Table 1.

Aim 1 Data Variables

Variable	Definition	Source
County	County Name	US Census 2000
Mortality rates for diabetes (ICD 10 E10-E14)	All ages and races, 2002-2010 mortality rates per 100,000, age adjusted to 2000 US standard population	National Center for Health Statistics, 2002-2010 National Cancer Institute SEER*Stat software version 8.0.4
Race	American Indian or non-Hispanic white	National Center for Health Statistics, 2002-2010 National Cancer Institute SEER*Stat software version 8.0.4
Tribe/Reservation	Federally recognized Tribes and counties that make up reservation and boundaries	US Census, Great Plains Tribal Chairman's Health Board (Giroux, 2013)

Table 2.

ERS Codes

ERS Codes and Counts (n) in the GPR

Metropolitan counties
1. Counties in metro areas of 1 million population or more (n=0)
2. Counties in metro areas of 250,000 to 1 million population(n=15)
3. Counties in metro areas of fewer than 250,000 population (n=30)

Nonmetropolitan counties
4. Urban population of 20,000 or more, adjacent to a metro area (n=5)
5. Urban population of 20,000 or more, not adjacent to a metro area (n=20)
6. Urban population of 2,500 to 19,999, adjacent to a metro area (n=43)
7. Urban population of 2,500 to 19,999, not adjacent to a metro area (n=89)
8. Completely rural or less than 2,500 urban population, adjacent to a metro area (n=40)
9. Completely rural or less than 2,500 urban population, not adjacent to a metro area (n=148)

Table 3.

Aim 2 Measures

Variable	Definition	Source
Percentage AIAN/white	Percent of county resident population that is non-Hispanic White or American Indian Alaska Native Self Report	US Census Bureau, 2004 County Population Estimates
Diabetes Prevalence by County	Estimates of age-adjusted percentages of persons age > 20 with diabetes (gestational diabetes excluded).	CDC BRFSS for 2004
Tribal CHSDA region/non-CHSDA[i]	"0"=non-Tribal CHSDA county and "1" = Tribal CHSDA county	Seer*Stat CHSDA 2006 variable definitions and tribal identified county designations.
Rural-Urban Continuum Codes	Classified by 9 codes, metro 1-3, non-metro 4-9 based on population/proximity to metro area	USDA 2004 ERS County Typology
Housing Stress County	"0"= no, "1"=yes Counties where households met one or more of the following conditions: lacked complete plumbing, lacked complete kitchen, paid 30 percent or more of income for owner costs or rent, or had more than 1 person per room.	USDA 2004 ERS County Typology
Low Education County	"0"= no, "1"=yes Counties where 25 percent or more of residents 25-64 years old had neither a high school diploma nor GED in 2000	USDA 2004 ERS County Typology
Low Employment County	"0"= no, "1"=yes Counties where less than	USDA 2004 ERS County Typology

	65 percent of residents 21-64 years old were employed in 2000	
Persistent Poverty	“0”= no, “1”=yes Counties where the poverty rate of residents was 20% or more in 1970, 1980, 1990, and 2000; where 1=persistent poverty county and 0=otherwise	USDA 2004 ERS County Typology
Persistent Child Poverty	“0”= no, “1”=yes Counties where the poverty rate of children under age 18 was 20% or more in 1970, 1980, 1990, and 2000; where 1=persistent poverty county and 0=otherwise	USDA 2004 ERS County Typology
Obesity Prevalence	Estimates of age-adjusted percentages of persons age > 20 with obesity, where obesity is BMI is equal to a BMI < 30 kg / m2.	CDC BRFSS 2004
Physically Active	Percentage of self-reported "physically active" adults age > 18, where physically active = at least 150 minutes of moderate physical activity per week, or 75 minutes of vigorous activity per week, or an equivalent combination of moderate and vigorous physical activity; meeting U.S. public health guidelines for physical activity.	CDC BRFSS for 2004
Medically Underserved Areas/Populations (MUA/P)	“0”=not an MUA > 62, “1”= yes an MUA. Score Index of Medical Underservice (IMU) 0	HRSA 2004

	represents completely underserved and 100 represents best served or least underserved. Score of 62.0 or less qualifies for designation as an MUA	
Limited Food Access	Percent of county population who do not live close to a grocery store and who are low income.	County Health Rankings and USDA Food Atlas 2005
Smoking	Percent of adults that report smoking >= 100 cigarettes and currently smoking	CDC BRFSS 2005
College Degree	Percent of adults aged 25 years and older with a 4-year degree or higher.	American Community Survey 2005

Table 4.

2002-2010 Diabetes Mortality

		Rate[ii]	Lower CI	Upper CI	Rate Ratio[1]	RR Lower CI	RR Upper CI	RR P Value
Montana								
	White	20.6	19.7	21.5				
	AI	69.3#	59.7	79.8	3.36**	2.88	3.90	.0001
North Dakota								
	White	23.8	22.6	24.9				
	AI	93.2#	77.8	110.4	3.92**	3.25	4.68	.0001
South Dakota								
	White	20.4	19.5	21.5				
	AI	111.7#	99.3	125.2	5.47**	4.81	6.19	.0001
Nebraska								
	White	20.5	19.8	21.2				
	AI	48.6#	37.5	61.6	2.37**	1.82	3.01	.0001
Iowa								
	White	19.7	19.2	20.2				
	AI	21.9	14.9	30.4	1.10	.758	1.55	.600
Wyoming								
	White	23.1	21.8	24.6				
	AI	71.3#	52	94.4	3.1**	2.23	4.11	.0001

** Denotes statistical significance at the p<0.0001 level
# Rate per 100,000 deaths age adjusted
Rate Ratios are expressed as mortality rate ratios comparing American Indians to whites by State.

Table 5.

Mortality Rates[#] Tribal CHSDAs

Tribe, State	Rate	SE	Lower CI	Upper CI	Rate Ratio[1]	Lower CI RR	Upper CI RR	RR P-Value
Conf.SalishKootenai, MT	33.0	7.3	20.3	50.1	1.7809	1.083	2.7441	0.0238
Ponca, NE	43.8	7.2	30.8	59.6	2.0927	1.4668	2.8566	0.0001
ChippewaCree, MT	57.0	16.8	29	100.5	2.578	1.2264	4.9143	0.0132
AssiniboineGrosVentre, MT	67.0	19	35.1	114.3	3.4178	1.495	7.1011	0.0032
SpiritLakeDakota, ND	93.6	24.3	52.2	152.9	3.7002	1.9375	6.4828	0.0001
Crow, MT	81.5	12.5	58.9	109	3.8438	2.7371	5.2268	0.0001
TurtleMtnChippewa, ND	122.5	16.7	91.9	159.1	4.0267	2.0914	7.6671	0.0001
Winnebago, NE	104.0	19	70.3	146.5	4.1891	2.7878	6.001	0.0001
RosebudSioux,SD	101.4	13	77.5	129.8	4.2369	2.9419	5.9837	0.0001
Mandan,Hidatsa, Arikara, ND	125.6	15.3	97.4	158.7	4.6848	3.5864	5.997	0.0001
ShoshoneAraphoe, WY	113.8	18.9	79.9	155.7	4.7675	3.2253	6.8021	0.0001
AssiniboineSioux, MT	119.1	21.2	81.3	166.7	4.9187	3.1595	7.3424	0.0001
Blackfeet, MT	106.7	16.6	76.7	143.6	5.1251	3.0315	8.5108	0.0001
StandingRock, SD	125.8	19	91.4	167.7	5.3091	3.696	7.4051	0.0001
OgalaSioux, SD	110.9	8.9	94.2	129.5	5.7702	4.6963	7.0486	0.0001
CrowCreekSioux, SD §	148.7	32.3	92.3	222.3	5.841	3.4478	9.249	0.0001
NorthernCheyenne, MT	114.5	17.7	82.4	153.6	5.914	3.4923	9.9261	0.0001
CheyenneRiverSioux, SD	146.9	18.4	113	186.8	6.0418	4.3844	8.1949	0.0001
SissetonWahpetonOyate, SD	142.0	29.9	89.6	210.3	7.0434	4.3181	10.7774	0.0001
YanktonSioux, SD	154.3	30.3	100.7	223.7	7.0494	4.4112	10.6624	0.0001
Omaha, NE	181.9	34.8	120.1	261.3	9.0453	5.6827	13.7165	0.0001
Sac&Fox, IA	173.0	57.3	79.6	315.1	10.2525	4.3261	20.6571	0.0001
Santee Sioux	^							
Flandreau	^							
Lower Brule Sioux §	^							

^ Less than 10 cases

[1] Rate Ratio American Indian vs. Whites

Death Rate per 100,000

§ GPTCHB requested Tribal county be used instead of CHSDA AI population

Surveillance Research Program, National Cancer Institute SEER*Stat software (www.seer.cancer.gov/seerstat) version 8.0. Surveillance, Epidemiology, and End Results (SEER) Program (www.seer.cancer.gov) SEER*Stat Database: Mortality - All COD, Public-Use With County, Total U.S. for Expanded Races (2002-2010), National Cancer Institute, DCCPS, Surveillance Research Program, Cancer Statistics Branch, released July 2013. Underlying mortality data provided by NCHS (www.cdc.gov/nchs)

Table 6.

Characteristics of the Great Plains Region (n=390), 2004

Characteristic	Mean or %	SD	Range
Rural, mean	7.09	(2.1)	2-9
American Indian, %	4.62	(13.66)	0.0-83.0
Smoking, %	19.49	(5.48)	1.0-46.0
Obesity, %	25.05	(2.83)	12.4-37.2
Physical Inactivity, %	25.04	(2.95)	11.2-32.2
Diabetes, %	7.67	(1.26)	4.2-14.6
Limited Food Access, %	16.43	(15.25)	0.0-71.0
College Degree, mean	17.19	(5.62)	5.0- 48.0
Housing Stress, %	7.4	(.263)	
Low Employment, %	3.6	(.186)	
Persistent Poverty, %	5.6	(.231)	
Persistent Child Poverty, %	11.0	(.314)	
Medical Underservice, %	75.1	(.432)	
CHSDA Status, %	27.9		

Table 7.

Aim 2 Regression Model

	Model 1[a]	Model 2[b]
Predictors	B (SE)	B (SE)
Current Smoker	.012 (.009)	.003 (.008)
Obesity	.286 (.019)**	.190 (.016)**
Inactivity	.024 (.017)	-.020 (.014])
Rural Urban		.129 (.020)**
Housing Stress		-.083(.173)
Low Employment		.872 (.279)**
Persistent Poverty		.834 (.249)**
Persistent Child Poverty		.055 (.164)
Limited Food Access		.008 (.003) **
Medical Underservice		.088 (.083)
College Degree		-.054 (.008) **
CHSDA		.113 (.081)
Model 1[a] Model 2[b]		
F ratio	117.126 **	35.623**
R^2	.496	.738
R^2 Change[c]		.242**

*p<.05; **p<.01.

Note. Parameter estimates first, then SEs in parentheses. 360 GPR counties, 2004

[a] Model 1 includes covariates current smoker, obesity, inactivity.

[b] Model 2 includes select predictors.

[C] Reflects the change in F values with covariates and variables for Model 2.

Figure 1.

Rising Diabetes Prevalence

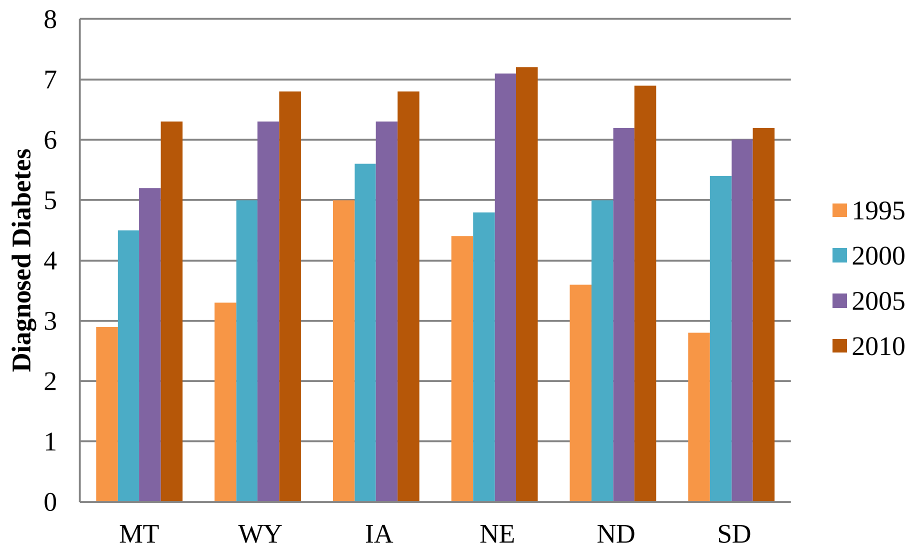

Figure 2.

Multiple Regression Equation

$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_{7\,+}\ b_8X_8 + b_9X_9$
$+b_{10}X_{10\,+}\ b_{11}X11 + b_{12}X_{12} + b_{13}X_{13} + b_{14}X_{14}$ *error*

X1= percentage AIAN (expressed as a percent of county population)
X2= Tribal CHSDA region (from Aim 1)
X3= rural urban continuum designation (1-9)
X4= housing stress (0/1)
X5= low education (0/1)
X6= low employment (0/1)
X7= persistent poverty (0/1)
X8= persistent child poverty (0/1)
X9= medically underserved area/persons (0/1)
X10= limited food access (0/1)
X11= smoking (expressed as a percent of county population)
X12= obesity (expressed as a percent of county population)
X13 =physical activity (expressed as a percent of adults in county)
X14= percent college degree (expressed as a percent of adults in county)

Figure 3.

Reservation and Non-Reservation Comparison

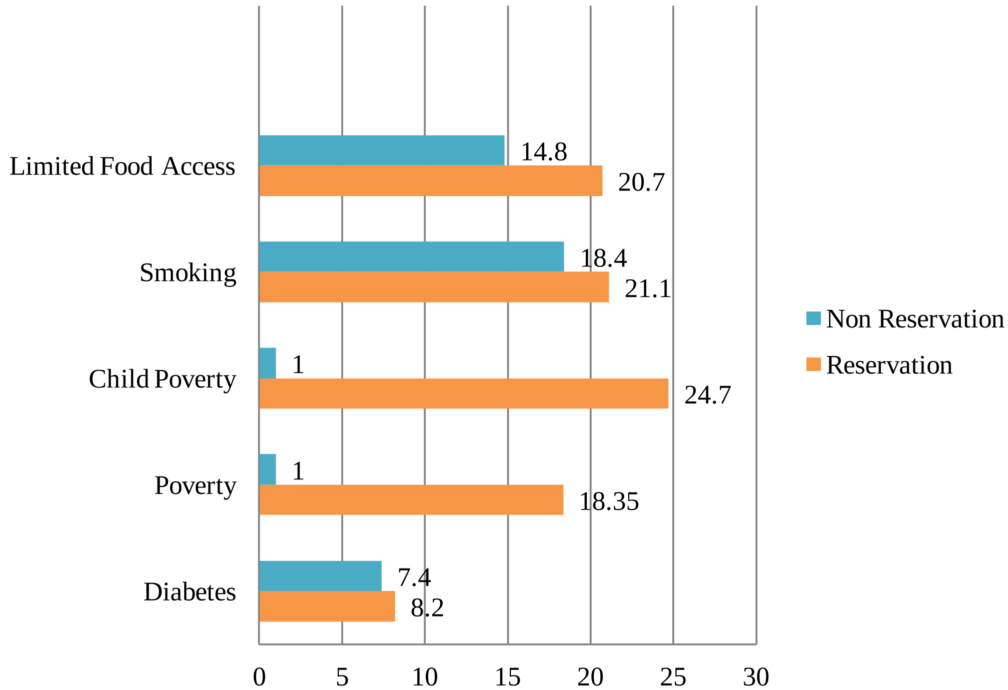

Figure 4.

Social Determinants of Health Framework

APPENDIX C

ERS INFLUENCE CODES (UICS)

The Economic Research Service (ERS) designates UICs based on county definitions from the OMB designation of metropolitan and nonmetropolitan status. ERS then classifies counties into 9 groups, 2 metropolitan and 7 nonmetropolitan. The ERS was updated based on changes associated with the OMB metropolitan/nonmetropolitan definitions changes in 2003 based on the 2000 census data (Hart et.al., 2005). The strengths of the ERS is it differentiates counties with several small towns and this method is preferred for identifying the level of locally available services. The adjacency criteria also suggest the degree of integration with a metropolitan county. The limitations of the ERS is that overbounding and underbounding occurs, and in the case of larger counties, it is difficult to determine differences between counties (Hart, et.al, 2005). For example, underbounding may occur in rural area when a large county has a large city, but if the area has less population density and has more rural economic activities, landscape, and services it may be classified as urban (Hart, et.al, 2005). The same could be said for underbounding for urban counties. While it is not possible to eliminate this problem, this study recognizes the limitations of underbounding and overbounding with UIC codes. The following excerpt from Hart and colleagues describes the use of UIC's to address urban and rural differences (2005).

> *The Urban Influence Codes (UIC) taxonomy is a county-based definition that builds on the OMB metropolitan and nonmetropolitan dichotomy. UIC's are based on the 2000 Census. Counties are classified into 9 groups: 2 metropolitan and 7 nonmetropolitan. The nonmetropolitan counties are grouped according to their adjacency and nonadjacency to metropolitan counties and the size of the largest urban settlement within the county. To qualify as adjacent to a metropolitan county, a nonmetropolitan county must share a boundary with a metropolitan county and must meet a minimum work commuting threshold. The UICs' use of the size of the largest town in a county is as a taxonomic criterion. The largest town, as used for health care purposes, is associated with the likelihood of local availability of hospitals, clinics, and specialty services. While the codes are often used for research, they are infrequently used in federal and state policies.*

APPENDIX D

BIVARIATE CORRELATION MATRIX

Correlations

		rururb2003	DiabPercent04	Obesity_Pct_04	Inactivity_Pct_04	Limited_Food_Access_06	%CollegeDegree	SmokingNew
rururb2003	Pearson Correlation	1	.430**	.117*	.257**	.425**	-.424**	-.184**
	Sig. (2-tailed)		.000	.021	.000	.000	.000	.000
	N	390	390	390	390	390	390	361
DiabPercent04	Pearson Correlation	.430**	1	.713**	.345**	.387**	-.570**	.247**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
	N	390	390	390	390	390	390	361
Obesity_Pct_04	Pearson Correlation	.117*	.713**	1	.427**	.230**	-.398**	.292**
	Sig. (2-tailed)	.021	.000		.000	.000	.000	.000
	N	390	390	390	390	390	390	361
Inactivity_Pct_04	Pearson Correlation	.257**	.345**	.427**	1	.182**	-.455**	.008
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.874
	N	390	390	390	390	390	390	361
Limited_Food_Access_06	Pearson Correlation	.425**	.387**	.230**	.182**	1	-.235**	-.101
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.055
	N	390	390	390	390	390	390	361
%CollegeDegree	Pearson Correlation	-.424**	-.570**	-.398**	-.455**	-.235**	1	-.132*
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.012
	N	390	390	390	390	390	390	361
SmokingNew	Pearson Correlation	-.184**	.247**	.292**	.008	-.101	-.132*	1
	Sig. (2-tailed)	.000	.000	.000	.874	.055	.012	
	N	361	361	361	361	361	361	361

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Bivariate correlations assessed for continuous variables to assess the interdependence of predictor variables. This also shows the linear relationship between variables, as one increases the other decreases or as one decreases the other increases. For the dichotomous variables only scatter plots were used.

APPENDIX E

SIMPLE LINEAR REGRESSION

Results of individual simple linear regression with covariates and predictors on diabetes prevalence: 390 GPR counties, 2004

Determinants	β	*t*	R^2
Current Smoker	.056*	4.82	r^2=.061**
Obesity	.317*	20.04	r^2=.509**
Inactivity	.148*	7.24	r^2=.119**
Rural Urban	.261*	9.37	r^2=.185**
Housing Stress	.761*	3.16	r^2=.025**
Low Employment	3.486*	11.83	r^2=.263**
Persistent Poverty	3.098*	13.57	r^2=.322 **
Persistent Child Poverty	1.91*	10.63	r^2=.226**
Percent AIAN	.051*	13.07	r^2=.306**
Limited Food Access	.032*	8.27	r^2=.150**
Medical Underservice	.550*	3.78	r^2=.036**
Low Education	2.605*	2.60	r^2=.054**
College Degree	-.128*	-13.65	r^2=.324**
CHSDA	.740*	5.38	r^2=.069**

*p<.05; **p<.01.

The individual simple linear regression is not included in the manuscript because it might be both misleading and confusing for the reader. Again, the overall purpose was to determine which SDH were useful in predicting diabetes, not their individual predictive abilities. However, results of the individual regressions are described in the results section and explanation about how the r^2 values relate to diabetes and how they are influenced by one another are described.

APPENDIX F

MULTIPLE REGRESSION EXPLANATION

Results from the simple linear regression show that only obesity was a significant predictor of diabetes and other covariates not but this is to be expected because these covariates correlate with other predictors in the model and therefore their predictive power may be absorbed by other variables. The fact that physical inactivity was negative in model 2 is not necessarily cause for concern because this it was not statistically significant. Based on the results from model 1 and 2 the full model explains more variance in diabetes than the covariates alone and this was a significant finding. One of the main limitations of multiple regression is that we do not know which of these predictors alone is the strongest, but we can say, that some are more predictive than others. These are further explained in the discussion section and include college degree, rural location, limited food access, employment, and poverty.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.704[a]	.496	.492	.8814	.496	117.126	3	357	.000
2	.859[b]	.738	.729	.6440	.242	35.623	9	348	.000

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	272.966	3	90.989	117.126	.000[b]
	Residual	277.334	357	.777		
	Total	550.300	360			
2	Regression	405.951	12	33.829	81.557	.000[c]
	Residual	144.349	348	.415		
	Total	550.300	360			

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.369	.477		-.774	.440		
	Obesity_Pct_04	.286	.019	.658	14.840	.000	.717	1.394
	Inactivity_Pct_04	.025	.017	.060	1.411	.159	.784	1.276
	SmokingNew	.012	.009	.054	1.356	.176	.896	1.116
2	(Constant)	3.061	.572		5.348	.000		
	Obesity_Pct_04	.190	.016	.439	11.692	.000	.536	1.867
	Inactivity_Pct_04	-.020	.014	-.049	-1.457	.146	.657	1.523
	SmokingNew	.003	.008	.014	.402	.688	.611	1.636
	rururb2003	.129	.020	.220	6.444	.000	.648	1.544
	house	-.083	.173	-.018	-.478	.633	.553	1.807
	lowemp	.872	.279	.127	3.124	.002	.458	2.182
	perpov	.834	.249	.151	3.352	.001	.372	2.689
	perchldpov	.055	.164	.014	.337	.736	.465	2.152
	Limited_Food_Access_06	.008	.003	.089	2.506	.013	.604	1.655
	Dichoto_MUA	.088	.083	.031	1.057	.291	.883	1.133
	NewCHSDA	.113	.081	.042	1.388	.166	.840	1.190
	%CollegeDegree	-.054	.008	-.245	-6.627	.000	.550	1.819

In Model 2 the variance inflation factor and tolerance were assessed. Mutlicolinearity is when 2 or more predictors in regression model are highly correlated meaning that one can be linearly predicted from others. To address this coefficient estimates were examined using the VIF statistics from the SPSS output in the regression model. Tolerance is related to multicollinearity; however, one only needs to report one or other. A tolerance less than .20 or .10 and or a VIF of 5 or 10 above is a problem and often means the variables are multicollinearity. This was described by in the following article: O'Brien, Robert M. 2007. "A Caution Regarding Rules of Thumb for Variance Inflation Factors," *Quality and Quantity* 41(5)673-690.

APPENDIX G

TRIBAL CHSDA DESIGNATIONS

State	**Tribe**	**County, State**
Iowa	Sac & Fox	Tama, IA
Nebraska	Omaha	Burt, NE; Cuming, NE; Monona, IA; Thurston*, NE; Wayne*, NE
	Ponca	Boyd, NE; Burt, NE; Charles Mix, SD; Douglas, NE; Hall, NE; Holt, NE; Lancaster, NE; Madison, NE; Platte, NE; Pottawattamie, IA; Sarpy, NE; Stanton, NE; Wayne, NE; Woodbury, IA
	Santee Sioux	Bon Homme, SD; Knox, NE
	Winnebago Tribe of Nebraska	Dakota, NE; Dixon, NE; Monona, IA; Thurston*, NE; Wayne*, NE; Woodbury, IA
North Dakota	Mandan, Hidatsa, Arikara	Dunn, ND; McKenzie, ND; McLean, ND; Mercer, ND; Mountrail, ND; Ward, ND
	Spirit Lake Dakota	Benson, ND; Eddy, ND; Nelson, ND; Ramsey, ND
	Turtle Mountain Chippewa	Rolette, ND
South Dakota	Cheyenne River Sioux	Corson, SD; Dewey, SD; Haakon, SD; Meade, SD; Perkins, SD; Potter, SD; Stanley, SD; Sully, SD; Walworth, SD; Ziebach, SD
	Crow Creek Sioux§	Brule, SD; Buffalo, SD; Hand, SD; Hughes, SD; Hyde, SD; Lyman, SD;* Stanley, SD*
	Flandreau	Moody, SD**

	Standing Rock Sioux	Adams, ND; Campbell, SD; Corson, SD; Dewey, SD; Emmons, ND; Grant, ND; Morton, ND; Perkins, SD; Sioux, ND; Walworth; Ziebach, SD
	Lower Brule Sioux§	Brule, SD; *Buffalo, SD;* Hughes, SD; *Lyman, SD; Stanley, SD
	Oglala Sioux	Bennett, SD; Cherry, NE; Custer, SD; Dawes, NE; Fall River, SD; Jackson, SD; Mellette, SD; Pennington, SD; Shannon, SD; Sheridan, NE; Todd, SD
	Rosebud Sioux	Bennett, SD; Cherry, NE; Gregory, SD; Lyman, SD; Mellette, SD; Todd, SD; Tripp, SD
	Sisseton-Wahpeton Oyate	Codington, SD; Day, SD; Grant, SD; Marshall, SD; Richland, ND; Roberts, SD; Sargent, ND; Traverse, MN
	Yankton Sioux	Bon Homme, SD; Boyd, NE; Charles Mix, SD; Douglas, SD; Gregory, SD; Hutchison, SD; Knox, NE
Montana	Crow	Big Horn, MT, Carbon, MT, Treasure, MT , Yellowstone, MT, Big Horn, WY, Sheridan, WY
	Northern Cheyenne	Big Horn, MT, Carter, MT, Rosebud MT
	Blackfeet Tribe of Blackfeet Reservation	Glacier, MT, Pondera, MT
	Confederated Salish & Kootenai Tribes of Flathead Reservation	Flathead, MT, Lake, MT, Missoula, MT, Sanders, MT
	Chippewa-Cree Indians of Rockyboy Reservation	Chouteau, MT, Hill, MT, Liberty, MT

	Assiniboine and Sioux Tribes Fort Peck Reservation	Daniels, MT, McCone, MT, Richland, MT, Roosevelt, MT, Sheridan, MT, Valley, MT
	Fort Belknap	Blaine, MT, Phillips, MT
Wyoming	Shoshone Tribe of the Wind River Reservation	Hot Springs, WY, Fremont, WY, Sublette, WY
	Arapaho Tribe of the Wind River Reservation	Hot Springs, WY, Fremont, WY, Sublette, WY

**Counties excluded based on tribal health director input.*