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Estimation of County-Level Diabetes Prevalence Using Bayesian Hierarchical Model

Israel Anbessa Hora

ESTIMATION OF COUNTY-LEVEL DIABETES PREVALENCE USING BAYESIAN HIERARCHICAL MODEL

by

ISRAEL HORA

Under the Direction of RUIYAN LUO, PhD

ABSTRACT

Because of budget constraints a survey has two major limitations when it comes to availing data on prevalence of diabetes in small areas as Counties. First, it is costly for a survey to cover all relevant areas. And second, a survey often comes short of taking large samples for adequate representations. Examining such limitations and shortcomings of a direct method of estimation which uses data from such surveys, this dissertation attempted to apply Bayesian Hierarchical Model of estimation to provide reliable data on prevalence of Diabetes in small areas (counties). In doing so a range of Bayesian Hierarchical models which provide reliable data on prevalence of diabetes for small areas as counties were explored.

The Estimation Models used data of Behavioral Risk Factor Surveillance System (BRFSS [1]) survey. In total the analysis examined survey data made on 1,497 counties (including the 644 counties in the CDC diabetes belts [2] in 16 states in the US.

The statistical models used in this analysis are aimed at reducing estimation error of diabetes prevalence in direct estimation methods, so as to help an efficient policy formulation and budget allocation. In this regard we generated estimates on the prevalence of diabetes for 1,188 Counties having a complete set of information and another 295 which were not covered in BRFSS survey and among the 1188 Counties 824 Counties that have smaller sample size (Healthy people 2020 data suppression for BRFSS [3]).

Unlike the direct method usually applied for such estimation the result in this analysis brought about statistical significance of the estimates in our study.

INDEX WORDS: Bayesian Hierarchical Model, Conditional Autoregressive (CAR), Small Area Estimation, Diabetes Belt, Deviance Information Criterion (DIC), Random Effect

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DEDICATION

To my wife, Haime and beloved sons Biruk Israel and Yacob Israel

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1 INTRODUCTION

1.1 Purpose of the Study

According to CDC (Center for Diseases Control and Prevention) diabetes is the seventh leading cause of death in the U.S. (National Diabetes Statistics Report, 2014 [4]). The CDC fact sheet, reported that in 2013 alone 29 million people which is 9.3 % of the U.S. population is affected by this disease. Among these, 21 million are diagnosed while 8.1 million are yet to know they have the disease. Diabetes can bring substantial economic cost to people with the disease as well as their families.

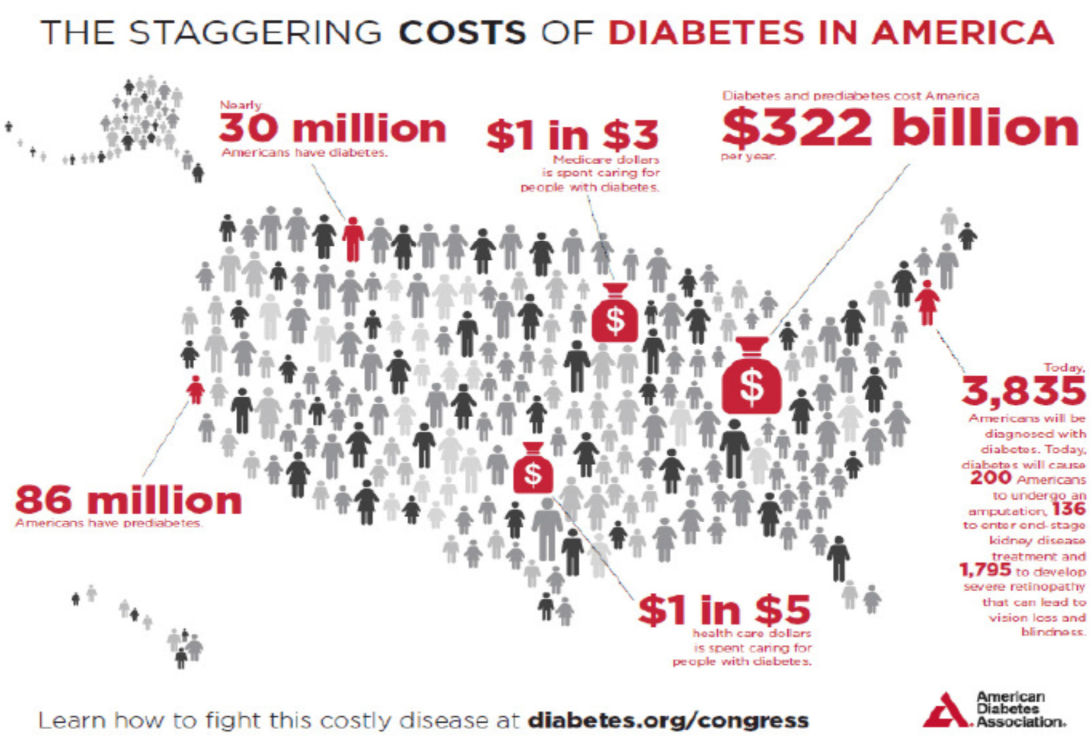


Figure 1-1 Direct Medical Expense for Diabetes Cost in U.S. from 2007 to 2012

The cost associated to this disease is overwhelmingly high and increasing as years go by. According to the American Diabetes Association (ADA [5]), the cost of diagnosed diabetes went from $174 billion in 2005 to a staggering $245 billion in 2012. This data does not include resources from care provided by non-paid care givers and the burden associated with undiagnosed diabetes. $1 in $3 Medicare dollars and $1 in $5 health care dollars are spent in caring for people with diabetes (American Diabetes Association (ADA [5])). The physical and psychological stress resulted from complication on different parts of the body on people with diabetes brings health issues to be treated by health institutions.

Addressing this chronic diseases at local level, in our case counties, depends on

I. Reliable estimates at local level

II. Appropriate budget allocation

III. Applicable health policy

The demand for I) is extremely important so that II) and III) can be implemented efficiently using a methodology that effectively estimates the burden of diabetes at the county level.

Due to shortage of budget, most national surveys that are used widely for a variety of analysis and decision making, have hard time to cover all local areas or counties in a given state. For instance, from among 1,497 counties in 16 states that we included in our analysis, 307 of the counties lacked information when we aggregated individuals surveyed in the BRFSS survey we have checked from 2000 to 2010. In fact these counties have zero sample size when we aggregated the respondent response for the question, “Has a doctor told you, you have diabetes?" according their age, sex, race, education attained, income and insurance status. In addition to this, there were other counties with small sample size.

Applying direct estimates on such data results in a large sampling coefficients of variation (CV) or Mean Square Error (MSE) (Rao, 2003 [6]). This estimation problem compounding with the budget constraints call for other methods of indirect estimation that help overcome these problems. These indirect methods, which are discussed in the next two chapters, have an advantage of borrowing information from neighboring counties (local area or domains, counties) using liking models (Rao, 2003 [6]). Rao, in his "Some New Development in Small Area Estimation" paper, explained in detail the advantages of indirect estimation methods based on the explicit linking models. One of the advantages listed in his paper is the handling of the binary or count and spatially-correlated data which we used in our analysis. Moreover, one can validate these models using the sample data found in the survey.

Small area or domains refer to an area such as counties, cities, zip codes, or local areas. There are many methods implemented to estimate the parameters of interest in these small areas for small sub-populations such as counties in the states or cities in the counties. One of the methods commonly used before the introduction of indirect method was direct estimation method. This method that uses only the survey data to provide results produces unreliable estimates especially for those small areas with no information or small sample size.

The purpose of this dissertation therefore is to address the above issues so that public health professionals, relevant federal, state, and local bodies, and other stakeholders will make use of reliable estimates at local level to tackle diabetes. This can be realized by applying small area estimation method which is the Bayesian Hierarchical method discussed in chapter 2 and 3.

We used the 2010 BRFSS [1] survey data which included auxiliary data to estimate the prevalence of diabetes for counties which are located in the CDC's Diabetes belt. We fitted Empirical Best Linear Unbiased (EBLUB) predictors extending the regression model to handle random effects model.

A Bayesian approach for small area estimation provides an advantage of handling many types of survey outcomes such as continuous, dichotomous or categorical variables. In addition to this, the Bayesian method handles different random effect structures such as correlated and uncorrelated structures. That particular advantage helps to extend the Bayesian methods to small area estimation to produce the needed reliable estimates for all areas including those small local areas with no direct survey information or not covered by the survey. On top of this, the Bayesian Hierarchical method is best in handling small areas with spars data since Bayesian posterior inference is exact and does not rely on asymptotic arguments (Bayesian Statistics for Small Area Estimation [7]).

1.2 Studies on Diabetes

Diabetes is one of the leading cause of deaths in the U.S. as well as around the world. People with diabetes develop a number of complication such as kidney failure, blindness, and amputation are some of the complication. In 2013, 30 million people are affected by diagnosed diabetes and 86 million who don't know they have diabetes. The cost associated with this disease is staggering. In 2007 it was $174Billion and this cost increased to $322Billion in 2012. An increased trend observed for both the diseases and cost.

Projection of the year 2050 burden of diabetes in the US adult population [21]paper studied a projection of this diseases and in their study they projected the total prevalence of diabetes to increase from 14% in 2010 to 21% in 2050 for U.S. adult population.

According to National Diabetes Statistics Report, 2014, the diabetes affected older age group, more prevalent in Men than Women and in Non-Hispanic blacks than Non-Hispanic White [20]

1.3 Spatial Effects Models

The application of Bayesian Hierarchical model to small area estimation has been widely used in recent year due the fast development in the powerful computational computer and applicable software. Analyzing the HB model using WinBUGS software which applies the Markov Chain Monte Carlo (MCMC, Gilks et al., 1996). The MCMC requires regress computation and the development of such fast computer has been a plus for the HB analysis. The WinBUGS, developed by a team of UK researcher [22] which uses the BUGS(Bayesian inference using Gibbs Sampling), designed to handle a range of Bayesian Hierarchical model incorporating geographical variation also an advantage for the researchers interested in this study area. This dissertation widely used both the BH modelling and the Win BUGS.

Direct method has been used but this methods has a number of draw back when we come to do small area estimation since it doesn't take into consideration geographical variation and the reliability of the estimation can be hindered by small sample size. In order to overcome these drawback a variety of indirect method has been proposed by researcher to estimate the mean of small area characteristics. Among the methods are

i. synthetic estimator(Gonzalez, 1973) assumes a fixed mean across a domain(small area)

ii. Small-Area level Model estimation (Rao, 2003 [6])

Throughout this dissertation we applied the second method by including the geographical variation (in our case counties) , i.e. by including CAR (Conditional Autoregressive Model).

Glen Meeden, in a Non-informative Bayesian approach to small are estimation paper[23], highlighted applying the conditional autoregressive model to estimate the variable of interest at small area level which strength the reliability of the estimates since this methods have the advantage using data from neighboring small area which known as "Borrowing Strength".

Ying C. MacNab [24] summarized the Bayesian Hierarchical model for spatially correlated small area health services outcomes. The paper used the BH method to identify spatial variation in small area incidence rates of interventricular hemorrhage (IVH) that occurred to NICU neonates in census division across Canada.

In Bayesian Small Area Estimates of Diabetes Prevalence by U.S. Counties (2005, [] pp185) recommended a research on the addition of spatial effect and county level covariates and also highlight the advantage of using the recommendation.

2 ESTIMATING COUNTY-LEVEL DIABETES PREVALENCE IN FLORIDA USING BAYESIAN HIERARCHICAL MODEL

2.1 Background

Type 2 diabetes, a condition in which body cells fail to use insulin properly [8], affected 29.1 million Americans (9.1% of the U.S. population in 2013 [4]). One of the surveys used in the U.S. to predict the risk and prevalence of Type 2 diabetes is the Behavioral Risk Factor Surveillance System (BRFSS [1]).

In this chapter we attempted to explore a method suitable for accurately estimating the annual prevalence of diagnosed diabetes in Florida counties based on the BRFSS survey. Tackling to reduce the burden of this disease requires an effort from all responsible parties that includes the analyst, policy formulators and fund allocators. Providing reliable health data for all the parties involved facilitates the decision making process to this end.

The demand for health information for policy formulation and fund allocation for small areas such as counties are strongly increasing. The same is true with information on diabetes. One of the major factors that determine success of policies and budget allocation in this regard is the quality of health data presented and accessed for that decision making process.
The need for best spatial analysis[9] of health data has been found to be essential in producing accurate and representative estimate for small areas such as counties, since generating direct estimates from the survey data is usually hindered by insufficient sample size or even lack of specific data. Getting reliable estimate for small areas helps the effective implementation of

public health policy, especially in allocating fund to target an area with high burden of diseases [10].

In the following discussion an attempt was made to build an appropriate Bayesian hierarchical (BH [11]) small area model which can be used to estimate the probability of having diabetes among residents in counties in Florida. However, this method can be extended for other U.S. counties with some modifications.

2.2 Methods

The Behavioral Risk Factor Surveillance System (BRFSS) is an ongoing, state -based telephone survey of the non-institutionalized, adult civilian U.S. population (18 years of age or older). The survey provides state-specific information on behavioral risk factors and preventive care practices. The survey includes demographic and socioeconomic information about survey respondents. It also collects the respondent's health status, including chronic health conditions like diabetes [11].

But the BRFSS doesn't cover all counties in the U.S. Even it does, it may lack a reliable sample size for each and every county. For instance, the Florida state has 63 out of 67 counties with the above information. Since a direct estimate based on an inadequate sample size is not reliable, we construct Bayesian Hierarchical models to compute more accurate estimates of the prevalence of diabetes for all 63 Florida counties.

Since neighboring counties tend to have similar chronic health condition, we incorporate the spatial correlation by the Conditional Autoregressive (CAR [12]) model in our analysis.

Variables of Interest [1]

A. Diagnosed Diabetes (Type II diabetes): Respondent who participated in the BRFSS survey and answered "Yes" to the question "Has a doctor told you, you have diabetes?" was considered as having diabetes. If the respondent was a woman and indicated that the diagnosis of diabetes was only during pregnancy, then the respondent would be excluded.

B. Salient Covariates

A. **Age Group**: we grouped those who answered the question "How old were you on your last birthday?" as follows:

I. 18 to 44 - age group 1(reference group)

II. 45 to 64 - age group 2

III. 65 and above - age group 3

B. **Education level**: Using BRFSS question, "What is your highest grade or year of school you have completed?", we grouped the respondents into

I. Less than high school(reference group)

II. High school graduate or GED

III. Under graduate degree

IV. Graduate degree and above

C. **House hold income**: Based on the BRFSS question, “Which of the following categories best describes your annual income from all sources?” , we created four categories for income

   I. < $25,000(reference group)

   II. $25000 - <$50,000

   III. $50000 - <$75000

   IV. >=$75,000

D. **County Poverty**: The U.S. Census Bureau use a set of income thresholds based on the family size to determine if a person is below the federal poverty level. If a family’s total income is below the respective threshold, then the whole family is considered in the state of poverty.(US Census Bureau)

2.3 Analysis

We estimated the prevalence of diagnosed diabetes for Florida counties using the 2010 BRFSS survey data. We aggregate the individual data according to their age group (18 – 44, 45-64 or 65+), gender (Male or Female), race (White or Black), income level (< $25,000, $25,000 - $49,999, $50,000 - $74,999), ≥$75,000) and education level (<high School, high School, college degree and graduate or above). So we have 192 possible groups in total, which corresponds to all possible combination of age, gender, race, income level, and education level.

A Bayesian Hierarchical (BH [11], [15]) statistical model was built, which models the number of diabetes cases for each group within each county using a binomial distribution, uses the logic link function to include the predictors age group, gender, race, income level, education level, interactions between age and gender, age and race, gender and race, and county poverty, as well as the spatial effects with the conditional autoregressive (CAR [12]) model. Estimations from a logistic regression model (PROC GENMODE) were used as initial values for the parameters in BH analysis, where the logistic regression model contains the same set of predictors as the BH model, excluding the CAR model. From the BH model, and estimating the proportion of individuals within each group for each county using BRFSS survey data we estimated the small area (county-level) prevalence of diabetes by age group, sex, and race. The prevalence of diabetes for each county were also estimated. Below we presented our BH model in more detail.

2.4 Model

2.4.1 Bayesian Hierarchical with CAR (spatial dependency) model

Let $\mathrm{Y_{jk}}$ be the number of people from class j in the county k with diagnosed diabetes (j=1, 2… 192, and k=1, 2… 67) and $\mathrm{N_{jk}}$ be the total number of people in class j of county k (k=1, 2… 63). We assume that $\mathrm{Y_{jk}} \sim \mathrm{Binomial}\left(\mathrm{N_{jk}}, \theta_{\mathrm{jk}}\right)$ and the link equation $\mathrm{logit}\left(\theta_{\mathrm{jk}}\right) = \mathrm{X_j^T}\beta + \mathrm{b_k}$ where j=1, 2… 192 classes, k=1, 2… 63 counties and $\mathrm{X_j^T} = \left(1, \mathrm{x_{1j}}, \mathrm{x_{2j}}, \cdots, \mathrm{x_{17j}}\right)$ is the vector of dummy variables for the socioeconomic categorical variables and the interactions using reference coding, and county poverty, $\beta = (\beta_0, \beta_1, \beta_2, \cdots, \beta_{17})^{\mathrm{T}}$ is the corresponding coefficient vector. This model assumes that the effect of a predictor is the same across counties.

The term b_k (k = 1, 2… 63) captures the random spatial effect and we use the conditional autoregressive model (CAR [12]) to describe the spatial correlation.

That is $\mathrm{b_k} \sim \mathrm{CAR}\left(\overline{\mathrm{b_k}}, \tau_{\mathrm{k}}^2\right)$, where $\overline{b_k} = \frac{1}{\sum_{\mathrm{i}} \mathrm{w_{ik}}} \sum_{\mathrm{i}} \mathrm{b_k}\, \mathrm{w_{ik}}$

$\tau_{\mathrm{k}}^2 = \frac{\tau^2}{\sum_{\mathrm{i}} \mathrm{w_{ik}}}$ and $\mathrm{w_{ik}} = \begin{cases} 1 & \text{if i and k are adjacent} \\ 0 & \text{otherwise} \end{cases}$

2.4.2 The CAR Model [12]

The CAR model also known as Auto-Normal model or Gauss-Markov model is used usually to do "local investigation", i.e. it allows to analyze phenomena that occur in a geographical area immediately surrounding the site analyzed(in our case the geographical area is county).

Let C (counties) = {1, 2… 63) and N_i represent neighborhood of the county i where i is in C, then a random field $x = (x_1, x_2 \cdots x_n)$ is called CAR Model, if it is characterized by

$$f(x_i/x_{N_i}) = \sqrt{\frac{1}{2\pi\sigma_i^2}} \exp\left\{-\frac{\left[(x_i-\mu_i)-\rho\sum_{i^*\epsilon N_i}\beta_{ii^*}(x^*-\mu^*)\right]^2}{2\sigma_i^2}\right\}$$

For i ϵ C, $\mu_i \in R$ (Real number),$\sigma_i \in R$, $|\rho| < 1$ and β_{ii}^* ϵR, β_{ii} =0 and $\beta_{ii^*} = \beta_{i^*I}$ with I, i_* ϵC

For the priors, we assume that for each (m=1, 2… 17) $\beta_m \sim \mathrm{Normal}(0, \sigma_b)$, β is the coefficient of the covariates and σ_b^{-2} ~ Gamma (0.5, 0.5). By giving a small values for the gamma distribution (such as 0.5 for shape and scale), we let

2.4.3 Alternative Models

We also considered three alternative models, including the model with county-specific coefficients, the model that ignores the random spatial effect b_k, and the model that includes both uncorrelated and correlated spatial random effects.

2.4.3.1 Model with county-specific coefficients and CAR [12]

$Y_{jk} \sim \mathrm{Binomial}(N_{jk}, \theta_{jk})$ where N_{jk} is the total number of people in a given class j and county k with the link equation logit (θ_{jk}) = $x_j^T\beta_m + b_k$ where j=1, 2, …, 192 classes, k=1, 2,…, 67 counties and X^T_j = ($1, x_{1j}, x_{2j}, \ldots, x_{17j}$), β_m = (β_1, β_1, β_2, …, , β_{17}) represent the county –specific coefficient vector. We assume that β_{km} ~ Normal (β_m, σ_b^2), for k=1, 2… 67 and m=0, 1… 16 and β_m ~ Normal (0, σ_b^2), σ_b^{-2} ~ Gamma (0.5, 0.5)

2.4.3.2 Model without CAR [12]

$Y_{jk} \sim \text{Binomial}(N_{jk}, \theta_{jk})$ where N_{jk} is the total number of people in a given class j and county k with the link equation $\text{logit}(\theta_{jk}) = X_j^T\beta_m$ where j=1, 2… 192 classes, k=1, 2… 67 counties, $X_j^T = (1, x_{1j}, x_{2j}, \cdots, x_{17j})$ and $\beta = (\beta_0, \beta_1, \beta_2, \cdots, \beta_{17})^T$.The above model is the second alternative model without spatial correlation between neighboring areas or without the Conditional Autoregressive (CAR [12]) model.

2.4.3.3 Model with both uncorrelated and correlated spatial random effects

$Y_{jk} \sim \text{Binomial}(N_{jk}, \theta_{jk})$ where N_{jk} is the total number of people in a given class j and county k with the link equation $\text{logit}(\theta_{jk}) = X_j^T\beta_m + b_k + e_k$ where j=1, 2… 192 classes, k=1, 2… 67 counties.

2.5 Counties with Missing Data

The BRFSS survey may not cover all counties every year but the state may do additional survey to cover all counties in their state, even this may not be conducted every year. But by applying the CAR [12] model we can overcome this problem and get estimates of missing counties by borrowing information from neighboring counties. For instance, the 2010 BRFSS public survey data which can be downloaded from BRFSS website[2] had 4 counties not covered in the survey. For those counties with missing or uncovered in the survey, we used the BH model with the CAR model to estimate their prevalence of diabetes as follows:

Based on the BH model with the CAR model, the spatial effect for the m^{th} missing or uncovered county (m=1, 2, 3 and 4) has a normal distribution with mean

$\bar{b}_m = \sum_{i=1}^{n} b_m$ and the precision $v_m = \frac{1}{(v*n)^{0.5}}$

where v is the precision parameter in the CAR model, and n is the number of neighbor counties for the m^{th} missing county. With the MCMC samples of b_k from the simulation, we also get samples of b_m for the m^{th} missing counties using $\bar{b}_m \sim \mathrm{Normal}(b_m , v_m)$.

Using the simulated samples for b_m and $\beta = (\beta_1, \beta_2 \ldots \beta_{17})$, we can simulate the posterior distribution for the prevalence of diabetes for the missing counties in the same way as we do for the other 63 counties without missing information, and hence estimate its posterior mean and credible interval.

We used the WinBugs software [13] to fit these models. The model was run for 100,000 iterations with single chain but the first 2,000 samples were used as a burn-in (discarded) which implies that the rest 98,000 samples were used to make inference. We chose the model that has the same coefficients across counties and the CAR [12] model, which has the smallest Deviance information criterion (DIC [14]).

With the MCMC samples of parameters in this model, we can infer the posterior distribution of the overall prevalence rate for each county in the following way. Similarly we can get the prevalence rate by race or sex for each county.

Plugging in the sampled values of β and b_k, and specifying the values of x, we can get the prevalence rate of diabetes in a group of a county.

Let $\hat{\theta}_{jk}^{(i)}$ denote the ith sample of θ_{jk} , the prevalence rate of diabetes in the j-th group of the k-th county, from the MCMC procedure (i=1… 17, j=1 … 192 and k=1… 63), the corresponding overall prevalence rate of the k-th county is estimated by

$$\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk} \qquad (1)$$

where p_{jk} represents the proportion of individuals belonging to the jth group in county k, which is obtained from $\{\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk}\}$ (i=1,2,…) simulate the posterior distribution of the overall prevalence rate of county k. $\frac{1}{I}\sum_{i=1}^{I}\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk}$, the mean of $\{\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk}\}$(i=1,2,…), estimates the posterior mean of the overall prevalence rate of county k. The 2.5th and 97.5th percentiles of $\{\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk}\}$ (i=1, 2…) form the 95% credible interval for the overall prevalence rate of county k. Similarly we can simulate the posterior distribution of the prevalence rate by race, or by sex, for each county, and then get the posterior mean and 95% credible intervals. The results are shown in Tables1-4 and Figures 1-4.

We validate our estimates by comparing with estimates from National Center for Chronic Prevention and Health Promotion [15] and Florida Health Department estimates [16] using Pearson and Spearman Correlation coefficients, Mean Square Error (MSE), Mean Absolute difference (MAD), Mean Relative absolute differences (MRAD), and Rank statistics ([17] See table 5).

2.6 Results

The estimated prevalence of diabetes in the counties ranges from 6.2% (Monroe county) to 13.9% (Jackson county) (see the table1 and fig1). Almost all counties, except Monroe (6.2%) and St. Johns (6.9%), have estimated prevalence of diabetes above the national average (6.92%) and 54 out of the 67 counties had higher estimated prevalence of diabetes than the Florida state estimate (8.6%). Most of these counties were found in the north part of the state and had higher percentage poverty compared to those counties with lower prevalence of diabetes. This was also clearly indicated by the house hold income, where those counties with low house hold income resides in those counties with high estimated prevalence of diabetes. In all counties in this study, blacks had higher estimated prevalence of diabetes than white (see table 2 and fig 2 below).

The prevalence of estimated diabetes was higher among men than women ranging 7.2% - 15.1% in men and 5.0% - 13.3% in women. In almost all counties, the Blacks had the higher prevalence than whites.

Monroe County has the lowest prevalence by sex (Men (7.2%) and Women (5%) while Putnam County had the highest male (15.1%) prevalence. The estimated prevalence of diabetes tended to increase with age.

For counties with missing data in the 2010 public BRFSS data, as it discussed in the method section we used CAR [12] model which helped us to borrow information from the surrounding counties. We checked our findings with the Florida public health direct estimate and by running Bayesian hierarchical model for the complete data we got from the Florida BRFSS. For your information, some state may do complete survey but the survey may not be done every year. Our CAR model can estimate for every year regardless of the survey cover all counties or not.

Table 2-1 Estimates for missing counties with complete data vs BH Estimates

	Franklin		Glades		Lafayette		Liberty	
	Gold Standard*	CAR Model Estimate	Gold Standard*	CAR Model Estimate	Gold Standard*	CAR Model Estimate	Gold Standard*	CAR Model Estimate
Overall	10.1 (8.3-12.1)	10.8 (7.1-15.4)	12.8 (10.6-15.2)	12.5 (9.8-15.3)	9.1 (7.7-10.6)	9.2 (7.1-11.7)	9.2 (7.7-11)	11.8 (9.3-14.6)
Age Groups								
18-44	3.9 (3.0-5.0)	4.1 (2.4-6.3)	4.8 (3.7-6.1)	4.4 (3.2-5.8)	3.8 (3.0-4.7)	3.9 (2.6-5.0)	3.9 (3.0-4.9)	5.0 (3.6-6.7)
45-64	13.7 (11.2-16.4)	14.7 (9.7-21.0)	15.7 (12.9-18.7)	15.5 (12.1-19.2)	14.1 (11.9-16.5)	13.8 (11.3-18.8)	13.8 (11.4-16.3)	17.5 (13.9-21.6)
65 and abov	16.7 (13.9-19.7)	17.8 (12-24.6)	21.4 (18.0-25.0)	21.0(16.9-25.5)	17.8 (15.2-20.5)	18.1 (14.0-22.1)	18.1 (15.3-21.2)	23.3 (18.8-28.2)
Gender								
Male	10.5 (8.6-12.6)	11.4 (7.5-16.1)	13.9 (11.6-16.5)	13.5 (10.7-16.6)	9.4 (7.9-11.1)	9.7 (7.4-12.3)	9.7 (8-11.5)	12.5 (9.8-15.5)
Female	9.5 (7.7-11.4)	9.9 (6.4-14.3)	11.1 (9.1-13.3)	10.9 (8.5-13.6)	8.5 (7.1-10.0)	8.5 (6.5-10.9)	8.5 (7-10.1)	10.7 (8.3-13.3)
Race								
White	10(8.2-12.0)	10.7 (7.0-15.3)	12.8 (10.6-15.2)	12.4 (9.8-15.3)	9.5 (8.0-11.1)	9.0 (7.2-12.0)	9.0 (7.5-10.7)	11.6 (9.1-14.4)
Black	10.6(8.6-12.7)	11.1 (7.4-15.8)	12.8 (10.5-15.4)	12.6 (9.9-15.8)	7.5 (6.1-9.1)	10.1 (6.3-11)	10.1 (8.2-12.1)	12.7 (9.9-15.9)

* Estimates calculated using the complete counties data give by Florida BRFSS and applying the Bayesian Hierarchical

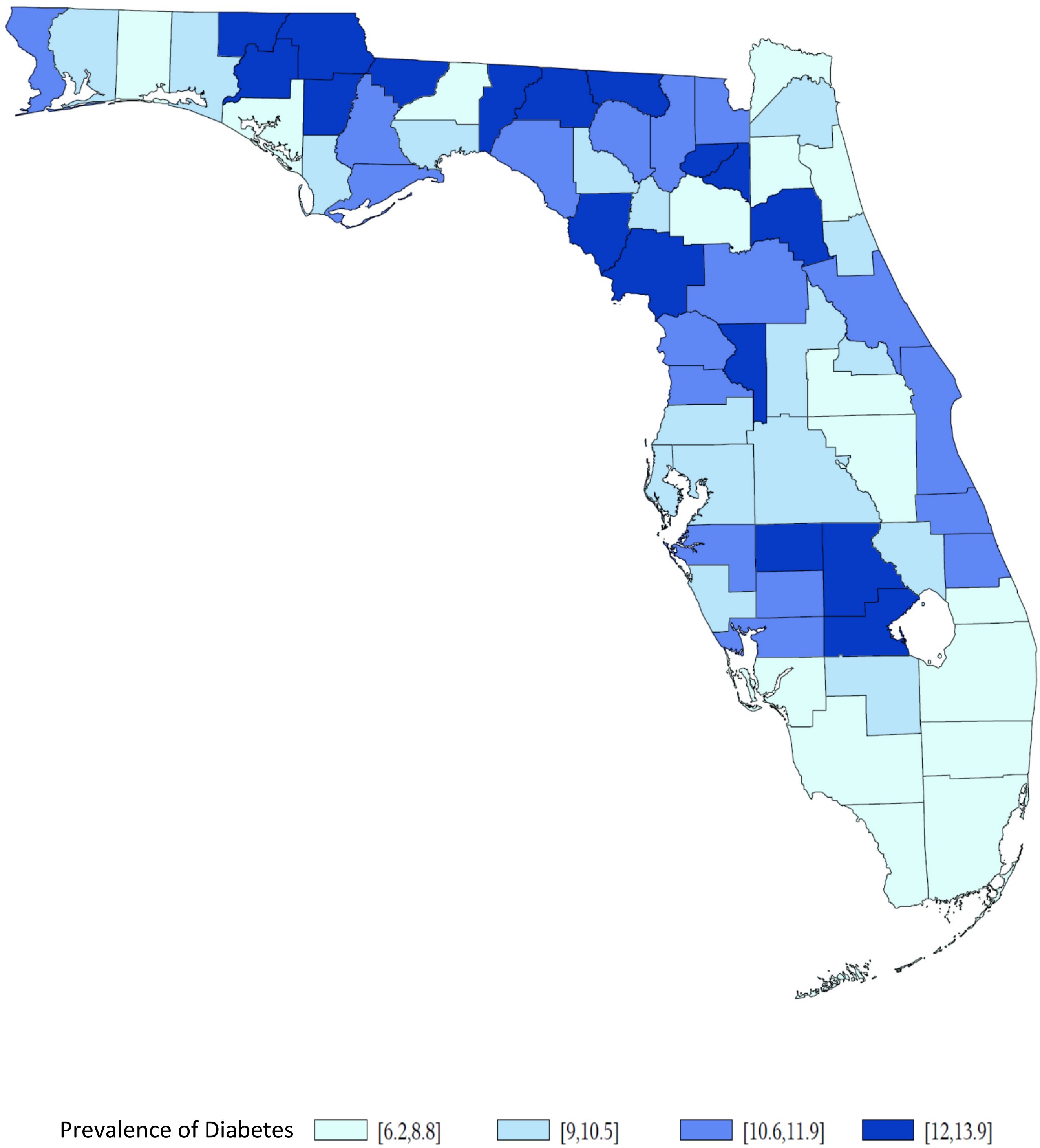


Figure 2-2 Estimated Prevalence of Diabetes, Overall, Florida Counties using Bayesian

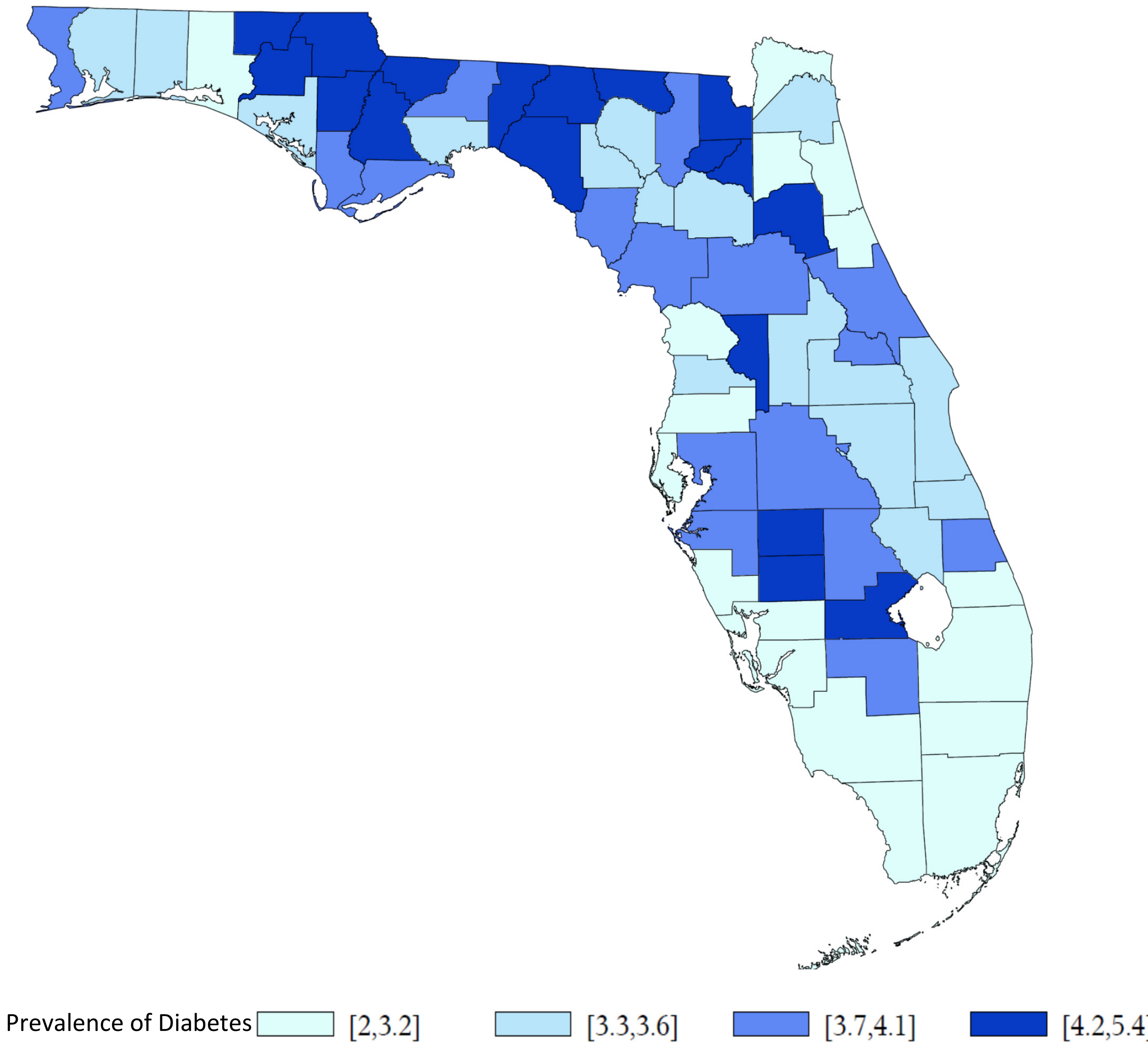


Figure 2-3 Estimated Prevalence of Diabetes, Aged 18-44, Florida Counties using Bayesian

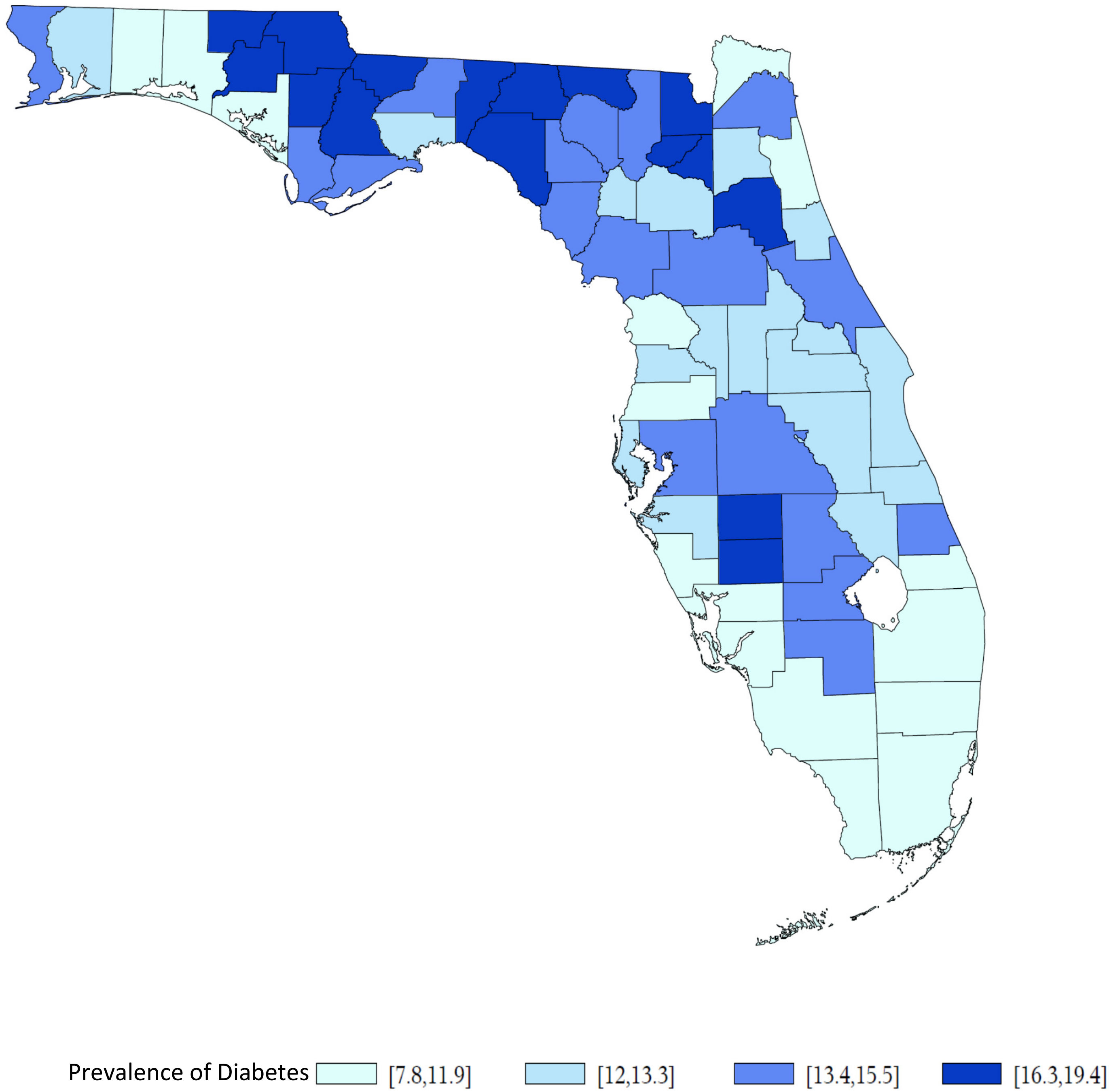


Figure 2-5 Estimated Prevalence of Diabetes, Aged 45-64, Florida Counties using Bayesian

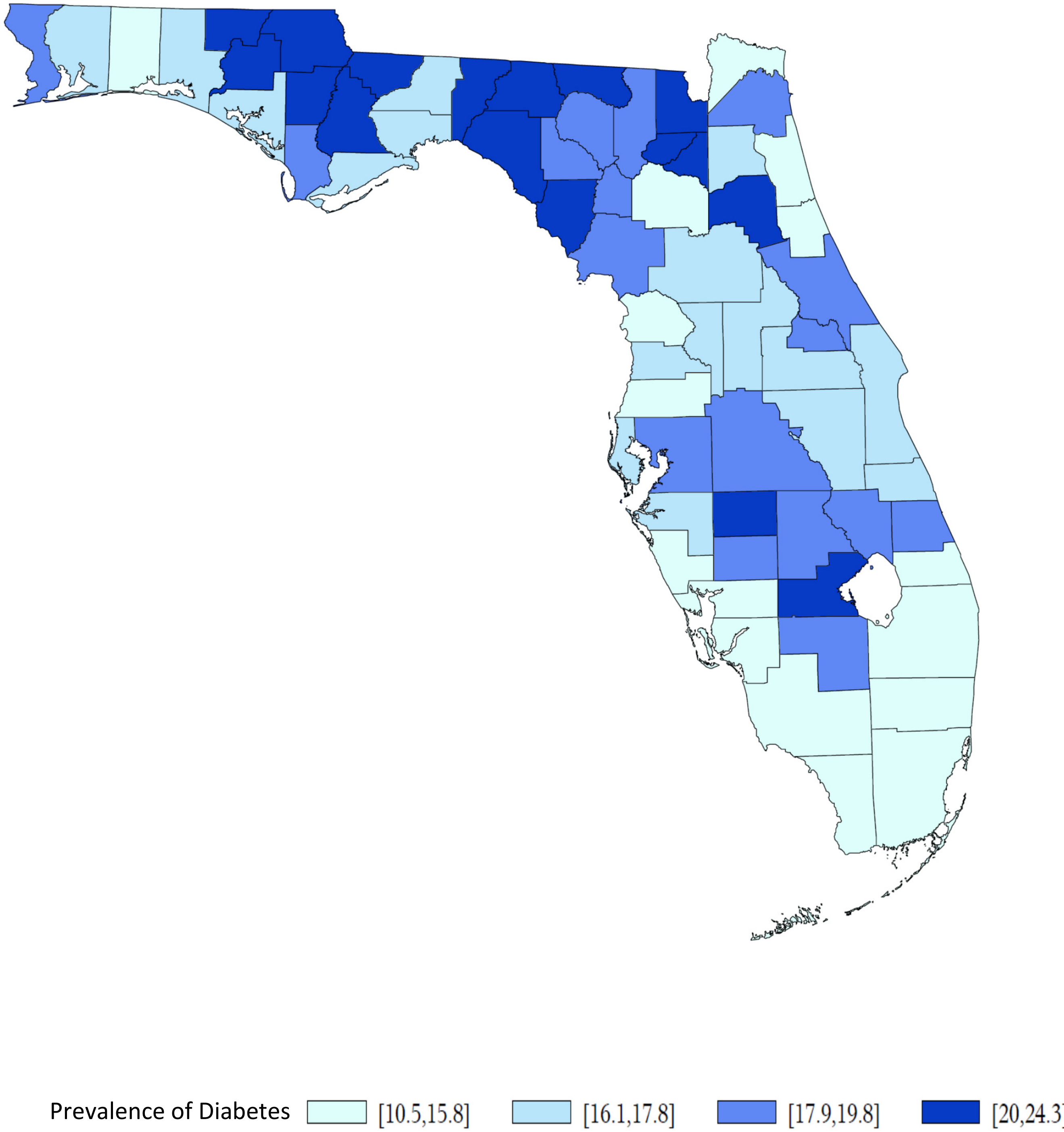


Figure 2-7 Estimated Prevalence of Diabetes, Aged 65 and above, Florida Counties using Bayesian Hierarchical Model

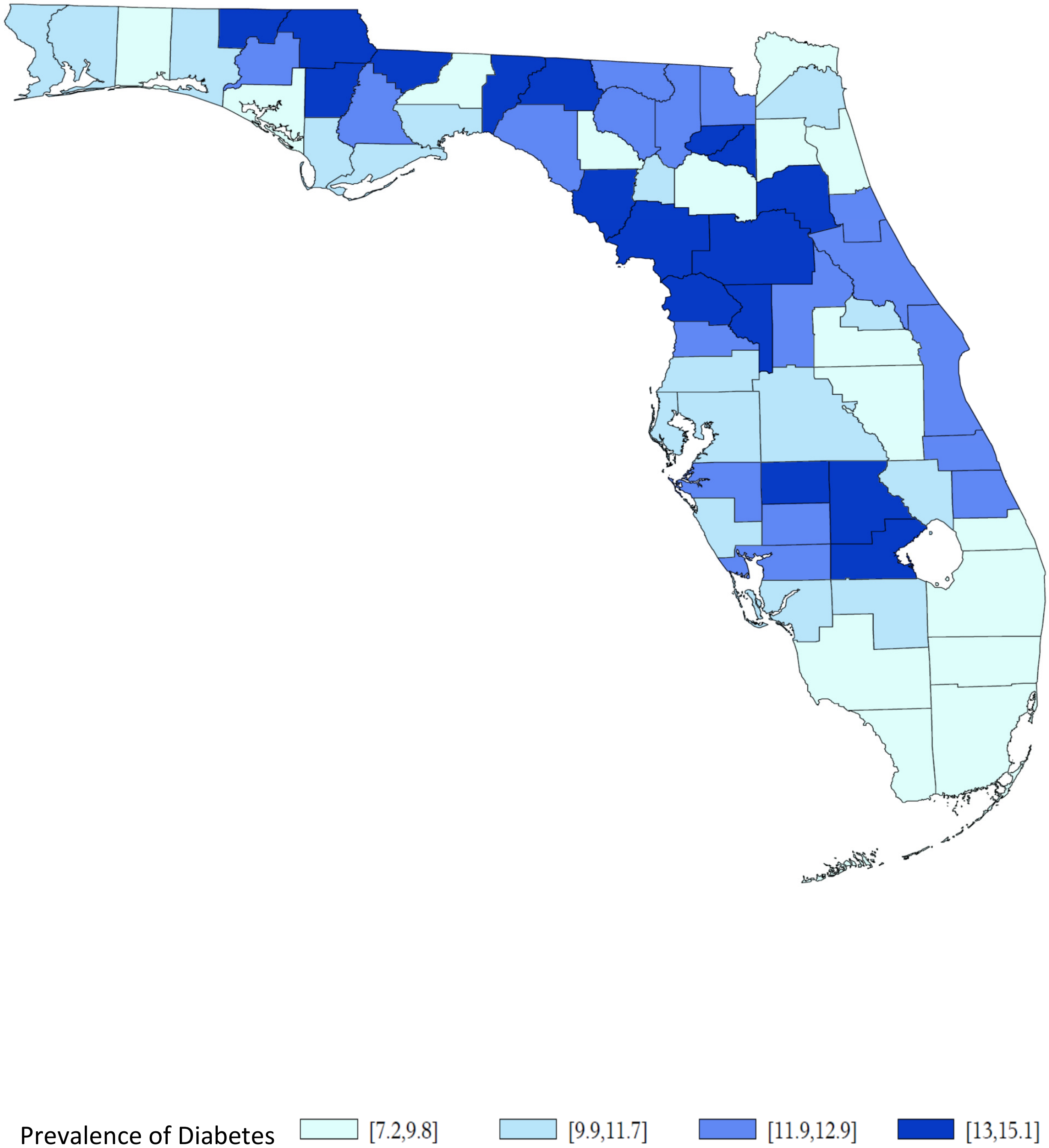


Figure 2-8 Estimated Prevalence of Diabetes, Male, Florida Counties using Bayesian Hierarchical Model

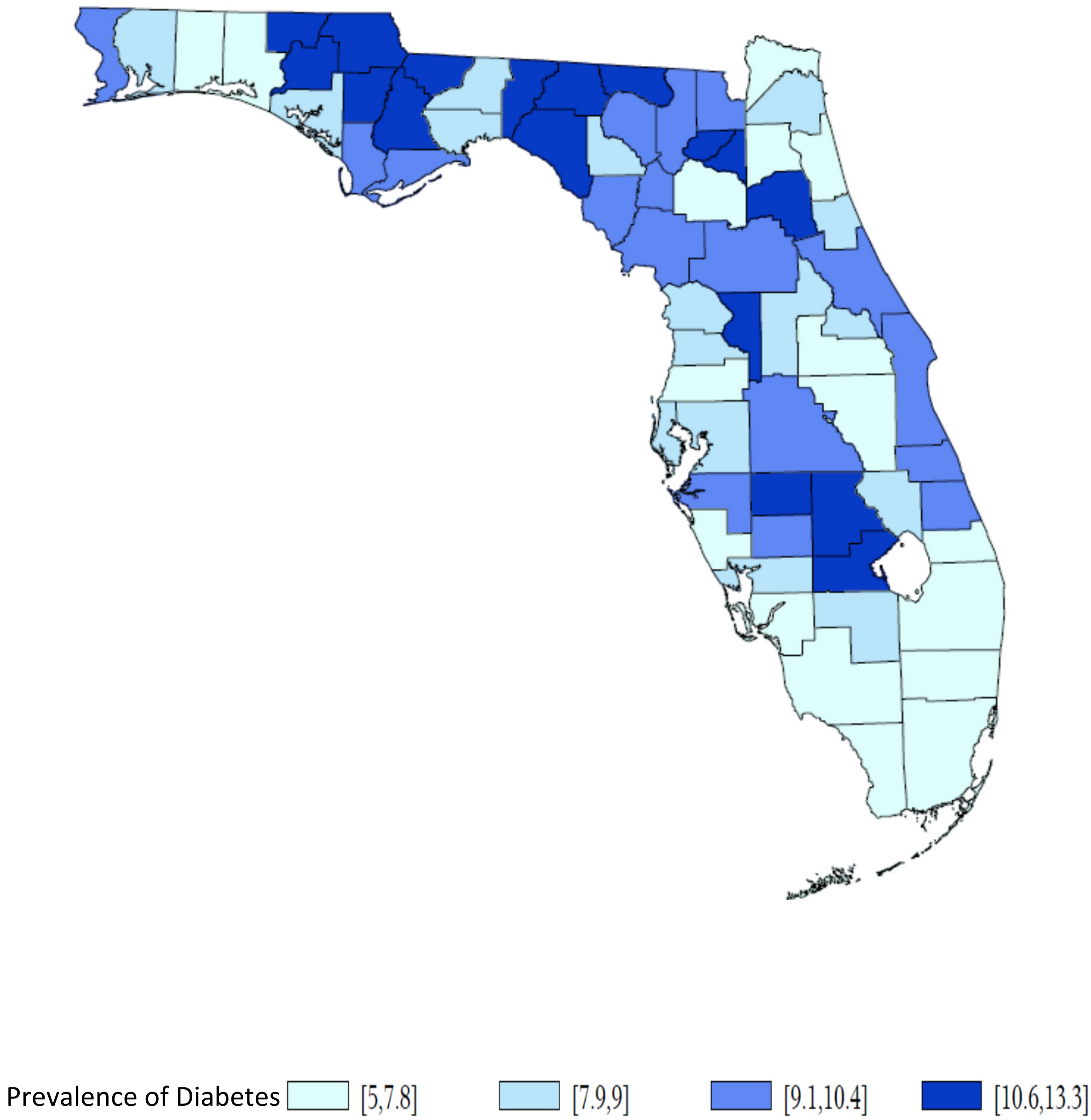


Figure 2-10 Estimated Prevalence of Diabetes, Female, Florida Counties using Bayesian Hierarchical Model

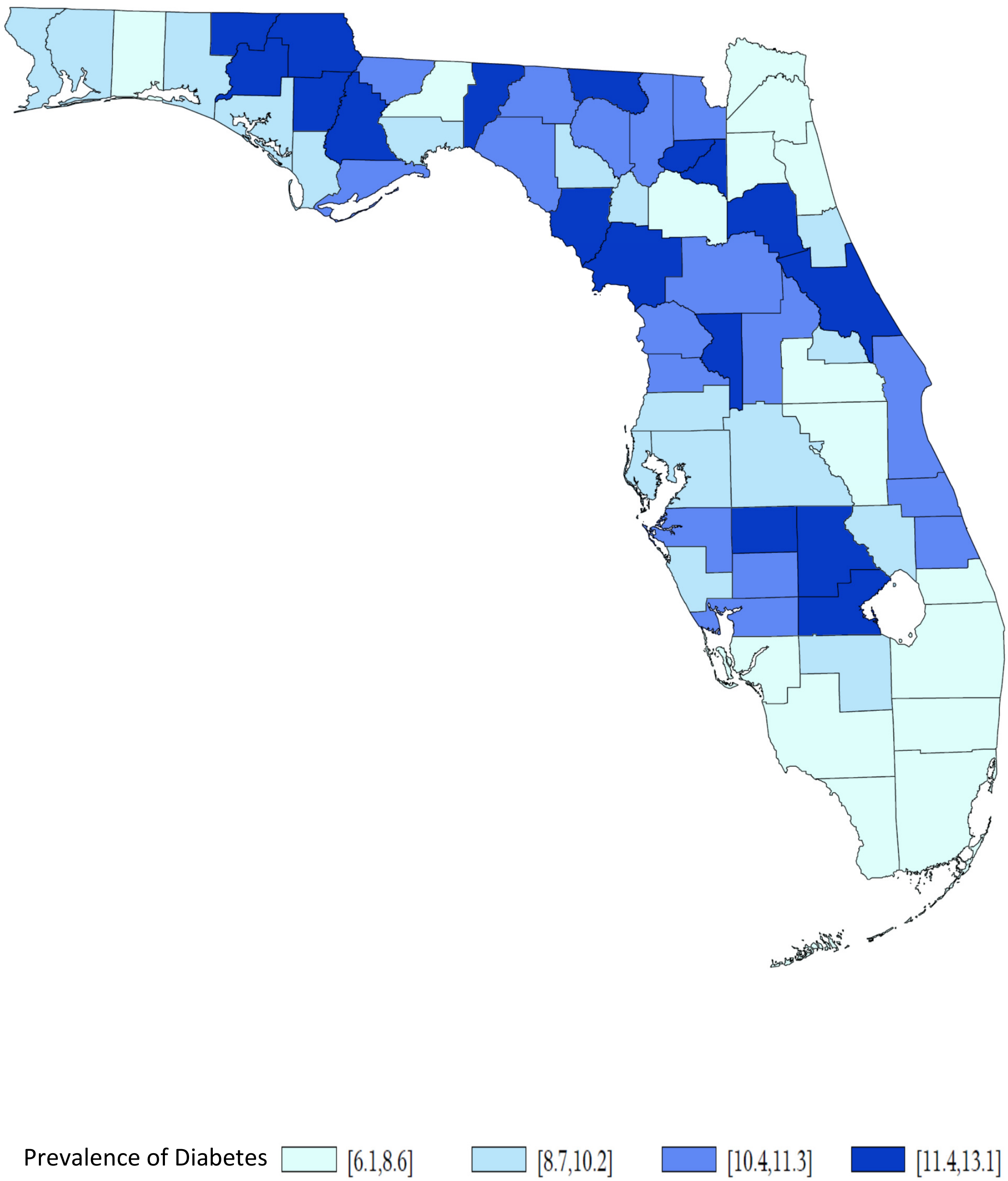


Figure 2-12 Estimated Prevalence of Diabetes, White, Florida Counties using Bayesian Hierarchical Model

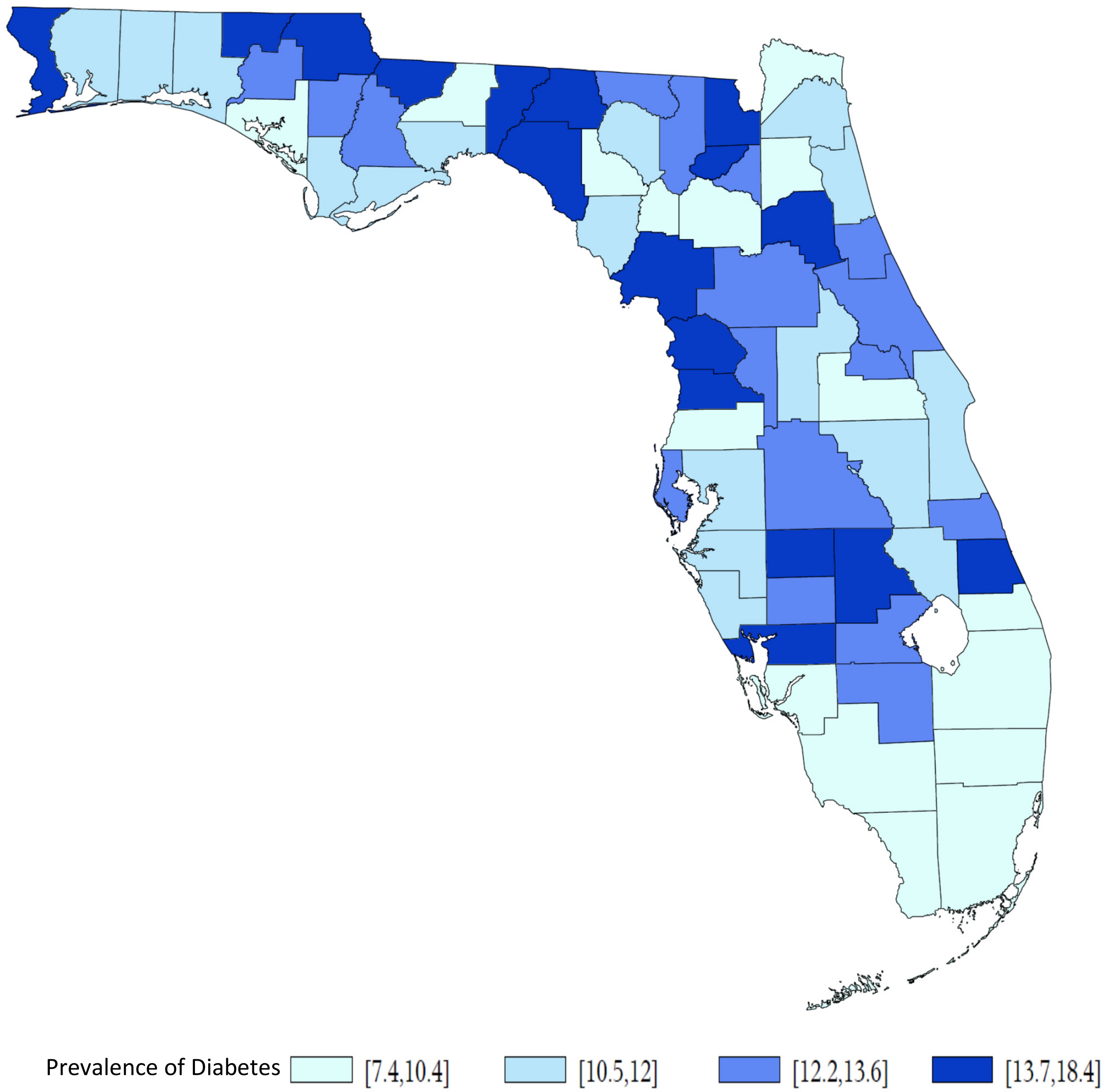


Figure 2-13 Estimated Prevalence of Diabetes, Black, Florida Counties using Bayesian Hierarchical Model

Table 2-2 Overall County Estimated Prevalence of Diabetes

County Name	Overall	County Name	Overall
Alachua	7.8 (6.4 - 9.2)	Lee	8.6 (6.9 - 10.4)
Baker	11.6 (9.8 - 13.6)	Leon	8.5 (6.9 - 10.3)
Bay	8.8 (7.3 - 10.6)	Levy	12.0 (10.2 - 13.9)
Bradford	12.4 (10.5 - 14.5)	Liberty	11.8 (9.3 - 14.6)
Brevard	10.7 (9.0 - 12.6)	Madison	12.4 (10.4 - 14.5)
Broward	7.1 (5.7 - 8.6)	Manatee	10.8 (9.0 - 12.7)
Calhoun	12.1 (10.2 - 14.3)	Marion	11.4 (9.7 - 13.2)
Charlotte	10.9 (9.0 - 12.9)	Martin	7.8 (6.2 - 9.4)
Citrus	11 (9.1 - 13.1)	Miami-Dade	7.8 (6.2 - 9.5)
Clay	8.7 (7.2 - 10.4)	Monroe	6.2 (4.7 - 7.8)
Collier	7.6 (6.2 - 9.2)	Nassau	8.1 (6.4 - 10)
Columbia	11.3 (9.6 - 13.2)	Okaloosa	8.3 (6.5 - 10.3)
Desoto	11.4 (9.6 - 13.4)	Okeechobee	9.9 (8.4 - 11.6)
Dixie	12.2 (10.0 - 14.6)	Orange	8.2 (7.0 - 9.5)
Duval	9.5 (7.9 - 11.3)	Osceola	8.7 (7.4 - 10.1)
Escambia	10.7 (8.7 - 13.0)	Palm Beach	7.7 (6.3 - 9.3)
Flagler	10.2 (8.3 - 12.3)	Pasco	9.2 (7.6 - 10.9)
Franklin	10.8 (7.1 - 15.4)	Pinellas	10.0 (8.0 - 12.1)
Gadsden	12.9 (10.8 - 15.2)	Polk	10.4 (8.9 - 11.9)
Gilchrist	10.0 (8.2 - 11.9)	Putnam	13.5 (11.5 - 15.6)
Glades	12.5 (9.8 - 15.3)	St. Johns	6.9 (5.5 - 8.4)
Gulf	10.5 (8.5 - 12.6)	St. Lucie	11.1 (9.2 - 13.3)
Hamilton	13.0 (10.8 - 15.4)	Santa Rosa	9.4 (7.5 - 11.5)
Hardee	12.8 (10.8 - 14.9)	Sarasota	9.0 (7.3 - 10.8)
Hendry	9.7 (8.1 - 11.5)	Seminole	9.6 (7.9 - 11.5)
Hernando	10.6 (8.7 - 12.8)	Sumter	12.8 (10.7 - 15.0)
Highlands	13.0 (11.1 - 15.1)	Suwannee	10.7 (8.8 - 12.7)
Hillsborough	9.4 (7.8 - 11.1)	Taylor	11.9 (9.9 - 13.9)
Holmes	13.2 (11 - 15.5)	Union	12.7 (10.6 - 14.9)
Indian River	10.8 (8.9 - 12.9)	Volusia	11.5 (10 - 13.1)
Jackson	13.9 (11.8 - 16.1)	Wakulla	9.2 (7.4 - 11.3)
Jefferson	12.6 (10.6 - 14.8)	Walton	9.0 (7.4 - 10.8)
Lafayette	9.2 (7.1 - 11.7)	Washington	12.0 (10.1 - 14.1)
Lake	10.5 (9.0 - 12.2)		

Highlighted in yellow are county with missing data but estimates are calculated using CAR model.

Table 2-3 Estimated Diabetes Prevalence by Age Group, Florida Counties, 2010

County Name	Age Group		
	18 - 44	45 - 64	≥65
Alachua	3.4 (2.6 - 4.3)	12.9 (10.6 - 15.3)	15.6 (13.0 - 18.3)
Baker	4.4 (3.5 - 5.5)	16.5 (13.9 - 19.3)	23.6 (20.3 - 27.2)
Bay	3.4 (2.6 - 4.2)	11.9 (9.8 - 14.3)	16.1 (13.4 - 19.0)
Bradford	4.7 (3.7 - 6.0)	17.8 (15.0 - 20.9)	21.6 (18.5 - 25.0)
Brevard	3.5 (2.7 - 4.4)	13.1 (10.9 - 15.6)	17.4 (14.7 - 20.3)
Broward	2.4 (1.8 - 3.1)	9.8 (7.9 - 12.0)	13.1 (10.6 - 15.7)
Calhoun	4.6 (3.5 - 5.8)	16.6 (13.9 - 19.6)	21.8 (18.6 - 25.3)
Charlotte	3.1 (2.4 - 3.9)	11.0 (9.0 - 13.2)	15.4 (12.8 - 18.1)
Citrus	3.2 (2.5 - 4.1)	11.7 (9.5 - 14.1)	15.6 (13.0 - 18.5)
Clay	3.2 (2.5 - 4.1)	12.0 (9.9 - 14.4)	16.7 (14.0 - 19.7)
Collier	2.4 (1.9 - 3.1)	9.0 (7.3 - 11.0)	11.6 (9.5 - 14.0)
Columbia	4.1 (3.2 - 5.1)	15.5 (13.1 - 18.2)	19.3 (16.5 - 22.4)
De Soto	4.2 (3.2 - 5.3)	16.3 (13.6 - 19.1)	19.4 (16.5 - 22.5)
Dixie	4.0 (3.0 - 5.1)	15.4 (12.5 - 18.4)	20.0 (16.6 - 23.6)
Duval	3.6 (2.8 - 4.6)	14.2 (11.7 - 16.8)	18.4 (15.5 - 21.6)
Escambia	4.0 (3.0 - 5.2)	15.1 (12.2 - 18.3)	19.7 (16.2 - 23.5)
Flagler	3.1 (2.3 - 4.0)	12.0 (9.7 - 14.5)	15.8 (13.0 - 18.9)
Franklin	4.1 (2.4 - 6.3)	14.7 (9.7 - 21.0)	17.8 (12.0 - 24.6)
Gadsden	4.7 (3.6 - 6.1)	18.5 (15.4 - 21.8)	21.2 (17.8 - 24.7)
Gilchrist	3.6 (2.7 - 4.5)	12.8 (10.5 - 15.3)	18.1 (15.2 - 21.3)
Glades	4.4 (3.2 - 5.8)	15.5 (12.1 - 19.2)	21.0 (16.9 - 25.5)
Gulf	4.0 (3.0 - 5.2)	14.4 (11.6 - 17.4)	18.0 (14.8 - 21.5)
Hamilton	4.8 (3.7 - 6.2)	19.2 (16.0 - 22.7)	24.2 (20.4 - 28.3)
Hardee	5.2 (4.1 - 6.6)	18.7 (15.8 - 21.8)	24.3 (21.0 - 27.9)
Hendry	3.9 (3.0 - 4.9)	14.6 (12.2 - 17.3)	19.5 (16.5 - 22.7)
Hernando	3.5 (2.6 - 4.5)	12.0 (9.7 - 14.5)	16.4 (13.5 - 19.5)
Highlands	3.8 (3.0 - 4.7)	14.3 (12.0 - 16.7)	18.8 (16.1 - 21.6)
Hillsborough	3.7 (2.9 - 4.6)	13.8 (11.5 - 16.4)	18.1 (15.3 - 21.1)
Holmes	4.7 (3.6 - 5.9)	17.7 (14.7 - 20.9)	22.4 (19.0 - 26.0)
Indian River	3.4 (2.6 - 4.3)	12.2 (10.0 - 14.6)	16.2 (13.5 - 19.2)
Jackson	5.4 (4.2 - 6.7)	19.4 (16.5 - 22.5)	23.4 (20.2 - 26.7)
Jefferson	4.4 (3.4 - 5.5)	16.4 (13.7 - 19.3)	21.3 (18.0 - 24.7)
Lafayette	3.6 (2.6 - 5.0)	14.8 (11.3 - 18.8)	17.9 (14.0 - 22.1)
Lake	3.3 (2.6 - 4.1)	12.2 (10.3 - 14.3)	16.8 (14.4 - 19.4)

County Name	Age Group		
	18 - 44	45- 64	≥65
Lee	2.8 (2.1 - 3.6)	10.3 (8.2 - 12.6)	13.6 (11.1 - 16.4)
Leon	4.1 (3.1 - 5.2)	14.1 (11.5 - 16.9)	17.5 (14.6 - 20.8)
Levy	3.9 (3.1 - 4.9)	14.6 (12.3 - 17.0)	19.8 (17.0 - 22.8)
Liberty	5.0 (3.6 - 6.7)	17.5 (13.9 - 21.6)	23.3 (18.8 - 28.2)
Madison	4.4 (3.4 - 5.5)	17.6 (14.8 - 20.7)	20.3 (17.3 - 23.6)
Manatee	3.7 (2.9 - 4.6)	12.5 (10.4 - 14.9)	17.2 (14.6 - 20.1)
Marion	3.9 (3.1 - 4.8)	13.4 (11.3 - 15.6)	17.2 (14.8 - 19.7)
Martin	2.3 (1.7 - 3.0)	8.5 (6.8 - 10.4)	11.8 (9.5 - 14.2)
Miami-Dade	2.8 (2.1 - 3.6)	11.1 (8.9 - 13.7)	15.2 (12.3 - 18.3)
Monroe	2.0 (1.5 - 2.7)	7.8 (5.9 - 9.9)	10.5 (8.1 - 13.1)
Nassau	2.8 (2.0 - 3.6)	10.1 (7.9 - 12.5)	14.5 (11.6 - 17.7)
Okaloosa	3.3 (2.5 - 4.4)	11.5 (9.0 - 14.3)	14.6 (11.6 - 17.8)
Okeechobee	3.5 (2.8 - 4.4)	13 (10.9 - 15.2)	18.1 (15.4 - 20.8)
Orange	3.4 (2.7 - 4.1)	12.9 (11.0 - 14.9)	17.5 (15.2 - 19.9)
Osceola	3.4 (2.7 - 4.2)	12.7 (10.7 - 14.8)	17.4 (14.9 - 20.1)
Palm Beach	2.5 (1.9 - 3.2)	9.7 (7.8 - 11.7)	12.6 (10.4 - 15.1)
Pasco	2.9 (2.3 - 3.7)	11.2 (9.2 - 13.4)	15.6 (13.1 - 18.3)
Pinellas	3.2 (2.4 - 4.2)	12.1 (9.6 - 14.7)	16.3 (13.3 - 19.6)
Polk	3.8 (3.0 - 4.6)	13.4 (11.5 - 15.4)	17.9 (15.5 - 20.3)
Putnam	4.4 (3.5 - 5.4)	17.0 (14.4 - 19.8)	22.0 (18.9 - 25.3)
St. Johns	2.3 (1.7 - 3.0)	8.7 (6.9 - 10.7)	12.2 (9.8 - 14.8)
St. Lucie	3.7 (2.8 - 4.7)	14.5 (11.9 - 17.4)	17.9 (14.9 - 21.1)
Santa Rosa	3.4 (2.6 - 4.5)	13.0 (10.4 - 15.9)	17.0 (13.8 - 20.5)
Sarasota	2.7 (2.0 - 3.4)	9.7 (7.9 - 11.8)	13.1 (10.7 - 15.6)
Seminole	3.7 (2.8 - 4.7)	13.2 (10.8 - 15.9)	18.7 (15.7 - 22.1)
Sumter	4.2 (3.2 - 5.4)	12.7 (10.5 - 15.0)	16.4 (13.8 - 19.2)
Suwannee	3.5 (2.6 - 4.4)	13.5 (11.1 - 16.2)	18.0 (15.1 - 21.2)
Taylor	4.2 (3.3 - 5.3)	16.7 (14.0 - 19.7)	20.0 (17.0 - 23.2)
Union	4.7 (3.6 - 5.9)	19.2 (16.0 - 22.6)	22.7 (19.3 - 26.3)
Volusia	4.0 (3.2 - 4.8)	13.7 (11.8 - 15.7)	19.2 (16.9 - 21.7)
Wakulla	3.5 (2.6 - 4.6)	13.3 (10.7 - 16.3)	17.8 (14.5 - 21.3)
Walton	3.2 (2.4 - 4.1)	11.6 (9.4 - 14.0)	16.1 (13.3 - 19.0)
Washington	4.4 (3.4 - 5.5)	16.7 (14.0 - 19.6)	21.0 (17.9 - 24.3)

Highlighted in yellow are county with missing data but estimates are calculated using CAR model.

Table 2-4 Estimated Diabetes Prevalence by Gender, Florida Counties, 2010

County Name	Gender		County Name	Gender	
	Male	Female		Male	Female
Alachua	8.5 (6.9 - 10.1)	7.1 (5.8 - 8.4)	Lee	10.0 (8.1 - 12.2)	7.2 (5.7 - 8.8)
Baker	12.8 (10.8 - 15)	10.3 (8.6 - 12.1)	Leon	9.2 (7.4 - 11.1)	7.9 (6.4 - 9.6)
Bay	9.7 (8.0 - 11.6)	8.0 (6.5 - 9.6)	Levy	14.0 (12.0 - 16.3)	10 (8.5 - 11.8)
Bradford	13.1 (11.1 - 15.4)	11.3 (9.5 - 13.4)	Liberty	12.5 (9.8 - 15.5)	10.7 (8.3 - 13.3)
Brevard	12.1 (10.2 - 14.3)	9.4 (7.8 - 11.1)	Madison	13.2 (11.1 - 15.5)	11.5 (9.6 - 13.5)
Broward	8.0 (6.4 - 9.7)	6.3 (5.0 - 7.7)	Manatee	12.1 (10.2 - 14.3)	9.6 (8 - 11.3)
Calhoun	13.3 (11.1 - 15.6)	10.7 (8.9 - 12.7)	Marion	13.0 (11.1 - 15.0)	10.0 (8.4 - 11.6)
Charlotte	12.9 (10.7 - 15.3)	9.0 (7.4 - 10.7)	Martin	8.9 (7.1 - 10.8)	6.7 (5.3 - 8.1)
Citrus	13.3 (10.9 - 15.7)	9 .0(7.3 - 10.8)	Miami-Dade	8.7 (6.9 - 10.6)	7.0 (5.6 - 8.6)
Clay	9.8 (8.1 - 11.7)	7.7 (6.3 - 9.3)	Monroe	7.2 (5.5 - 9.1)	5.0 (3.8 - 6.3)
Collier	8.8 (7.1 - 10.6)	6.6 (5.3 - 8.0)	Nassau	9.1 (7.2 - 11.2)	7.2 (5.7 - 8.9)
Columbia	12.3 (10.4 - 14.4)	10.2 (8.6 - 12)	Okaloosa	8.9 (7.0 - 11.1)	7.7 (6.0 - 9.6)
DeSoto	12.2 (10.2 - 14.4)	10.4 (8.7 - 12.3)	Okeechobee	11.3 (9.5 - 13.2)	8.3 (7.0 - 9.8)
Dixie	13.8 (11.3 - 16.4)	10.4 (8.4 - 12.5)	Orange	9.0 (7.7 - 10.4)	7.4 (6.3 - 8.6)
Duval	10.2 (8.4 - 12.1)	8.8 (7.3 - 10.5)	Osceola	9.7 (8.2 - 11.3)	7.8 (6.5 - 9.1)
Escambia	11.5 (9.3 - 14.0)	10.0 (8.0 - 12.1)	Palm Beach	8.8 (7.2 - 10.6)	6.7 (5.4 - 8.1)
Flagler	11.9 (9.7 - 14.3)	8.7 (7 - 10.5)	Pasco	10.8 (8.9 - 12.7)	7.8 (6.4 - 9.3)
Franklin	11.4 (7.5 - 16.1)	9.9 (6.4 - 14.3)	Pinellas	11.2 (9.0 - 13.6)	8.9 (7.1 - 10.9)
Gadsden	13.3 (11.0 - 15.7)	12.6 (10.5 - 14.9)	Polk	11.7 (10.1 - 13.5)	9.1 (7.8 - 10.5)
Gilchrist	10.8 (8.9 - 12.9)	9.1 (7.5 - 10.9)	Putnam	15.1 (12.8 - 17.5)	11.9 (10.1 - 14)
Glades	13.5 (10.7 - 16.6)	10.9 (8.5 - 13.6)	St. Johns	8.0 (6.3 - 9.7)	5.9 (4.6 - 7.2)
Gulf	10.8 (8.7 - 13.1)	9.9 (8.0 - 12.0)	St. Lucie	12.6 (10.5 - 15.1)	9.7 (7.9 - 11.6)
Hamilton	12.8 (10.6 - 15.3)	13.3 (11 - 15.8)	Santa Rosa	10.5 (8.4 - 12.9)	8.2 (6.5 - 10.1)
Hardee	13.7 (11.6 - 16.1)	11.7 (9.8 - 13.7)	Sarasota	10.5 (8.6 - 12.6)	7.7 (6.2 - 9.2)
Hendry	10.6 (8.9 - 12.6)	8.6 (7.1 - 10.2)	Seminole	10.4 (8.6 - 12.5)	8.8 (7.2 - 10.6)
Hernando	12.4 (10.2 - 14.9)	9.0 (7.3 - 10.9)	Sumter	14.8 (12.4 - 17.3)	10.6 (8.8 - 12.6)
Highlands	14.9 (12.7 - 17.3)	11.2 (9.4 - 13.1)	Suwannee	12.0 (9.9 - 14.2)	9.3 (7.6 - 11.2)
Hillsborough	10.4 (8.6 - 12.3)	8.5 (7.0 - 10.1)	Taylor	12.5 (10.5 - 14.8)	10.9 (9.1 - 13.0)
Holmes	14.5 (12.1 - 17.0)	11.7 (9.7 - 13.9)	Union	13.4 (11.2 - 15.8)	11.1 (9.3 - 13.2)
IndianRiver	12.5 (10.4 - 14.9)	9.2 (7.6 - 11.1)	Volusia	12.7 (11.1 - 14.5)	10.4 (9.0 - 11.9)
Jackson	14.4 (12.3 - 16.8)	13.2 (11.2 - 15.4)	Wakulla	9.9 (7.9 - 12.0)	8.4 (6.7 - 10.4)
Jefferson	13.4 (11.3 - 15.8)	11.6 (9.7 - 13.8)	Walton	10.2 (8.3 - 12.2)	7.8 (6.4 - 9.5)
Lafayette	9.7 (7.4 - 12.3)	8.5 (6.5 - 10.9)	Washington	12.9 (10.9 - 15.2)	10.9 (9.1 - 12.9)
Lake	12.2 (10.4 - 14.2)	9.0 (7.6 - 10.5)			

Highlighted in yellow are county with missing data but estimates are calculated using CAR model.

Table 2-5 Estimated Diabetes Prevalence by Race, Florida Counties, 2010

County Name	Race		County Name	Race	
	White	Black		White	Black
Alachua	7.1 (5.8 - 8.5)	10.4 (8.4 - 12.3)	Lee	8.4 (6.8 - 10.3)	10.1 (8.1 - 12.3)
Baker	11.2 (9.4 - 13.1)	14.1 (11.8 - 16.6)	Leon	7.7 (6.2 - 9.4)	10.3 (8.3 - 12.5)
Bay	8.7 (7.1 - 10.4)	10.4 (8.5 - 12.5)	Levy	11.6 (9.9 - 13.5)	15.8 (13.4 - 18.4)
Bradford	12.1 (10.2 - 14.2)	13.5 (11.2 - 16.1)	Liberty	11.6 (9.1 - 14.4)	12.7 (9.9 - 15.9)
Brevard	10.6 (8.9 - 12.5)	12.0 (10.0 - 14.2)	Madison	11.3 (9.4 - 13.3)	14.2 (11.9 - 16.7)
Broward	6.6 (5.3 - 8.1)	8.3 (6.6 - 10.1)	Manatee	10.7 (9.0 - 12.6)	11.6 (9.6 - 13.8)
Calhoun	11.9 (10.0 - 14.0)	13.4 (11.0 - 15.9)	Marion	11.2 (9.6 - 13)	12.6 (10.6 - 14.7)
Charlotte	10.7 (8.9 - 12.7)	13.8 (11.4 - 16.4)	Martin	7.7 (6.2 - 9.4)	8.5 (6.8 - 10.5)
Citrus	10.9 (9.0 - 13.0)	14.0 (11.5 - 16.7)	Miami-Dade	7.2 (5.7 - 8.8)	10.4 (8.3 - 12.6)
Clay	8.6 (7.1 - 10.3)	9.8 (8.0 - 11.8)	Monroe	6.1 (4.6 - 7.7)	7.7 (5.8 - 9.8)
Collier	7.6 (6.2 - 9.2)	8.1 (6.5 - 9.9)	Nassau	8.0 (6.3 - 9.9)	10.1 (8.0 - 12.4)
Columbia	10.9 (9.2 - 12.8)	13.2 (11.0 - 15.5)	Okaloosa	8.0 (6.3 - 10.0)	10.9 (8.6 - 13.6)
DeSoto	11.1 (9.3 - 13.1)	13.4 (11.2 - 15.8)	Okeechobee	9.8 (8.3 - 11.5)	11.0 (9.1 - 13.0)
Dixie	12.3 (10.1 - 14.7)	11.5 (9.2 - 14.1)	Orange	7.6 (6.5 - 8.8)	10.3 (8.8 - 12.0)
Duval	8.4 (6.9 - 10.1)	12.0 (9.9 - 14.3)	Osceola	8.3 (7.0 - 9.7)	11.4 (9.6 - 13.4)
Escambia	9.8 (7.9 - 12.0)	14.0 (11.3 - 16.8)	Palm Beach	7.4 (6.0 - 8.9)	9.2 (7.4 - 11.1)
Flagler	9.8 (8.0 - 11.9)	13.3 (10.8 - 16)	Pasco	9.2 (7.6 - 10.9)	8.8 (7.2 - 10.6)
Franklin	10.7 (7.0 - 15.3)	11.1 (7.4 - 15.8)	Pinellas	9.7 (7.8 - 11.8)	12.4 (10.0 - 15.1)
Gadsden	10.8 (8.9 - 12.9)	14.7 (12.2 - 17.3)	Polk	10.0 (8.6 - 11.6)	12.2 (10.5 - 14.2)
Gilchrist	10.1 (8.4 - 12.1)	7.4 (6.0 - 9.1)	Putnam	13.1 (11.1 - 15.3)	15.6 (13.2 - 18.1)
Glades	12.4 (9.8 - 15.3)	12.6 (9.9 - 15.8)	St. Johns	6.7 (5.3 - 8.1)	10.5 (8.3 - 12.7)
Gulf	10.2 (8.2 - 12.3)	11.7 (9.3 - 14.3)	St. Lucie	10.4 (8.6 - 12.5)	14.1 (11.6 - 16.8)
Hamilton	12.7 (10.5 - 15.1)	13.6 (11.2 - 16.2)	Santa Rosa	9.2 (7.4 - 11.3)	11.8 (9.4 - 14.4)
Hardee	12.3 (10.4 - 14.4)	18.4 (15.7 - 21.3)	Sarasota	8.9 (7.2 - 10.7)	11.5 (9.3 - 13.9)
Hendry	9.2 (7.6 - 10.9)	12.8 (10.7 - 15.2)	Seminole	9.2 (7.6 - 11.1)	12.2 (10.0 - 14.6)
Hernando	10.5 (8.5 - 12.6)	13.7 (11.2 - 16.5)	Sumter	12.7 (10.7 - 15)	13.2 (10.7 - 15.9)
Highlands	12.8 (10.9 - 14.9)	15.0 (12.7 - 17.5)	Suwannee	10.6 (8.7 - 12.6)	11.5 (9.5 - 13.7)
Hillsborough	8.8 (7.3 - 10.5)	12.0 (9.9 - 14.2)	Taylor	11.3 (9.4 - 13.4)	13.9 (11.5 - 16.4)
Holmes	13.1 (10.9 - 15.4)	14.6 (11.9 - 17.6)	Union	12.1 (10.0 - 14.3)	14.4 (11.9 - 17.2)
IndianRiver	10.6 (8.8 - 12.6)	13.1 (10.8 - 15.6)	Volusia	11.4 (10.0 - 13)	12.2 (10.5 - 14.1)
Jackson	12.8 (10.8 - 14.9)	16.7 (14.2 - 19.5)	Wakulla	8.9 (7.1 - 10.9)	10.9 (8.7 - 13.4)
Jefferson	11.4 (9.5 - 13.5)	14.8 (12.4 - 17.4)	Walton	8.9 (7.3 - 10.7)	11.0 (8.9 - 13.2)
Lafayette	9.4 (7.2 - 12.0)	8.5 (6.3 - 11.0)	Washington	11.8 (9.9 - 13.9)	13.4 (11.1 - 15.8)
Lake	10.5 (8.9 - 12.2)	11.1 (9.4 - 13.0)			

Highlighted in yellow are county with missing data but estimates are calculated using CAR model.

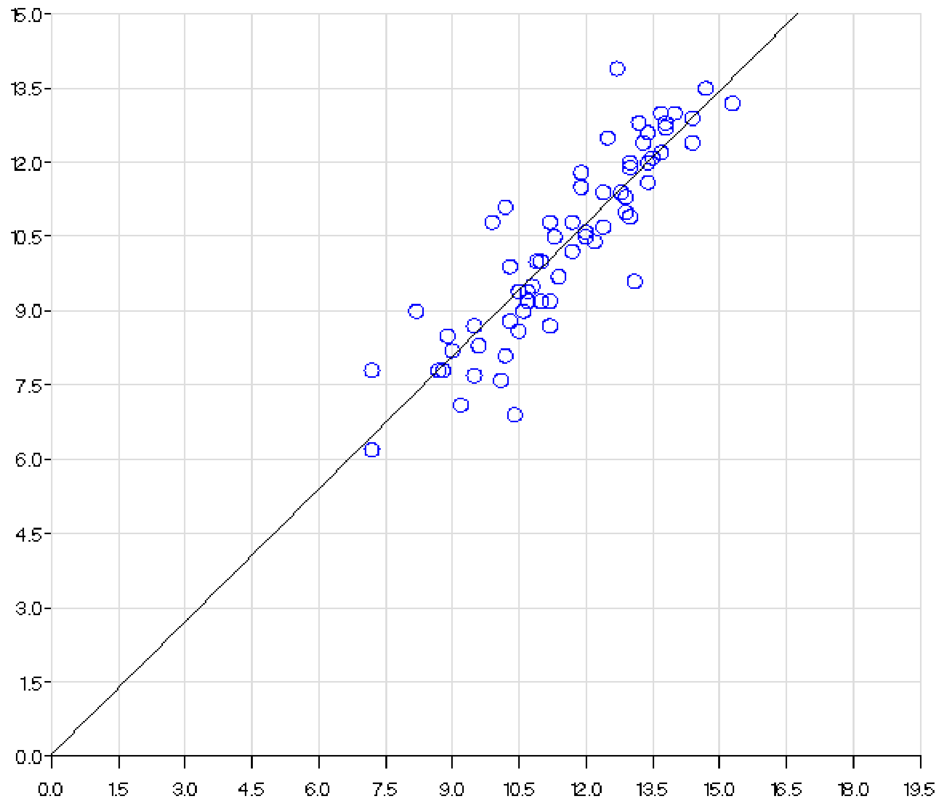


Figure 2-14 Scatterplot of Bayesian CAR model Estimates versus Division of Diabetes Bayesian model Estimates

Table 2-6 Discrepancy Statistics Comparing Overall County Estimate

Discrepancy Statistics	CAR vs Direct	CAR vs DDT
Pearson Correlation Coefficient*	0.56704	0.88305
Spearman correlation coefficient*	0.60587	0.89347
MSE	0.00115	0.00022
MAD	0.00026	0.00013
MRAD	0.00002	0.00001
Rank Statistics	-0.02500	-0.00780

* Correlation ~1 indicates no discrepancy and MSE, MAD, MRAD and Rank statistics~0 no or little [[17] discrepancy in the two estimates.

Table 2-7 WINBUGS estimate for the coefficients used in the model

Coefficient	Mean	STDERR	MC error	2.50%	Median	97.50%
beta1	-2.66	0.1503	0.005338	-2.952	-2.662	-2.368
beta2	1.494	0.1274	0.004269	1.246	1.494	1.746
beta3	1.779	0.1304	0.004393	1.524	1.779	2.036
beta4	-0.3373	0.1406	0.003398	-0.6121	-0.3363	-0.06312
beta5	-0.3353	0.1309	0.004615	-0.5871	-0.3362	-0.07391
beta6	0.3665	0.1328	0.002958	0.1084	0.3662	0.627
beta7	0.4783	0.1307	0.002907	0.2239	0.4779	0.7337
beta8	-0.3448	0.1416	0.004816	-0.6299	-0.344	-0.06813
beta9	-0.2638	0.1432	0.004958	-0.5496	-0.2627	0.01517
beta10	0.364	0.08772	0.001372	0.1929	0.3637	0.5367
beta11	-0.1904	0.03895	1.82E-04	-0.2676	-0.1903	-0.1148
beta12	-0.2761	0.05348	2.49E-04	-0.3817	-0.2758	-0.1722
beta13	-0.5997	0.05542	2.52E-04	-0.7084	-0.5996	-0.4912
beta14	-0.2715	0.0505	5.56E-04	-0.3701	-0.2714	-0.172
beta15	-0.2354	0.05324	5.96E-04	-0.3397	-0.2356	-0.1307
beta16	-0.4327	0.05764	6.33E-04	-0.5448	-0.4329	-0.3192
beta17	0.01895	0.005564	1.34E-04	0.008087	0.019	0.02995

Table 2-8 Selecting model where the regression coefficient doesn't depend on the counties based on the DIC [14]criteria

A model where the regression coefficient doesn't depend on the counties				
$\overline{D}$ = post. Mean of -2logL; $\widehat{D}$ = -2LogL at post. Mean of stochastic nodes				
	$\overline{D}$	$\widehat{D}$	pD	DIC
Diabetes	13469.8	13413.8	56.002	13525.8

County varying coefficients with Conditional Auto Regressive(CAR) Model				
$\overline{D}$ = post.mean of -2logL; $\widehat{D}$ = -2LogL at post.mean of stochastic nodes				
	$\overline{D}$	$\widehat{D}$	pD	DIC
Diabetes	13280	12871.6	408.374	13688.3

County varying coefficients without spatial correlation Conditional Auto Regressive(CAR) Model				
$\overline{D}$ = post.mean of -2logL; $\widehat{D}$ = -2LogL at post.mean of stochastic nodes				
	$\overline{D}$	$\widehat{D}$	pD	DIC
Diabetes	13280.1	12871.8	408.389	13688.5

3 ESTIMATING COUNTY-LEVEL DIABETES PREVALENCE FOR DIABETES BELT USING BAYESIAN HIERARCHICAL MODE

3.1 Introduction

In this chapter we focused on the diabetes belt identified by CDC scientist [2]. According the CDC scientists the diabetes belt which comprised of 644 counties is mostly located in the southern part of U.S. This finding indicates that people who live in this area are more likely to have diabetes than in any other part of the country. In addition to this the risk factor associated with diabetes such as obesity and physical inactivity are also highly prevalent in the belt areas than in other parts of the U.S.

There is, though, a variation among different counties due to external factors such as poverty, education, income and culture. In this chapter we discussed the effect of such factors on diabetes.

One of the challenges in effectively addressing this epidemic disease as discussed in chapter 2 lies on providing reliable local level estimates. Sample surveys that currently available, such as BRFSS (Behavioral Risk Factor Surveillance System), NHIS (National Health Interview Survey), and others are conducted throughout the year and are costly. For this and other reasons the surveys fail to cover all areas. The direct estimates from these national surveys generate imprecise estimates since 1) the survey for that particular local area(in our case county) may have smaller sample size 2) the local area in question may not be covered by the survey due to lack of budget. Deriving estimates based on this will lead to unreliable estimates.

Armed with good reliable estimates at local level, decision makers will have the ability to implement appropriate policies and allocate funds to address the burden caused by diabetes in these localities.

In this chapter we applied Bayesian Hierarchical models to produce better local area estimates on CDC diabetes belts. Even if we focused on the Diabetes belts, our model generates estimates for all other counties which are not in the Diabetes belts. We therefore included all counties that are located in the 16 states except those counties who had no information at all.

3.2 Methods

We used the 2010 BRFSS survey and 2000 US census. BRFSS as mentioned earlier is a national telephone survey which collects health related data in all 50 states, District of Columbia and the territories. The survey includes demographics and socioeconomic information about survey respondents. It completes more than 400,000 adult (aged 18 years and above) interviews each year throughout the US.

Among 1,497 counties in 16 states that are covered in this study, 314 of the counties have no data or were not covered by 2010 BRFSS survey. As a result, public health policy makers and other decision makers face difficulty in addressing the diabetes burden in such counties. In addition to those uncovered counties, there are also counties with small sample size.

To fill this gap in information, we applied a small area estimation method discussed in Rao, 2003 that addresses issues of estimating a target value in small area set. The method not only is capable of estimating for small area (such as counties in our case) but also for small areas that are not covered by the survey.

We built Bayesian Hierarchical model which gives us a more reliable estimates for prevalence of diabetes for all counties regardless of small sample size or for those uncovered in the survey.

A Bayesian Hierarchical model is a statistical model which applies a Bayesian method for data that are structured in many level of unites (hierarchical), in our case age, sex, race, education, income and insurance.

We estimated the prevalence of diagnosed diabetes for counties located in the Diabetes belt (644 counties) plus for all counties that are found in the 16 states (these states includes the 644 counties mentioned above). The SAS procedure "PROC GENMODE" and "PROC FREQ" were used to prepare the data and to get initial values for covariates (β) and to prepare adjacent counties for CAR model.

The 2010 BRFSS data was aggregated by age, sex, race, education, income and insurance making the analysis take less time than using individual level data. Using aggregated data, the analysis made on 16 states with 1,188 counties (this includes 644 counties found in the belt) took 17 hours of computational time while the individual level data took more than 2 days.

We considered a range of Bayesian Hierarchical models in our analysis. These models have a spatial and non-spatial mixed effect model (Rao, 2003 [6]). These models are discussed in detail in the next section.

Variables of Interest[2]

We used all variables that are listed in Chapter 2 and we also include

A. Insurance: Based on the BRFSS question, "Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?", we created two categories

   1) Yes

   2) No

B. County Poverty: The US census bureau use a set of income thresholds based on the family size to determine if a person is below the federal poverty level. If a family's total income is below the respective threshold, then the whole family is considered in the state of poverty (US Census Bureau). We made use of this measurement of poverty in our analysis.

3.3 Analysis

We used Bayesian Hierarchical small area estimation method to estimate the prevalence of diabetes for counties which are found in the Diabetes belt (in the16 states) using the 2010 BRFSS survey data and the U.S. census.

In the 16 states, 644 counties are located in the diabetes belt (CDC Identifies Diabetes Belt [2]). However, if a state has at least one county in the diabetes belt, we included all the other counties in our analysis. For this reason we have included a total of 1,497 counties in our study. Among these, 1,188 counties were covered in the BRFSS 2010 survey based on our aggregate data while the rest were not - not only in 2010 survey but also surveys from 2000 to 2010.

The prevalence of diagnosed diabetes then estimated for counties that are located in the 644 counties and counties in all 16 states. These states are Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Texas, Virginia and West Virginia.

The SAS 9.3 procedure called “PROC GENMODE” and “PROC FREQ” were used to prepare the data for WINBUGS 14.1 and get the covariates initial values as well as to format the adjacent (neighbor) counties need for CAR model to be used in the WINBUGS.

The 2010 BRFSS data was aggregated according to the respondent age, sex, race, education level, house hold income and insurance status. In doing so, we reduced the computational time very much, i.e. while it takes almost more than 48 hours to run all 16 states at individual level, it took us only 17 hours for aggregated data. By aggregating we mean we used 3 age groups (aged 18-44, 45-64 and 65+), sex(male and female), race(White and Black), education level(Below high School, High School graduate, some college and 1st degree and graduate degree and above), income(<15k, [15k,25k),[25k, 50k), [50k, 75k) and 75k and above) and insurance(having insurance, yes or no).

We applied a small area estimation discussed in Rao, 2003[6] that addresses issues of estimating a target value in a small area set. The method not only is capable of estimating for small area (such as counties in our case) but also for small areas that are not covered by the survey.

We considered a range of Bayesian Hierarchical (BH) models in our analysis (Table 3-1). These models have a spatial and non-spatial mixed effect model (Rao, 2003 [6]). Estimating the prevalence of diagnosed diabetes for small area, such as counties in our case, using BH small area spatial modeling produce a reliable estimates of the disease. The model are discussed in the detail in the next section.

3.4 Models

Dealing with binary outcome from the BRFSS survey for the question "Have you ever told by health professional that you have diabetes?" Yes/No, our model can be represented as:

$$Y_i \setminus N_i, \theta_i \sim Binomial(N_i, \theta_i), \qquad 3.1$$

where Y_i (i=1,2,…,74,192) is the number of individuals who respond "Yes" in given i[th] group

N_i is the total number of individuals in i[th] group

θ_i is the probability that an individual in the i[th] group responds "yes", where i[th] group is the aggregate individual class from all counties in the study (refer in chapter 2 for aggregated group). We applied the canonical link function for Generalized Linear Model (GLM) for Binomial distribution [19] to link θ and predictors. We consider a group of models (Table 3-1) which have general form as shown below,

$$logit(\theta_i) = \beta_{st(i),0} + X_{i,\nu_1}^{T}\beta_{st(i),\nu_1} + X_{i,\nu_2}^{T}\beta_{\nu_2} + b_{ct(i)} + b_{st(i)} \qquad 3.2$$

where i=1,2, …, N(groups),

st(i) indicates the state individuals in the i[th] group come from,

ct(i) indicates the county individuals in the i[th] group come from (1,497 counties),

v_1 is the set of indices for variables whose coefficients are the same across states, and

v_2 is the set of indices for variables whose coefficients are state-varying,

$b_{ct(i)}$ and $b_{st(i)}$ represent the county-level and state-level spatial effects, respectively.

For state varying coefficients, we assume the below prior for the hyper-parameters

$\beta_{st,j} \sim Normal\left(\mu_j^{\beta}, \sigma_j^{(\beta)2}\right)$, for j϶v2 .

$\mu_j^{\beta}, \sim Normal(0.0,0.001)$

$\sigma_j^{(\beta)2} \sim Gamma(0.5,0.5)$ and for coefficients that are the same across states, we assume

$\beta_j \sim Normal(0.0,\ 0.001)$, for j϶v1.

b_{ct}, which captures the random effect due to spatial variation, has a CAR(Conditional Autoregressive) model where the prevalence of diabetes in a given county depends on the prevalence of neighboring counties [19]. The b_c can be represented as

$$b_c / b_c', \tau_c^2 \sim Normal(\overline{b_c}, \tau^2)$$

where $\overline{b_c} = \frac{\sum_j b_j w_{cj}}{\sum_j w_{cj}}$, $\tau^2 = \frac{\tau_c^2}{\sum_j w_{cj}}$, $w_{cj} = \begin{cases} 1 & if\ c\ and\ j \text{ are neighbors} \\ 0 & other\ wise \end{cases}$

The variability among adjacent counties is controlled by τ_c^2. For all models in our analysis we used the following prior distribution for our coefficients of covariates and hyper parameters as indicated below:

$\tau_c^2 \sim Gamma(0.5,0.5)$ and the precision takes the inverse of τ_c^2, i.e. $\sigma_c = {}^{1}/_{\tau_c^2}$ (Bernardinelli et al, 1995b) where c=1,2,…, 1188(counties)

The state-level spatial effect is modeled similarly.

We explored a set of models and summarize them in Table 3-1. Our most complicated model assume all slope coefficients are state-varying:

$$logit(\theta_{ij}) = \sum_{j=0}^{16} \beta_{sj} X_{ijk}^T + \beta_{17i} X_i + b_{c(i)} \qquad 3.3$$

This model is computational expensive. We consider the following 3 models with the smallest DIC:

1. Binomial Regression Model with $v_1 = \beta_0(\text{Intercept})$ and $\beta_{16}(\text{insurance})$ and b_{ct} county level CAR model with DIC =85,350.8(Model 8)

   In this model all coefficients of covariates, except intercept and insurance, are the same across the state.

2. *Binomial Regression Model with* $v_1 = 0,1,2,,\ldots,9$ *and* 16 *and* b_{ct} *(county) CAR county level CAR model with DIC =85,315.4 (Model 9)*

   Here v_1 is the intercept, age, sex, race and their interaction and v_2 is income, education level and poverty

3. Binomial Regression Model with v_1=0,1,2,3,5,…,8 and 16 and b_{ct} county level CAR model with DIC =85,308.5 (Model 9_1)

   For model 9_1 the v_1 is the intercept, age, sex and their interaction and insurance where as v_2 is the race, income and education and poverty

The 3 models selected have very close DIC and produce similar prevalence of diabetes that can be seen in the scatter plot in Figure 3-1 but we picked Model 8 among the three model since

a) model 8 has smallest DIC like the other three(see Table 3-1)
b) The credible interval width among the three model is very similar (see Table 3-6 and Table 3-7) show the credible interval width validation check for Maryland and South Carolina and all other states followed similar conclusion.
c) Model 8 is the simplest model of the three for this reason we selected Model 8 as our final model.

We fitted all models discussed above using the BRFSS survey data in WinBUGS (14.1) software. A single chain with 52,000 iteration and 2000 burn-in was applied to all three models. For this reason (the 200 burn-in or discarded) iteration, we finally used the 50000 iteration for analysis.

Table 3-1 Investigated Models

Model	$\boldsymbol{\beta_{v_1}}$	$\boldsymbol{\beta_{v_2}}$	**CAR**		
			County	**State**	**DIC**
1	$\boldsymbol{\beta_0 - \beta_{17}}$	**No**	**Yes**	**No**	**85,354.1**
2	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1 - \beta_{17}}$	**No**	**No**	**85,574.1**
3	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1 - \beta_{17}}$	**No**	**Yes**	**85,574.5**
4	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1 - \beta_{17}}$	**Yes**	**No**	**85,419.0**
5	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1 - \beta_{17}}$	**Yes**	**Yes**	**85,430.6**
6	**No**	$\boldsymbol{\beta_0 - \beta_{17}}$	**No**	**No**	**85,598.6**
7	**No**	$\boldsymbol{\beta_0 - \beta_{17}}$	**Yes**	**No**	**85,424.5**
8	$\boldsymbol{\beta_0}$ *and* $\boldsymbol{\beta_{16}}$	$\boldsymbol{\beta_1 - \beta_{15}}$	**Yes**	**No**	**85,350.8**
9	$\boldsymbol{\beta_0}$ *and* $\boldsymbol{\beta_{16}}$	$\boldsymbol{\beta_1 - \beta_{15}}$	**Yes**	**Yes**	**85,362.0**
10	$\boldsymbol{\beta_0}$ *and* $\boldsymbol{\beta_{13} - \beta_{16}}$	$\boldsymbol{\beta_1 - \beta_{12}, \beta_{14}, \beta_{15}}$ *and* $\boldsymbol{\beta_{17}}$	**Yes**	**Yes**	**85,365.8**
11	$\boldsymbol{\beta_0 - \beta_9}$ *and* $\boldsymbol{\beta_{16}}$	$\boldsymbol{\beta_{10} - \beta_{15}}$ *and* $\boldsymbol{\beta_{17}}$	**Yes**	**No**	**85,315.4**
12	$\boldsymbol{\beta_0 - \beta_3, \beta_5 - \beta_8}$ *and* $\boldsymbol{\beta_{17}}$	$\boldsymbol{\beta_4}$ *and* $\boldsymbol{\beta_9 - \beta_{16}}$	**Yes**	**No**	**85,308.5**
13	$\boldsymbol{\beta_0 - \beta_4}$ *and* $\boldsymbol{\beta_{16}}$	$\boldsymbol{\beta_5 - \beta_{15}}$ *and* $\boldsymbol{\beta_{17}}$	**Yes**	**No**	**85,455.1**

$\boldsymbol{\beta_0}$	Overall effects across the states
$\boldsymbol{\beta_1}$	Aged 45-64
$\boldsymbol{\beta_2}$	Aged 65 and above
$\boldsymbol{\beta_3}$	Male
$\boldsymbol{\beta_4}$	White
$\boldsymbol{\beta_5}$	Male Aged 45-64
$\boldsymbol{\beta_6}$	Male Aged 65 and above
$\boldsymbol{\beta_7}$	White Aged 45-64
$\boldsymbol{\beta_8}$	White Aged 65 and above
$\boldsymbol{\beta_9}$	White Male
$\boldsymbol{\beta_{10}}$	Income2=[$35,000,$50,0000)
$\boldsymbol{\beta_{11}}$	Income3=[$50,000,$75,0000)
$\boldsymbol{\beta_{12}}$	Income4=$75,000 and above
$\boldsymbol{\beta_{13}}$	Education2= Grade 12 or GED (High school graduate)

$\boldsymbol{\beta_{14}}$	Education3= College 1 year to 3 years (Some college or technical school)
$\boldsymbol{\beta_{15}}$	Education4= College 4 years or more (College graduate)
$\boldsymbol{\beta_{16}}$	Insurance=No Insurance
$\boldsymbol{\beta_{17}}$	State Poverty percentage

Aged 18-44, Female, Black, Inceome1=<35,000, Education1=< High School and Insurance=Yes are reference groups. Highlighted in yellow are models selected for analysis due to low DIC

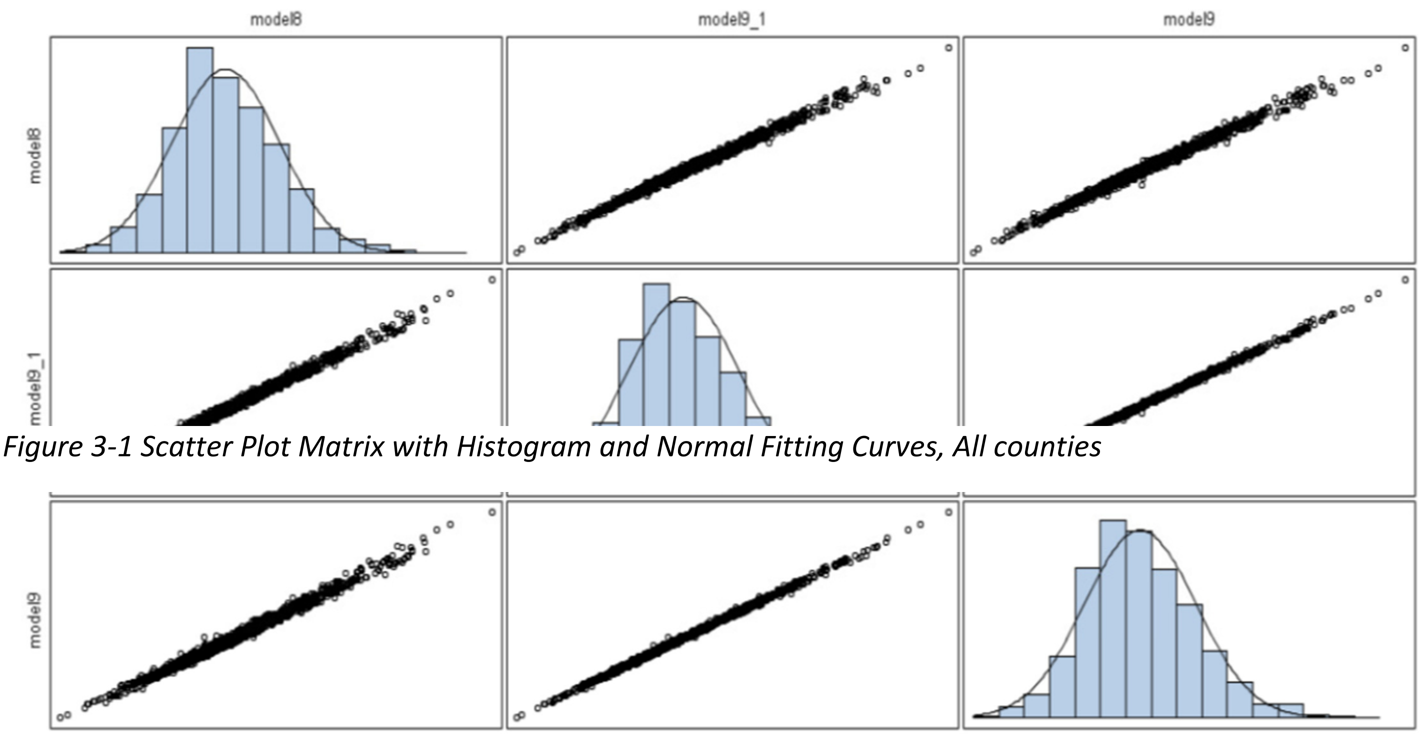


Figure 3-1 Scatter Plot Matrix with Histogram and Normal Fitting Curves, All counties

3.5 Handling Counties with Missing Data

The BRFSS survey may not cover all counties every year but the state may do additional survey to cover all counties in their state, even this may not be conducted every year. But by applying the CAR model we can overcome this problem and get estimates of missing counties by borrowing information from neighboring counties. For instance, the 2010 BRFSS public survey data which can be downloaded from BRFSS website had 305 counties not covered in the survey. For those counties with missing or uncovered in the survey, we used the BH model with the CAR model to estimate their prevalence of diabetes as follows:

Based on the BH model with the CAR model, the spatial effect for the m[th] missing or uncovered county (m=1, 2, …, 295) has a normal distribution with mean

$$\bar{b}_m = \sum_{i=1}^{n} b_m \text{ and he precision } v_m = \frac{1}{(v*n)^{0.5}}$$

where v is the precision parameter in the CAR model, and n is the number of neighbor counties for the mth missing county. With the MCMC samples of bk from the simulation, we also get samples of bm for the m[th] missing counties using b̅_m~Normal(b_m ,v_m).

Using the simulated samples for bm and and β = (β1, β2… β17), we can simulate the posterior distribution for the prevalence of diabetes for the missing counties in the same way as we do for the other 1188 counties without missing information, and hence estimate its posterior mean and credible interval.

We used the WinBugs software[13] to fit these models. The model was run for 52,000 iterations with single chain but the first 2,000 samples were used as a burn-in (discarded) which implies that the rest 50,000 samples were used to make inference. We chose the model that has the same coefficients across counties and the CAR model, which has the smallest Deviance information criterion (DIC [14].

With the MCMC samples of parameters in this model, we can infer the posterior distribution of the overall prevalence rate for each counties in the following way; similarly we can get the prevalence rate by race or sex for each counties.

Plugging in the sampled values of β and b_k, and specifying the values of x, we can get the prevalence rate of diabetes in a group of a county.

Plugging in the sampled values of β and b_k, and specifying the values of x, we can get the prevalence.

Let $\hat{\theta}_{jk}^{(i)}$ denote the i^{th} sample of θ_{jk} , the prevalence rate of diabetes in the j-th group of the k-th county, from the MCMC procedure (i=1… 17, j=1 … 384 and k=1… 1188), the corresponding overall prevalence rate of the k-th county is estimated by

$$\sum_{j=1}^{192} \hat{\theta}_{jk}^{(i)} p_{jk} \qquad (1)$$

where p_{jk} represents the proportion of individuals belonging to the j^{th} group in county k, which is obtained from $\left\{\sum_{j=1}^{384} \hat{\theta}_{jk}^{(i)} p_{jk}\right\}$ (i=1,2,…) simulate the posterior distribution of the overall prevalence rate of county k. $\left\{\frac{1}{I}\sum_{i=1}^{I}\sum_{j=1}^{384} \hat{\theta}_{jk}^{(i)} p_{jk}\right\}$, the mean of $\left\{\sum_{j=1}^{384} \hat{\theta}_{jk}^{(i)} p_{jk}\right\}$(i=1,2,…), estimates the posterior mean of the overall prevalence rate of county k. The 2.5^{th} and 97.5^{th} percentiles of $\left\{\sum_{j=1}^{384} \hat{\theta}_{jk}^{(i)} p_{jk}\right\}$ (i=1, 2…) form the 95% credible interval for the overall prevalence rate of county k. Similarly we can simulate the posterior distribution of the prevalence rate by race, or by sex, for each county, and then get the posterior mean and 95% credible intervals. The results are shown in Table 3-2 and Figures 3-4.

For Chapter 2 we validate our estimates by comparing with estimates from National Center for Chronic Prevention and Health Promotion[15] and Florida Health Department estimates[13] using Pearson and Spearman Correlation coefficients, Mean Square Error (MSE), Mean Absolute difference (MAD), Mean Relative absolute differences (MRAD), and Rank statistic[17](See *Table*

2-6). For chapter 3 we compared our 3 models for validation purpose and detail discussion in the next sections.

3.6 Result

According to CDC scientist, the diabetes belt has 644 counties located in the 16 south-Easter part of the U.S. This means 43% of the counties in this sixteen states are located in the diabetes belt. Georgia with 17% followed by Tennessee (14%), Mississippi (13%), Kentucky (11%) and Alabama (10%) are the first 5 states with higher number of counties where as Maryland and Pennsylvania with least number of county (1 each) in the diabetes belt. We highlight these states in our result discussion.

143 counties which were included in the belt didn't have information when we aggregated the 210 BRFSS survey, in addition to this, the 5 states listed above had only 105 counties with reliable sample size for direct estimate leaving 300 counties without estimates based on direct estimate (see Table 3-5) but the BH model with spatial effect helped us to have reliable estimates for these counties. By using the CAR model and adding a very small fraction in population proportion, we calculated an estimates for 1,479 counties located in the 16 states but 18 counties found in Kentucky, Pennsylvania, Tennessee, Texas, Virginia and West Virginia either they didn't have information or have neighboring counties not included in study.

The prevalence of diagnosed diabetes in these 1,479 counties ranges from 4.9% (Jackson county in Tennessee) to 20% (Green county in Alabama) (see the Table 3-1 and

Figure 3-1). 98% of the counties found in these states had an estimated prevalence of diagnosed diabetes higher than the nation average (6.9%) and most of these counties with higher prevalence the national estimate were located in the diabetes belt.

The male prevalence ranges from 4.6% (Arlington, Virginia) to 20.7% (Briscoe, Texas) and the female prevalence ranges 4.1% (Arlington, Virginia) to 22.1% (Green, Alabama).
In 1,176 counties, the prevalence of diabetes for male was higher than.
Georgia added 111 (out of 159 total counties) in the diabetes belt and was the highest states but Alabama with 65 out of 67 counties was the highest state where almost all counties were included in the belt. Below we discussed these three counties in detail.

Alabama

Alabama had 65 out of 67 counties located in the diabetes belt which shows how the burden of this diseases affecting the state. 6 of the counties didn't have aggregated information in the 2010 BRFSS but our model took care of these counties which discussed in detail in our discussion part. Based on our model estimate, the prevalence of diagnosed diabetes in Alabama ranged from 7.9% in Shelby to 20% in Green counties. The prevalence of men (8.4%-17.5%) was higher than the female (7.4%-18.15). This variation occurred in 68% (46 out of 67 counties) of the counties. The race disparities also noticed in the prevalence, Blacks (8.4%-21.2%) with higher prevalence than the white (7.7%-16.1%) in almost all counties. The socioeconomic factors such as income, education attainment and poverty level indicted this disparities in those counties with higher prevalence of diagnosed diabetes. Most of these counties with higher prevalence also had high percentage poverty compared to those counties with lower prevalence of diabetes. Figure 3-1 shows the scatter plot of prevalence of diagnosed diabetes for selected counties of Alabama.

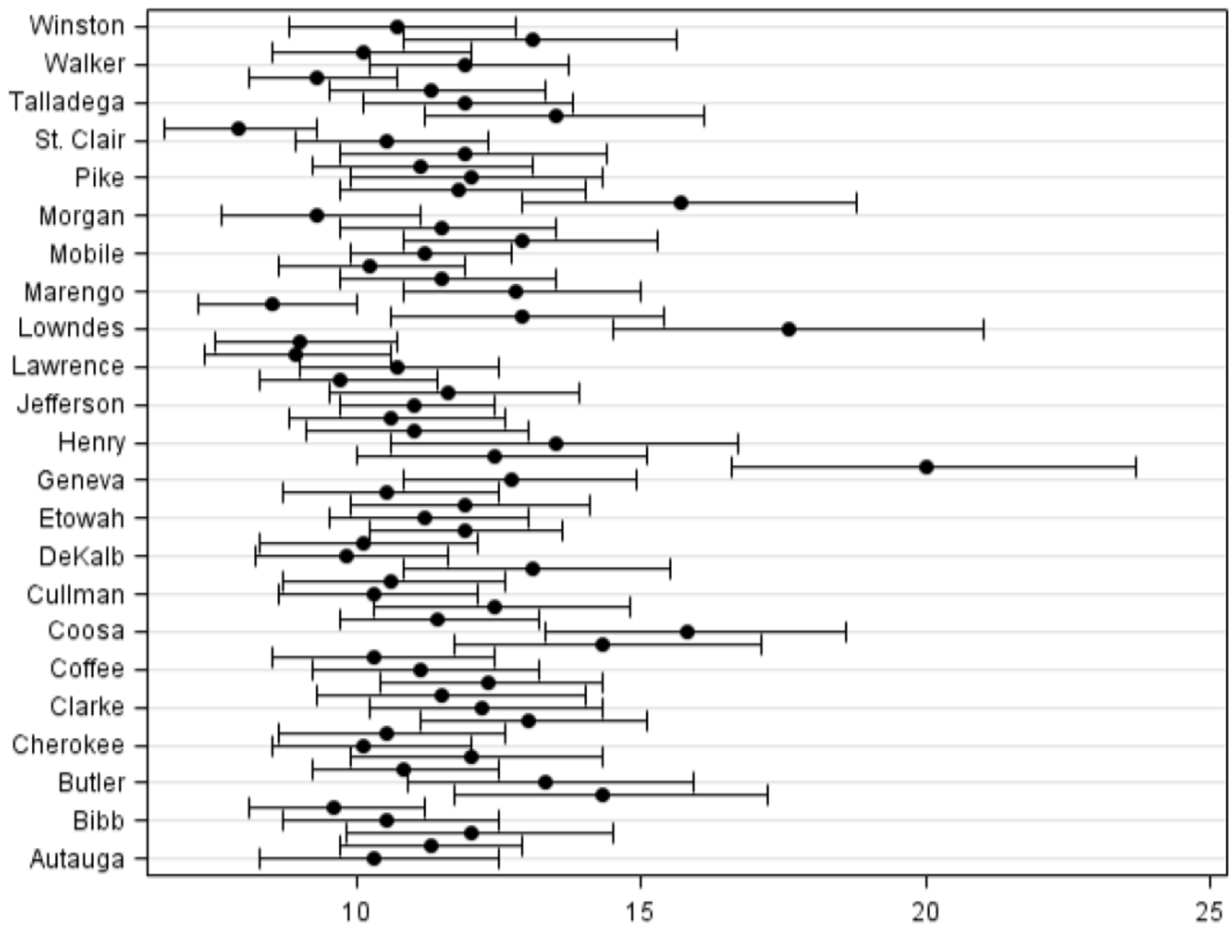
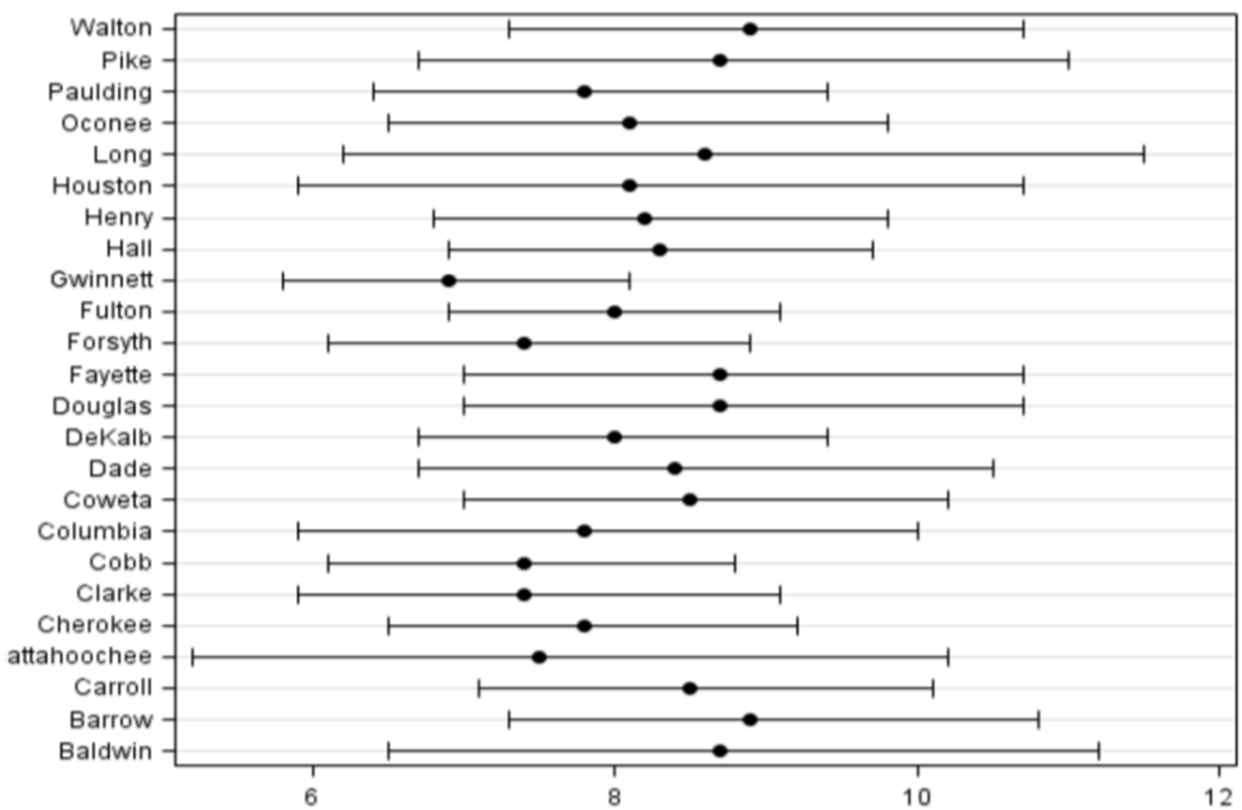


Figure 3-2 Alabama Scatter Plot of Mean with Credible Interval

Georgia

Georgia which hads111 counties in the diabetes belt had prevalence ranging from 6.9% (Gwinnett) to 16.8% (Clay). Compared to the national average (6.9%), all Georgian counties, except Gwinnett which is border, had higher prevalence of diagnosed diabetes in 2010. In Georgia and most of the other 15 states, counties not labeled as diabetes belt, had higher prevalence than the national average which indicates the level of the burden in the south-eastern part of the U.S. When we looked the gender gap again, the prevalence of male (ranged 6.3% -16.3) higher than the female (7.1% – 18.6%) in most of the Georgia counties. The prevalence for Blacks ranged from 8.1% (Gwinnett) to 18.9(Jeff Davis) while for whites ranged 5.9% (Fulton) to 16.3(Miller). Again in almost all counties Blacks had higher prevalence than Whites.



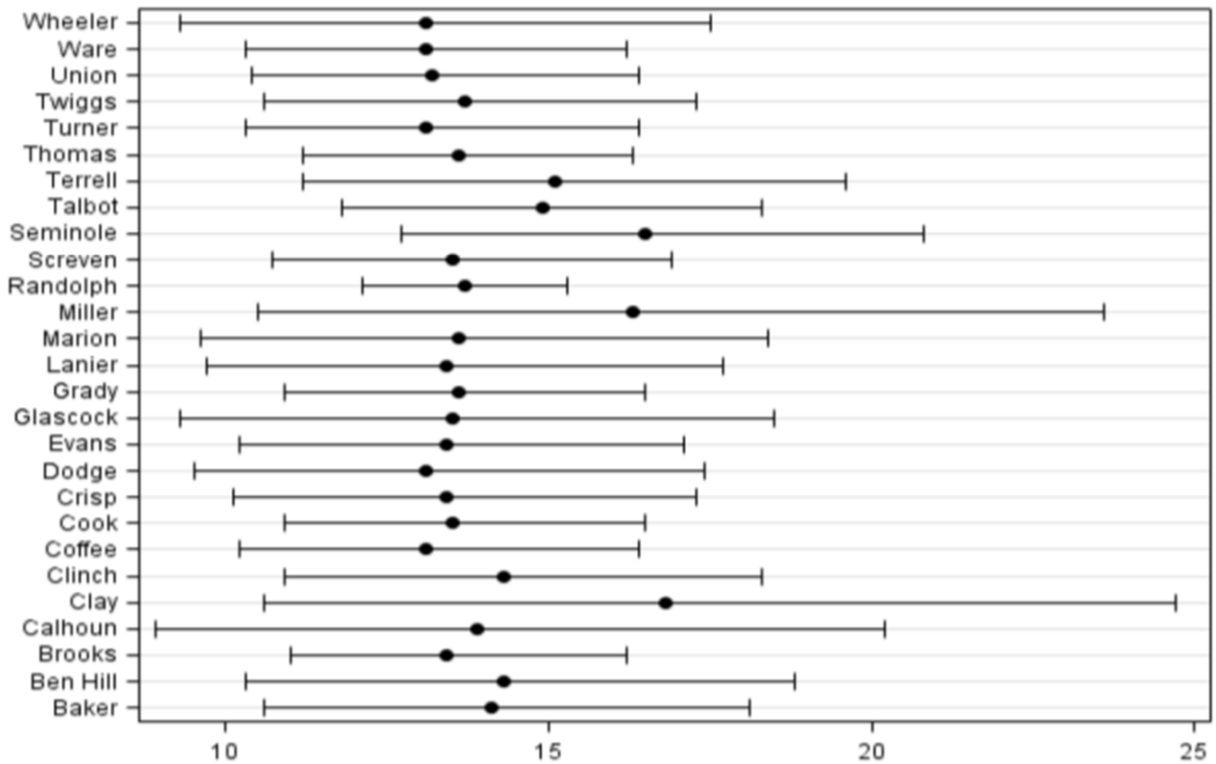


Figure 3-3 Georgia Scatter Plot of Mean (<10) and Mean (>13) with Credible Interval

Tennessee

This state had the 3rd highest number of counties (89 out of 95) in the diabetes belt. In 2010, this state had prevalence ranging from 6.3% (Williamson) to 14.4% (Pickett). Like the other counties in neighboring states, the prevalence was higher than the nation average for counties that were not part of the diabetes belt. Tennessee followed similar trend with Georgia in having counties with higher prevalence in Men than Female and in Blacks than Whites.

For instance if we take Alabama, among the 67 counties that we estimated, 61 counties had higher prevalence of diagnosed diabetes than the national average(6.9%) ranging from 9.4% to 15.5% and Georgia had 106 counties (among 158 counties we estimated) had higher estimates ranging from 9.4% to 16.2%. Florida, based on the diabetes belt estimate, had 57 out of 67 counties with higher estimates than the national. Most of these counties located in the diabetic belt and had higher percentage poverty compared to those counties with lower prevalence of diabetes. This was also clearly indicated by the house hold income, where those counties with low house hold income resides in those counties with high estimated prevalence of diabetes. In all counties under this study, blacks had higher estimated prevalence of diabetes than white (fig 3-2 below).

The prevalence of estimated diabetes was higher among men than women in 1,045 counties ranging from 3.4% - 18.5% in men and 2.2% - 18.4% in women. In almost all counties, the Blacks had the higher prevalence than whites.

Clayton County in Georgia has the lowest prevalence by sex, Men (3.4%) and Women (2.2%), while Marion County in Arkansas and Boyd County in Kentucky had the highest male (18.5%) prevalence. The estimated prevalence of diabetes tended to increase with age.
For counties with missing data in the 2010 public BRFSS data, as it discussed in the method section we used CAR model which helped us to borrow information from the surrounding counties. In Chapter 2 we checked our findings with the Division Diabetes and Translation (DDT) estimates and by running Bayesian hierarchical model for the complete data we got from the Florida BRFSS. For your information, some state may do complete survey but the survey may not be done every year. Our CAR model can estimate for every year regardless of the survey cover all counties or not.

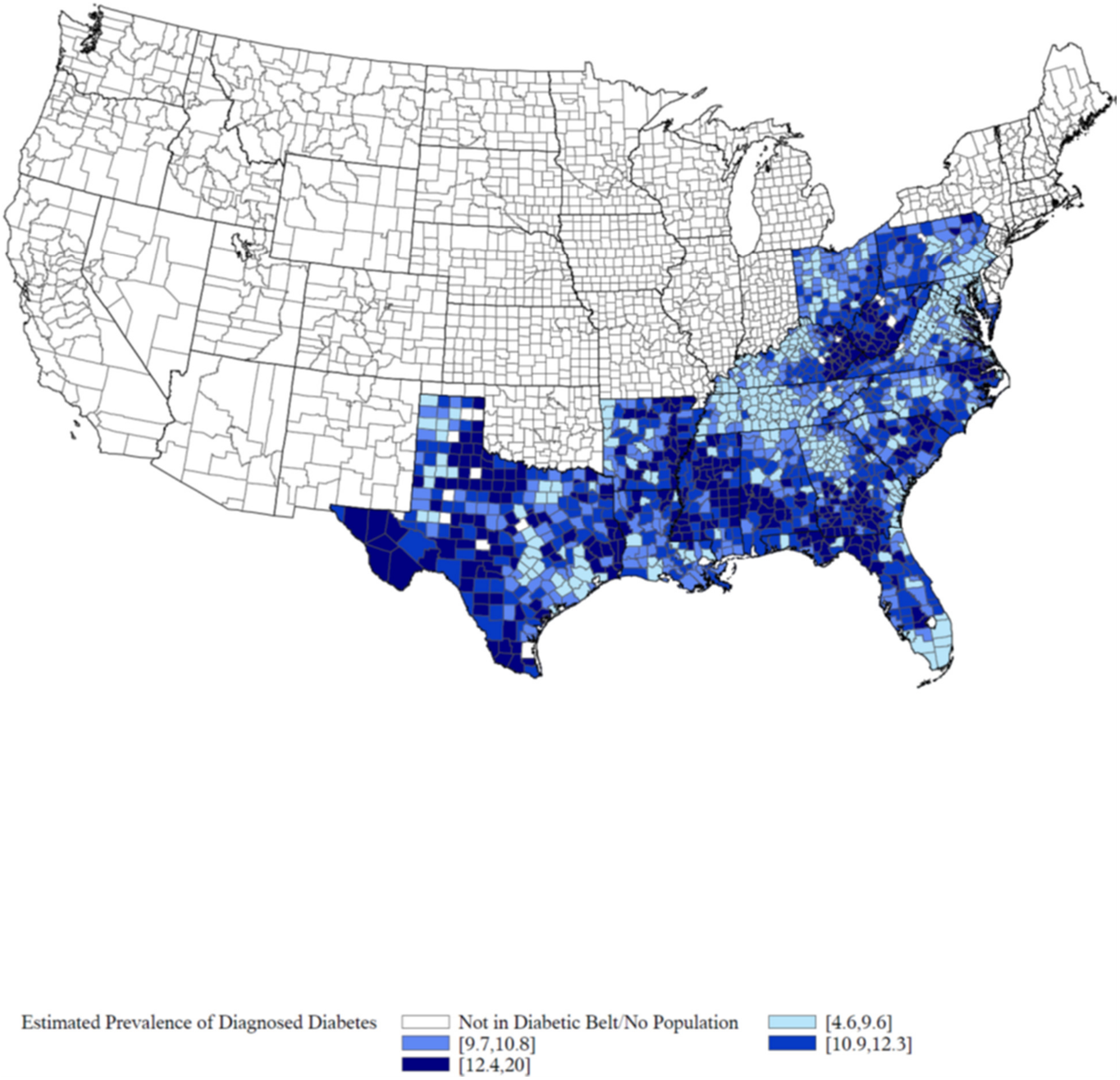


Figure 3-4 Estimated Prevalence of Diagnosed Diabetes, Overall, for counties in Diabetes Belt

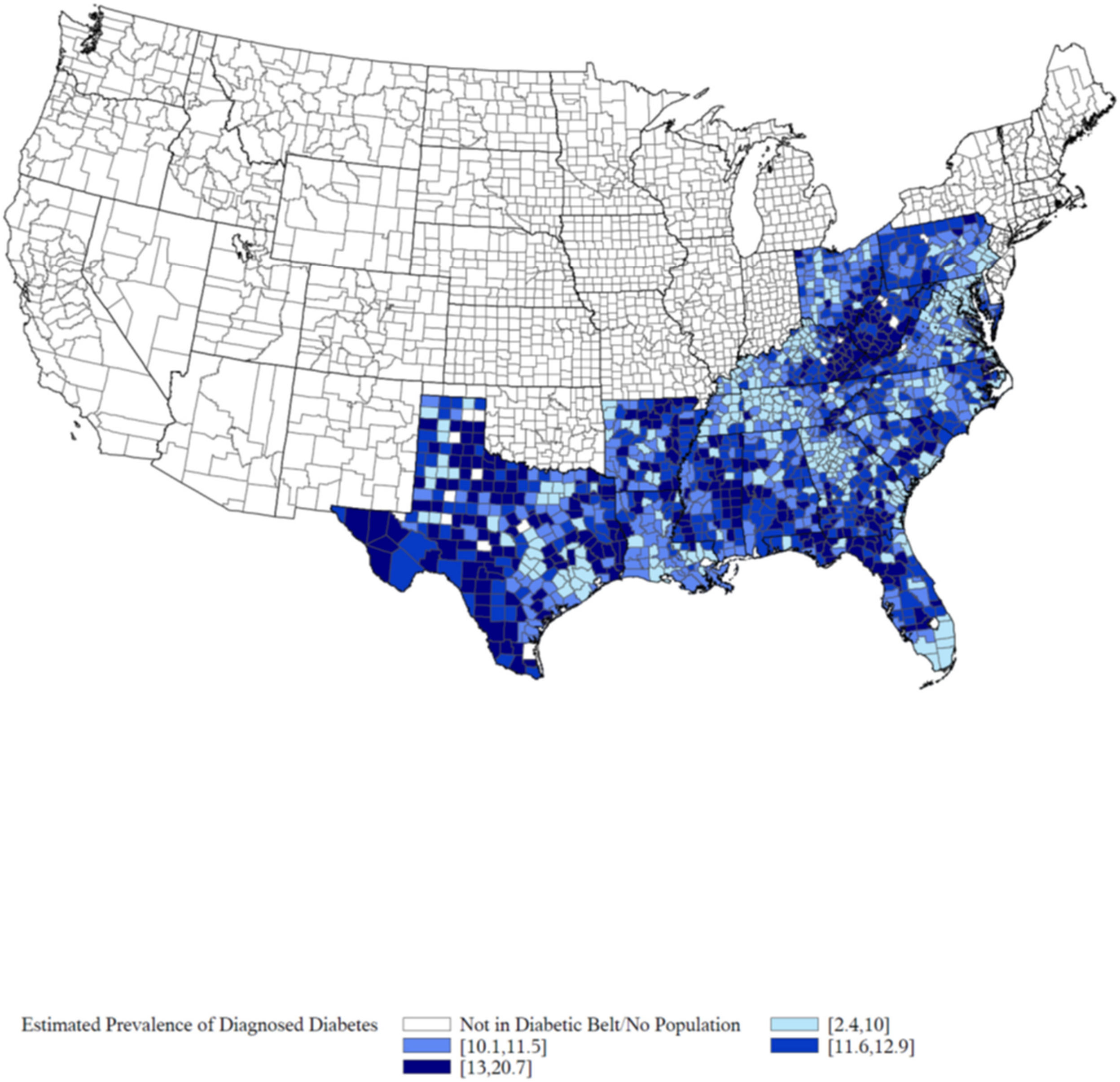


Figure 3-5 Estimated Prevalence of Diagnosed Diabetes, Male, for counties in Diabetes Belt

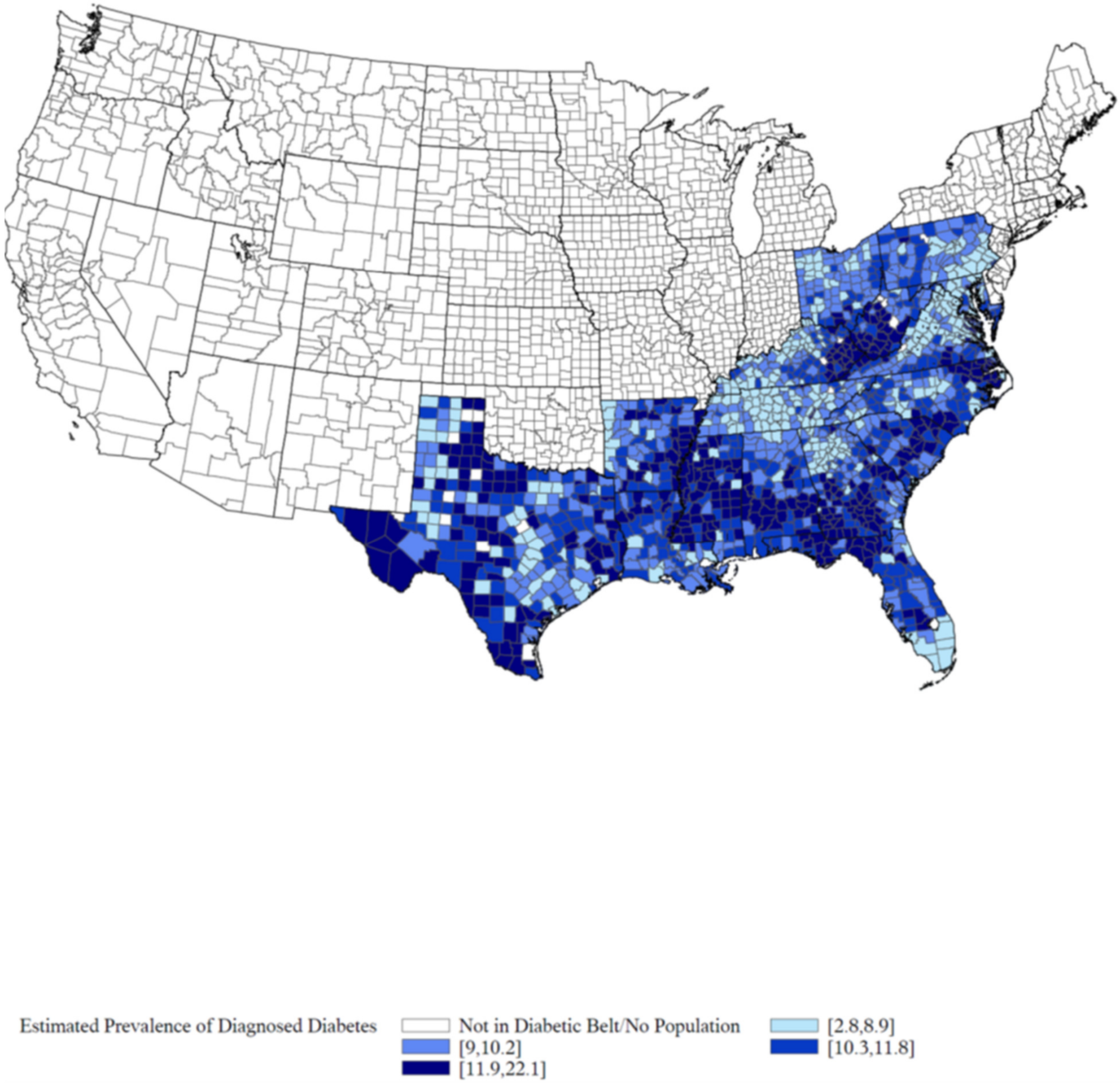


Figure 3-6 Estimated Prevalence of Diagnosed Diabetes, Female, for counties in Diabetes Belt

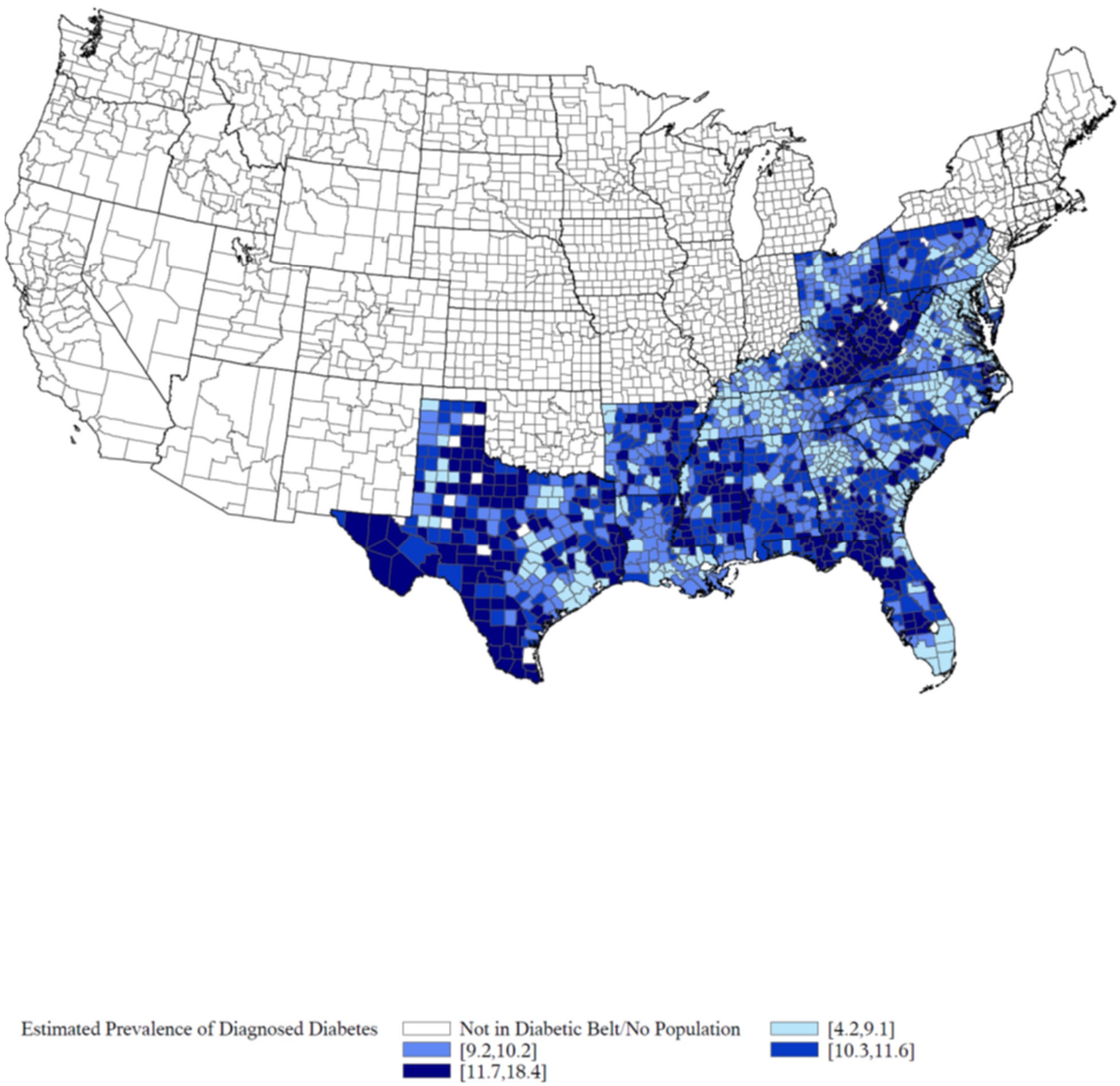


Figure 3-7 Estimated Prevalence of Diagnosed Diabetes, White, for counties in Diabetes Belt

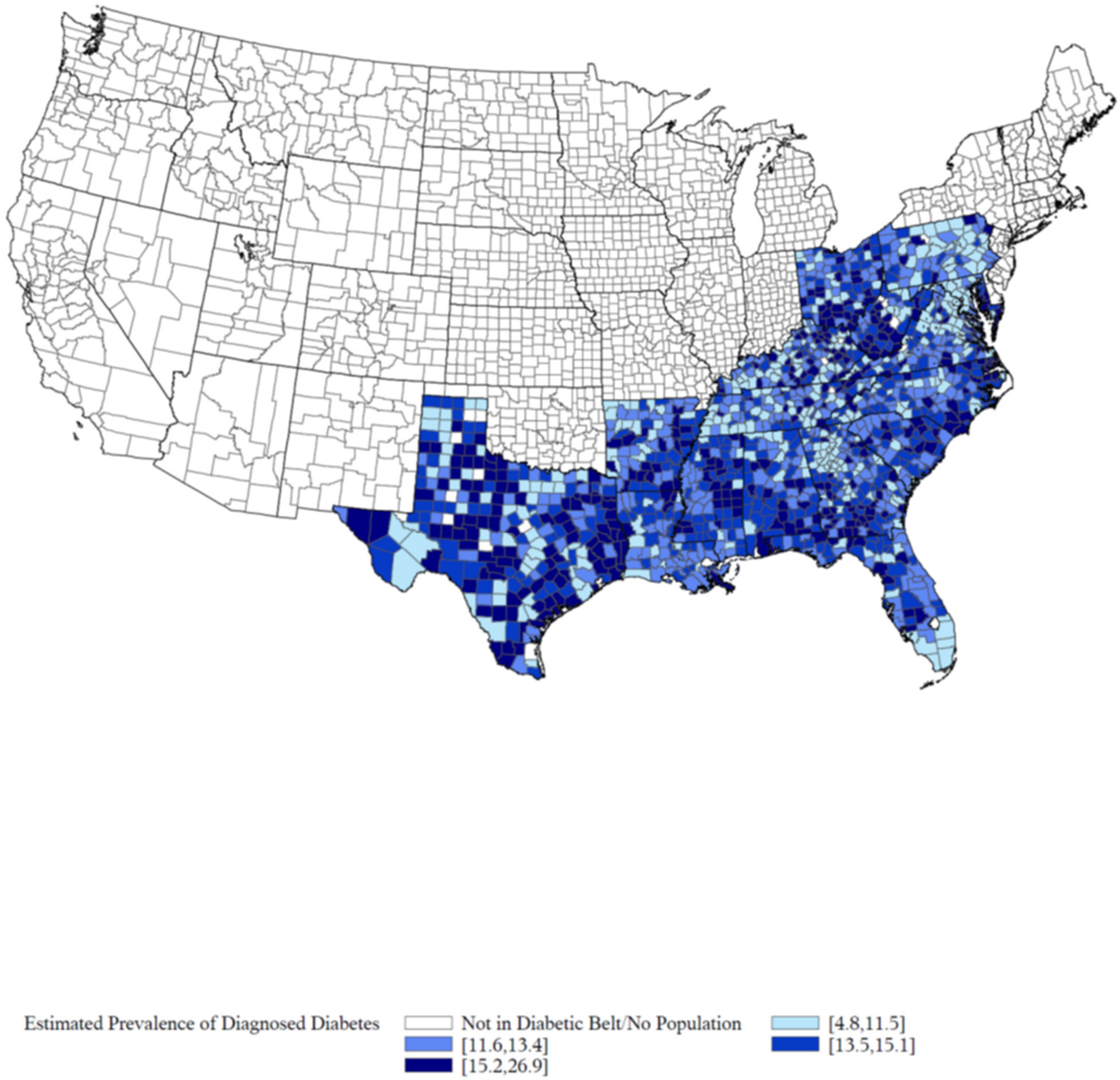


Figure 3-8 Estimated Prevalence of Diagnosed Diabetes, Black, for counties in Diabetes Belt

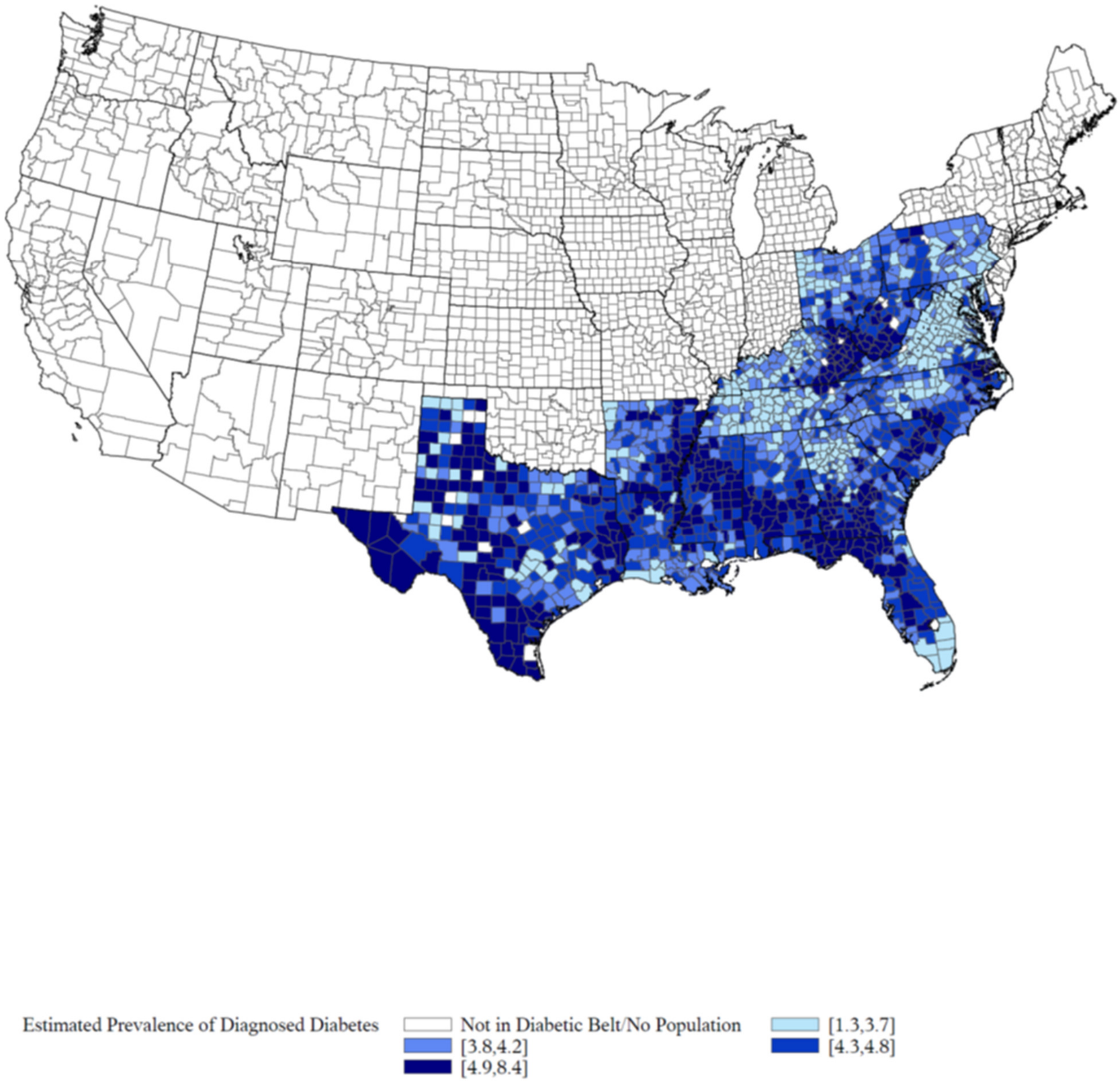


Figure 3-9 Estimated Prevalence of Diagnosed Diabetes, Aged 18-44, for counties in Diabetes Belt

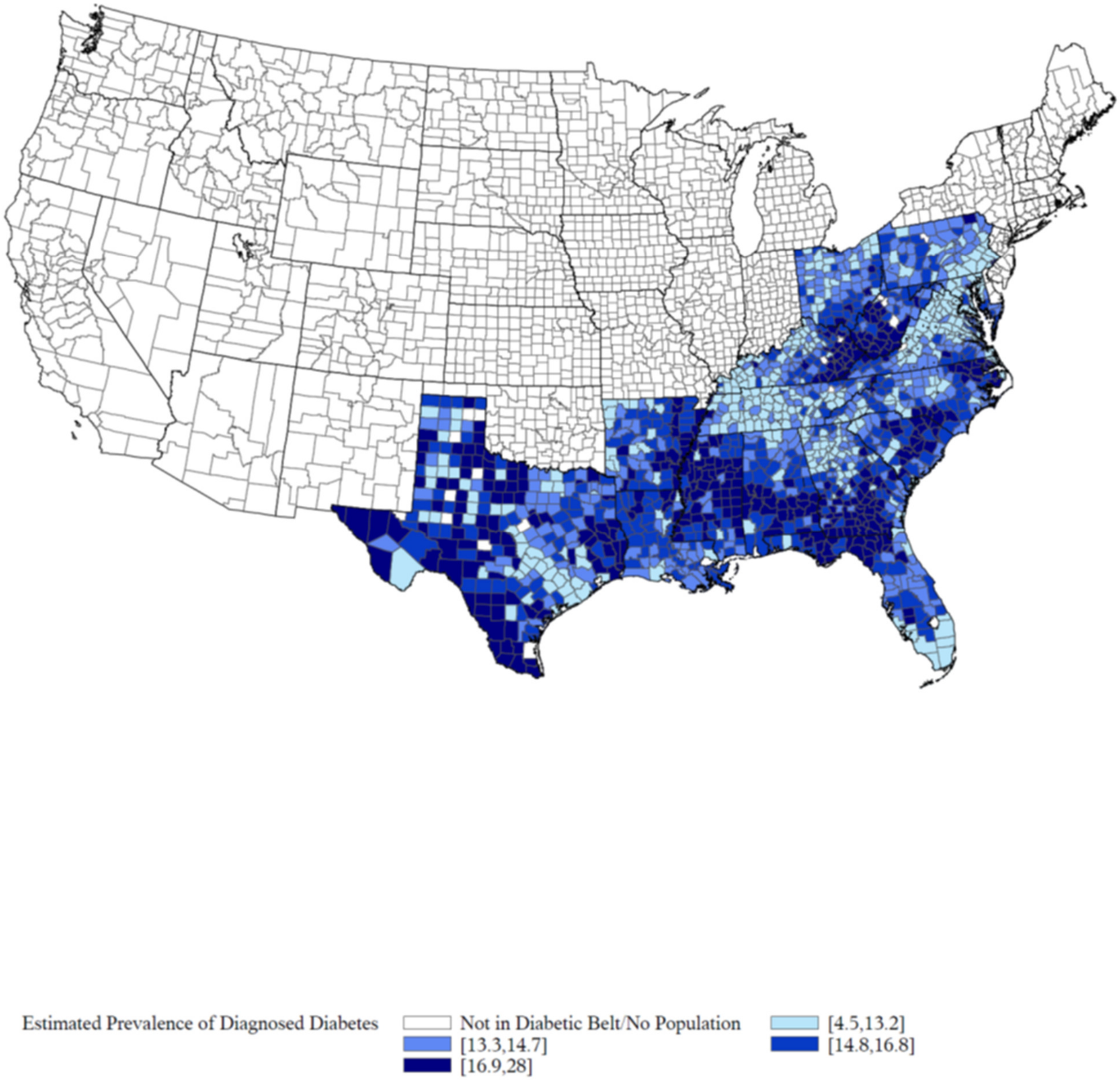


Figure 3-10 Estimated Prevalence of Diagnosed Diabetes, Aged 45-64, for counties in Diabetes Belt

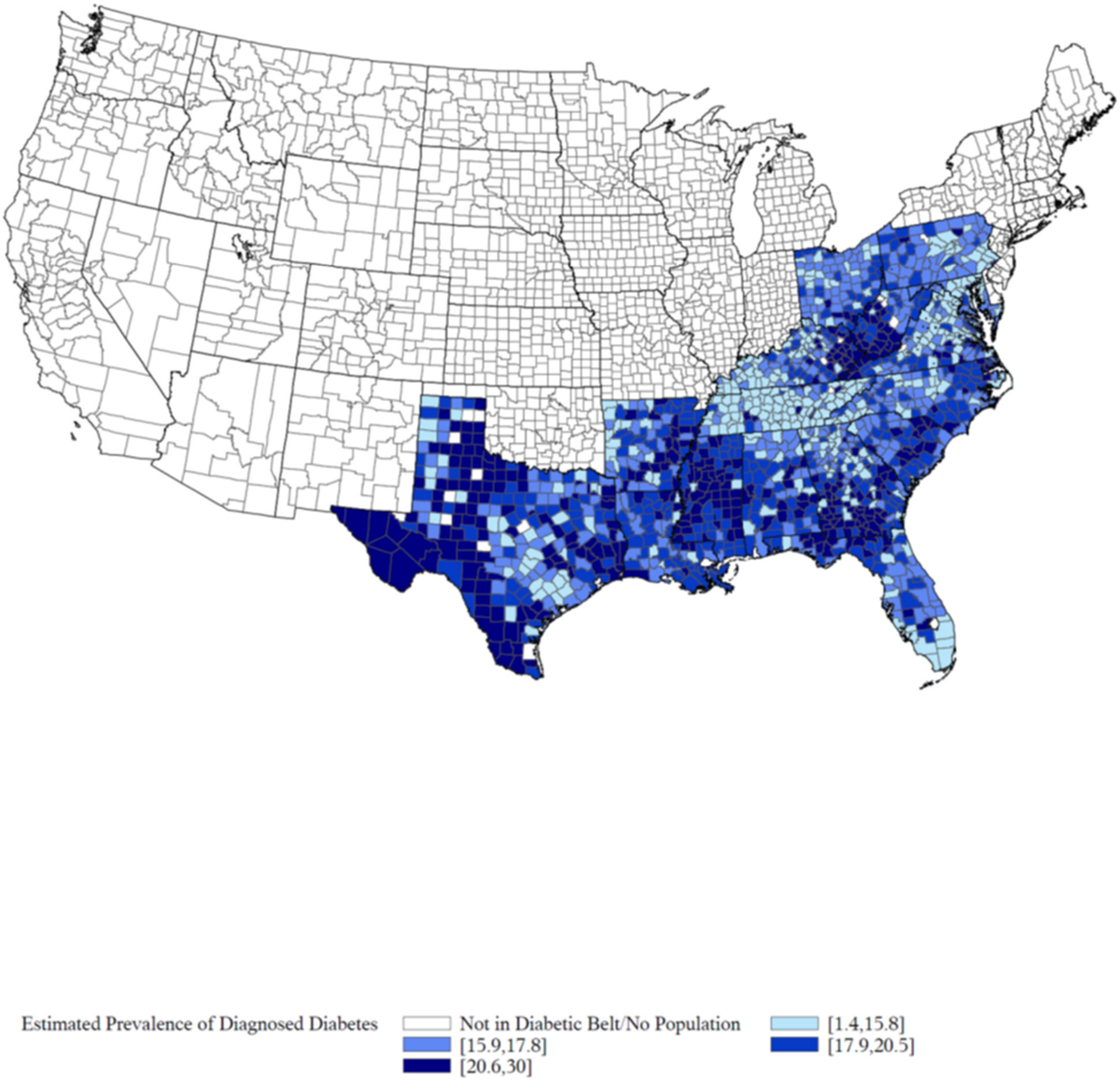


Figure 3-11 Estimated Prevalence of Diagnosed Diabetes, Aged 65 and above, for counties in Diabetes Belt

Table 3-2 Overall County Estimated Prevalence of Diabetes

State Name	County Name	Overall	State Name	County Name	Overall
Alabama	Autauga	10.3(8.3,12.5)	North Carolina	Stokes	10.4(8.7,12.4)
Alabama	Baldwin	11.3(9.7,12.9)	North Carolina	Surry	10.1(8.5,11.9)
Alabama	Barbour	12(9.8,14.5)	North Carolina	Swain	11.9(10,14)
Alabama	Bibb	10.5(8.7,12.5)	North Carolina	Transylvania	9.8(8.2,11.5)
Alabama	Blount	9.6(8.1,11.2)	North Carolina	Tyrrell	12.4(11,13.7)
Alabama	Bullock	14.3(11.7,17.2)	North Carolina	Union	8.3(7.1,9.6)
Alabama	Butler	13.3(10.9,15.9)	North Carolina	Vance	11.4(9.2,13.9)
Alabama	Calhoun	10.8(9.2,12.5)	North Carolina	Wake	6.5(5.7,7.5)
Alabama	Chambers	12(9.9,14.3)	North Carolina	Warren	13.7(11.5,16.2)
Alabama	Cherokee	10.1(8.5,12)	North Carolina	Washington	16(12.3,20.3)
Alabama	Chilton	10.5(8.6,12.6)	North Carolina	Watauga	9.3(7.6,11.2)
Alabama	Choctaw	13(11.1,15.1)	North Carolina	Wayne	10.4(8.9,11.9)
Alabama	Clarke	12.2(10.2,14.3)	North Carolina	Wilkes	11.6(9.9,13.5)
Alabama	Clay	11.5(9.3,14)	North Carolina	Wilson	11.5(9.6,13.5)
Alabama	Cleburne	12.3(10.4,14.3)	North Carolina	Yadkin	10.1(8.3,12)
Alabama	Coffee	11.1(9.2,13.2)	North Carolina	Yancey	12.2(9.9,14.7)
Alabama	Colbert	10.3(8.5,12.4)	Ohio	Adams	10.6(8.6,12.8)
Alabama	Conecuh	14.3(11.7,17.1)	Ohio	Allen	9.8(7.9,11.8)
Alabama	Coosa	15.8(13.3,18.6)	Ohio	Ashland	10.1(8.4,11.9)
Alabama	Covington	11.4(9.7,13.2)	Ohio	Ashtabula	10(8.2,12.1)

Alabama	Crenshaw	12.4(10.3,14.8)	Ohio	Athens	8.6(7.1,10.2)
Alabama	Cullman	10.3(8.6,12.1)	Ohio	Auglaize	9.6(7.9,11.5)
Alabama	Dale	10.6(8.7,12.6)	Ohio	Belmont	11.4(9.5,13.4)
Alabama	Dallas	13.1(10.8,15.5)	Ohio	Brown	11.2(9.1,13.5)
Alabama	DeKalb	9.8(8.2,11.6)	Ohio	Butler	9.8(8.1,11.8)
Alabama	Elmore	10.1(8.3,12.1)	Ohio	Carroll	12.6(10.4,15.1)
Alabama	Escambia	11.9(10.2,13.6)	Ohio	Champaign	10.5(8.7,12.6)
Alabama	Etowah	11.2(9.5,13)	Ohio	Clark	11.2(9.3,13.4)
Alabama	Fayette	11.9(9.9,14.1)	Ohio	Clermont	8.7(7.1,10.4)
Alabama	Franklin	10.5(8.7,12.5)	Ohio	Clinton	9.1(7.5,10.9)
Alabama	Geneva	12.7(10.8,14.9)	Ohio	Columbiana	11.9(10.1,14)
Alabama	Greene	20(16.6,23.7)	Ohio	Coshocton	11.1(9.2,13.1)
Alabama	Hale	12.4(10,15.1)	Ohio	Crawford	11.5(9.5,13.8)
Alabama	Henry	13.5(10.6,16.7)	Ohio	Cuyahoga	10(8.8,11.3)
Alabama	Houston	11(9.1,13)	Ohio	Darke	11.1(9.2,13.3)
Alabama	Jackson	10.6(8.8,12.6)	Ohio	Defiance	9.6(7.4,12.1)
Alabama	Jefferson	11(9.7,12.4)	Ohio	Delaware	7.4(6.2,8.8)
Alabama	Lamar	11.6(9.5,13.9)	Ohio	Erie	11.3(8.8,14.2)
Alabama	Lauderdale	9.7(8.3,11.4)	Ohio	Fairfield	9.4(7.8,11.2)
Alabama	Lawrence	10.7(9,12.5)	Ohio	Fayette	12.3(10.2,14.6)
Alabama	Lee	8.9(7.3,10.6)	Ohio	Franklin	9.2(8.1,10.4)
Alabama	Limestone	9(7.5,10.7)	Ohio	Fulton	10.3(7.9,13.1)
Alabama	Lowndes	17.6(14.5,21)	Ohio	Gallia	12(9.8,14.4)
Alabama	Macon	12.9(10.6,15.4)	Ohio	Geauga	8.6(7.1,10.2)
Alabama	Madison	8.5(7.2,10)	Ohio	Greene	8.5(7,10)
Alabama	Marengo	12.8(10.8,15)	Ohio	Guernsey	11.3(9.4,13.5)
Alabama	Marion	11.5(9.7,13.5)	Ohio	Hamilton	9.9(8.6,11.2)

Alabama	Marshall	10.2(8.6,11.9)	Ohio	Hancock	8.9(7.4,10.7)
Alabama	Mobile	11.2(9.9,12.7)	Ohio	Hardin	8.5(7,10.1)
Alabama	Monroe	12.9(10.8,15.3)	Ohio	Harrison	12.2(9.9,14.6)
Alabama	Montgomery	11.5(9.7,13.5)	Ohio	Henry	10.3(8.4,12.4)
Alabama	Morgan	9.3(7.6,11.1)	Ohio	Highland	11.4(9.4,13.7)
Alabama	Perry	15.7(12.9,18.8)	Ohio	Hocking	11.7(9.7,14)
Alabama	Pickens	11.8(9.7,14)	Ohio	Holmes	9.9(8.2,11.7)
Alabama	Pike	12(9.9,14.3)	Ohio	Huron	10(8.3,11.9)
Alabama	Randolph	11.1(9.2,13.1)	Ohio	Jackson	11.6(9.6,13.9)
Alabama	Russell	11.9(9.7,14.4)	Ohio	Jefferson	12.2(10.2,14.4)
Alabama	St. Clair	10.5(8.9,12.3)	Ohio	Knox	9.7(8.2,11.4)
Alabama	Shelby	7.9(6.6,9.3)	Ohio	Lake	9.8(7.8,12)
Alabama	Sumter	13.5(11.2,16.1)	Ohio	Lawrence	11.8(9.8,14)
Alabama	Talladega	11.9(10.1,13.8)	Ohio	Licking	10.3(8.8,11.9)
Alabama	Tallapoosa	11.3(9.5,13.3)	Ohio	Logan	10.2(8.3,12.3)
Alabama	Tuscaloosa	9.3(8.1,10.7)	Ohio	Lorain	10.2(8.5,12.2)
Alabama	Walker	11.9(10.2,13.7)	Ohio	Lucas	10.5(9.1,12)
Alabama	Washington	10.1(8.5,12)	Ohio	Madison	9.4(7.9,11.1)
Alabama	Wilcox	13.1(10.8,15.6)	Ohio	Mahoning	11.8(10.4,13.2)
Alabama	Winston	10.7(8.8,12.8)	Ohio	Marion	10.1(8.4,12)
Arkansas	Arkansas	13.2(10.5,16.2)	Ohio	Medina	8.4(6.9,10.1)
Arkansas	Ashley	12.2(9.3,15.5)	Ohio	Meigs	11.7(9.6,14.1)
Arkansas	Baxter	10.8(7.9,14.3)	Ohio	Mercer	10.3(8.2,12.8)
Arkansas	Benton	6.7(5.4,8.2)	Ohio	Miami	10.1(8.2,12.1)
Arkansas	Boone	10.1(7.3,13.5)	Ohio	Monroe	11.2(9.1,13.6)
Arkansas	Bradley	7.6(5.5,10)	Ohio	Montgomery	10.9(9.6,12.2)
Arkansas	Calhoun	9.2(6.4,12.5)	Ohio	Morgan	12.7(10.3,15.4)

Arkansas	Carroll	9.7(7.4,12.4)	Ohio	Morrow	10.3(8.4,12.4)
Arkansas	Chicot	14.2(11.1,17.7)	Ohio	Muskingum	10.3(8.6,12.3)
Arkansas	Clark	9.3(6.7,12.4)	Ohio	Noble	12(9.8,14.3)
Arkansas	Clay	13(9.4,17.4)	Ohio	Ottawa	10.8(8.4,13.6)
Arkansas	Cleburne	12.2(9.6,15)	Ohio	Paulding	9.8(7.4,12.5)
Arkansas	Cleveland	14.4(11.2,18)	Ohio	Perry	11.8(9.8,14)
Arkansas	Columbia	11.1(8.5,14)	Ohio	Pickaway	9.5(7.9,11.3)
Arkansas	Conway	11.6(9.2,14.5)	Ohio	Pike	12.3(10,14.9)
Arkansas	Craighead	10.1(8.2,12.4)	Ohio	Portage	8.9(7.5,10.4)
Arkansas	Crawford	9.4(7.3,11.7)	Ohio	Preble	10.3(8,12.8)
Arkansas	Crittenden	12(9.7,14.4)	Ohio	Putnam	8.9(7.2,10.7)
Arkansas	Cross	12.4(9.7,15.5)	Ohio	Richland	10.5(8.7,12.6)
Arkansas	Dallas	12.7(9.9,16)	Ohio	Ross	10.8(9,12.8)
Arkansas	Desha	12.9(10.2,16)	Ohio	Sandusky	10.7(8.6,12.9)
Arkansas	Drew	11.4(8.2,15.2)	Ohio	Scioto	12(9.9,14.3)
Arkansas	Faulkner	8.3(6.8,10)	Ohio	Seneca	9.7(8,11.6)
Arkansas	Franklin	10.5(8.3,13.1)	Ohio	Shelby	9.2(7.5,11.2)
Arkansas	Fulton	13.3(9.7,17.6)	Ohio	Stark	10.1(9,11.3)
Arkansas	Garland	10.2(8,12.7)	Ohio	Summit	9.9(8.7,11.2)
Arkansas	Grant	10.5(8.3,13)	Ohio	Trumbull	9.9(8.3,11.5)
Arkansas	Greene	11.2(8.6,14.2)	Ohio	Tuscarawas	10.8(9,12.7)
Arkansas	Hempstead	10.6(7.9,13.8)	Ohio	Union	8(6.7,9.4)
Arkansas	Hot Spring	10(7.9,12.4)	Ohio	Van Wert	10.1(8,12.5)
Arkansas	Howard	9.7(7,13)	Ohio	Vinton	12.7(10.4,15.3)
Arkansas	Independence	10.8(8.8,13.2)	Ohio	Warren	8.7(7.3,10.3)
Arkansas	Izard	11.9(8.9,15.3)	Ohio	Washington	11.4(9.2,13.7)
Arkansas	Jackson	13(10.6,15.7)	Ohio	Wayne	9.4(7.7,11.2)

Arkansas	Jefferson	12.7(10.6,14.9)	Ohio	Williams	11.4(8.7,14.6)
Arkansas	Johnson	9.3(7.2,11.7)	Ohio	Wood	8.3(6.8,9.8)
Arkansas	Lafayette	14.7(11.6,18.2)	Ohio	Wyandot	10(8.1,12.1)
Arkansas	Lawrence	12.7(10.1,15.6)	Pennsylvania	Adams	9.5(7.8,11.4)
Arkansas	Lee	14.2(10.7,18.1)	Pennsylvania	Allegheny	10.6(9.6,11.7)
Arkansas	Lincoln	12.1(9.1,15.5)	Pennsylvania	Armstrong	11.8(10,13.7)
Arkansas	Little River	10.8(8.1,14)	Pennsylvania	Beaver	11.1(9.4,13)
Arkansas	Logan	11.3(8.9,13.9)	Pennsylvania	Bedford	11.5(9.6,13.5)
Arkansas	Lonoke	9.7(7.9,11.6)	Pennsylvania	Berks	8.8(7.4,10.3)
Arkansas	Madison	11(8.9,13.4)	Pennsylvania	Blair	10.3(8.6,12.3)
Arkansas	Marion	11.4(8,15.5)	Pennsylvania	Bradford	10.8(8.8,13.1)
Arkansas	Miller	10.2(8,12.8)	Pennsylvania	Bucks	8.7(7.2,10.3)
Arkansas	Mississippi	11.9(9.7,14.4)	Pennsylvania	Butler	10(8.7,11.5)
Arkansas	Monroe	14.3(10.8,18.3)	Pennsylvania	Cambria	11.6(9.8,13.5)
Arkansas	Montgomery	13.4(10.8,16.4)	Pennsylvania	Carbon	11.4(9.5,13.6)
Arkansas	Nevada	14.1(10.8,17.9)	Pennsylvania	Centre	6.7(5.6,7.9)
Arkansas	Newton	13.8(10.9,17)	Pennsylvania	Chester	7.2(6,8.6)
Arkansas	Ouachita	12.7(9.7,16.2)	Pennsylvania	Clarion	10(8.1,12.2)
Arkansas	Perry	11.1(9.1,13.3)	Pennsylvania	Clearfield	11.3(9.6,13.2)
Arkansas	Phillips	13.4(10.4,16.8)	Pennsylvania	Clinton	9.6(7.9,11.5)
Arkansas	Pike	11.5(8.4,15.1)	Pennsylvania	Columbia	9.3(7.7,11)
Arkansas	Poinsett	11.2(9,13.8)	Pennsylvania	Crawford	11.3(9.5,13.2)
Arkansas	Polk	10(6.9,13.8)	Pennsylvania	Cumberland	8.3(6.9,9.9)
Arkansas	Pope	9.2(7.4,11.4)	Pennsylvania	Dauphin	9.9(8.5,11.4)
Arkansas	Prairie	13.7(10.5,17.3)	Pennsylvania	Delaware	8.6(7,10.5)
Arkansas	Pulaski	10.4(9,11.9)	Pennsylvania	Elk	11.6(9.4,14.1)
Arkansas	Randolph	13.5(10.3,17.1)	Pennsylvania	Erie	10(8.3,11.8)

Arkansas	St. Francis	12(8.9,15.7)	Pennsylvania	Fayette	11(9.3,12.9)
Arkansas	Saline	9.5(7.6,11.6)	Pennsylvania	Forest	13.2(10.9,15.7)
Arkansas	Scott	9.6(7.4,12.1)	Pennsylvania	Franklin	10.3(8.8,11.9)
Arkansas	Searcy	13.5(10.3,17.1)	Pennsylvania	Fulton	10(8.2,12.1)
Arkansas	Sebastian	9.3(7.3,11.8)	Pennsylvania	Greene	11.4(9.2,13.8)
Arkansas	Sevier	9.2(6.7,12.2)	Pennsylvania	Huntingdon	10.9(9.2,12.8)
Arkansas	Sharp	12.9(10,16.3)	Pennsylvania	Indiana	9.9(8.2,11.8)
Arkansas	Stone	15(11.8,18.4)	Pennsylvania	Jefferson	11.4(9.4,13.6)
Arkansas	Union	11.3(8.9,14)	Pennsylvania	Juniata	9.5(7.9,11.3)
Arkansas	Van Buren	11.5(9.1,14.4)	Pennsylvania	Lackawanna	9.9(8.1,11.7)
Arkansas	Washington	7.2(5.8,8.8)	Pennsylvania	Lancaster	9.5(8.2,11.1)
Arkansas	White	10.2(8.3,12.4)	Pennsylvania	Lawrence	11.5(9.7,13.4)
Arkansas	Woodruff	14.6(11.4,18.2)	Pennsylvania	Lebanon	9.2(7.5,11.1)
Arkansas	Yell	11.4(9.1,14.1)	Pennsylvania	Lehigh	9(7.7,10.4)
Florida	Alachua	8.2(7.2,9.3)	Pennsylvania	Luzerne	10.2(8.8,11.8)
Florida	Baker	12.1(10.8,13.6)	Pennsylvania	Lycoming	9.7(8.3,11.3)
Florida	Bay	10.8(9.4,12.3)	Pennsylvania	McKean	10.5(8.3,13.1)
Florida	Bradford	12.7(11.2,14.4)	Pennsylvania	Mercer	11.5(9.8,13.3)
Florida	Brevard	12.1(10.6,13.6)	Pennsylvania	Mifflin	10.4(8.5,12.5)
Florida	Broward	8.3(7.1,9.6)	Pennsylvania	Monroe	9.8(8.2,11.7)
Florida	Calhoun	13.8(12.1,15.6)	Pennsylvania	Montgomery	8.1(6.9,9.4)
Florida	Charlotte	12(10.5,13.7)	Pennsylvania	Montour	9.9(7.8,12.3)
Florida	Citrus	12(10.4,13.7)	Pennsylvania	Northampton	8.8(7.3,10.5)
Florida	Clay	9.8(8.6,11.1)	Pennsylvania	Northumberland	10.1(8.7,11.6)
Florida	Collier	9.2(8,10.5)	Pennsylvania	Perry	10.9(9.1,12.8)
Florida	Columbia	12.8(11.4,14.3)	Pennsylvania	Philadelphia	11.2(10.1,12.4)
Florida	De Soto	12.1(10.6,13.6)	Pennsylvania	Pike	10.6(7.9,13.8)

Florida	Dixie	14(12.1,16)	Pennsylvania	Potter	11.6(9.3,14.1)
Florida	Duval	10(8.7,11.4)	Pennsylvania	Schuylkill	10.4(8.9,12)
Florida	Escambia	11.7(10,13.5)	Pennsylvania	Snyder	9.5(7.8,11.3)
Florida	Flagler	11.2(9.6,12.9)	Pennsylvania	Somerset	11.5(9.7,13.5)
Florida	Franklin	13(9.7,16.7)	Pennsylvania	Sullivan	13.5(11,16.2)
Florida	Gadsden	14.2(12.5,16)	Pennsylvania	Susquehanna	12.4(9.9,15.2)
Florida	Gilchrist	11.6(10.1,13.1)	Pennsylvania	Tioga	10.5(8.3,12.9)
Florida	Glades	13.2(11.4,15.1)	Pennsylvania	Union	9(7.5,10.7)
Florida	Gulf	12.3(10.5,14.3)	Pennsylvania	Venango	11(9.2,13)
Florida	Hamilton	13.7(12,15.6)	Pennsylvania	Warren	11.4(9.4,13.7)
Florida	Hardee	12.3(10.9,13.8)	Pennsylvania	Washington	10.8(9.3,12.4)
Florida	Hendry	10.2(9,11.5)	Pennsylvania	Wayne	11(8.7,13.6)
Florida	Hernando	11.5(9.8,13.2)	Pennsylvania	Westmoreland	10.1(8.8,11.4)
Florida	Highlands	13.2(11.7,14.8)	Pennsylvania	Wyoming	10.2(8.1,12.6)
Florida	Hillsborough	10(8.7,11.4)	Pennsylvania	York	9.4(8.1,10.8)
Florida	Holmes	14.1(12.4,15.9)	South Carolina	Abbeville	11.8(9.9,13.9)
Florida	Indian River	11.8(10.2,13.5)	South Carolina	Aiken	9.9(8.6,11.3)
Florida	Jackson	13.6(12.2,15.1)	South Carolina	Allendale	10(8.2,11.9)
Florida	Jefferson	13.7(12.2,15.4)	South Carolina	Anderson	10.1(8.6,11.7)
Florida	Lafayette	13(10.8,15.3)	South Carolina	Bamberg	13.1(11,15.3)
Florida	Lake	11.5(10.3,12.9)	South Carolina	Barnwell	12(10,14.3)
Florida	Lee	9.6(8.2,11.2)	South Carolina	Beaufort	8.2(6.9,9.5)
Florida	Leon	9.3(8.1,10.7)	South Carolina	Berkeley	9.9(8.6,11.2)
Florida	Levy	13.2(11.7,14.8)	South Carolina	Calhoun	14.4(12.2,16.9)
Florida	Liberty	16.3(13.9,19)	South Carolina	Charleston	9.8(8.6,11.1)
Florida	Madison	14.1(12.5,15.8)	South Carolina	Cherokee	10.8(8.9,12.8)
Florida	Manatee	11.4(9.9,12.9)	South Carolina	Chester	12(9.7,14.5)

Florida	Marion	12.3(11,13.7)	South Carolina	Chesterfield	12.6(10.8,14.6)
Florida	Martin	8.7(7.4,10.1)	South Carolina	Clarendon	13.6(11.8,15.7)
Florida	Miami-Dade	8.6(7.2,10)	South Carolina	Colleton	12.2(10.6,14)
Florida	Monroe	7.8(6.4,9.3)	South Carolina	Darlington	13.1(11.1,15.4)
Florida	Nassau	9.6(8.1,11.2)	South Carolina	Dillon	12.9(11,15)
Florida	Okaloosa	9(7.6,10.5)	South Carolina	Dorchester	9.8(8.2,11.6)
Florida	Okeechobee	10.8(9.6,12)	South Carolina	Edgefield	10.1(8.4,12)
Florida	Orange	9.4(8.4,10.4)	South Carolina	Fairfield	13.2(11.2,15.4)
Florida	Osceola	9.7(8.6,10.9)	South Carolina	Florence	11.5(10.1,13.1)
Florida	Palm Beach	8.5(7.3,9.8)	South Carolina	Georgetown	11.2(9.6,12.9)
Florida	Pasco	10.4(9.1,11.8)	South Carolina	Greenville	9.4(8.2,10.6)
Florida	Pinellas	10.7(9,12.6)	South Carolina	Greenwood	9.8(8.3,11.5)
Florida	Polk	11.5(10.4,12.7)	South Carolina	Hampton	12(10.1,14)
Florida	Putnam	13.9(12.4,15.6)	South Carolina	Horry	11(9.7,12.5)
Florida	St. Johns	8.2(7,9.5)	South Carolina	Jasper	10.8(8.8,13)
Florida	St. Lucie	11.9(10.2,13.6)	South Carolina	Kershaw	11.6(9.9,13.4)
Florida	Santa Rosa	11.2(9.6,12.9)	South Carolina	Lancaster	10.8(9.1,12.6)
Florida	Sarasota	10.3(8.8,11.8)	South Carolina	Laurens	11.3(9.8,12.9)
Florida	Seminole	10.3(8.9,11.8)	South Carolina	Lee	13.3(11.3,15.6)
Florida	Sumter	13.3(11.7,15.1)	South Carolina	Lexington	9.3(7.9,10.8)
Florida	Suwannee	13.1(11.4,14.8)	South Carolina	McCormick	13.9(11.3,16.8)
Florida	Taylor	13(11.3,14.7)	South Carolina	Marion	13.6(11.6,15.8)
Florida	Union	12.9(11.3,14.7)	South Carolina	Marlboro	12.9(11.1,14.8)
Florida	Volusia	11.7(10.5,12.9)	South Carolina	Newberry	11.7(10,13.5)
Florida	Wakulla	11.4(9.7,13.2)	South Carolina	Oconee	9.8(8.3,11.5)
Florida	Walton	11.4(10,12.9)	South Carolina	Orangeburg	13.7(12.3,15.2)
Florida	Washington	13.7(12.1,15.5)	South Carolina	Pickens	8.8(7.2,10.7)

Georgia	Appling	11.4(8.6,14.6)	South Carolina	Richland	9.6(8.5,10.8)
Georgia	Atkinson	12.8(9.6,16.6)	South Carolina	Saluda	10.9(9.1,12.9)
Georgia	Bacon	12.8(9.8,16.3)	South Carolina	Spartanburg	10.1(8.7,11.6)
Georgia	Baker	14.1(10.6,18.1)	South Carolina	Sumter	12.1(10.5,13.8)
Georgia	Baldwin	8.7(6.5,11.2)	South Carolina	Union	12.8(11,14.7)
Georgia	Banks	9.9(8,12.1)	South Carolina	Williamsburg	14.4(12.5,16.5)
Georgia	Barrow	8.9(7.3,10.8)	South Carolina	York	9.6(8.1,11.2)
Georgia	Bartow	9(7.4,10.6)	Tennessee	Anderson	8.3(6.9,9.9)
Georgia	Ben Hill	14.3(10.3,18.8)	Tennessee	Bedford	7.6(6,9.3)
Georgia	Berrien	12.9(10.2,16)	Tennessee	Benton	10.5(8.3,12.9)
Georgia	Bibb	9.5(7.4,11.9)	Tennessee	Bledsoe	9.6(7.6,11.8)
Georgia	Bleckley	10.6(7.7,13.9)	Tennessee	Blount	9.4(7.7,11.2)
Georgia	Brantley	11.2(8.6,14.2)	Tennessee	Bradley	9.6(8,11.4)
Georgia	Brooks	13.4(11,16.2)	Tennessee	Campbell	11.5(9.3,14)
Georgia	Bryan	9.3(7.1,11.9)	Tennessee	Cannon	9.3(7.5,11.4)
Georgia	Bulloch	9(7,11.3)	Tennessee	Carroll	9.4(7.7,11.3)
Georgia	Burke	12.1(9.8,14.6)	Tennessee	Carter	10.7(8.9,12.7)
Georgia	Butts	9.2(7.4,11.3)	Tennessee	Cheatham	8.5(6.9,10.5)
Georgia	Calhoun	13.9(8.9,20.2)	Tennessee	Chester	6.4(5.2,7.9)
Georgia	Camden	9(6.7,11.7)	Tennessee	Claiborne	9.9(8.1,12)
Georgia	Candler	12.3(9.4,15.6)	Tennessee	Clay	11.4(8.1,15.5)
Georgia	Carroll	8.5(7.1,10.1)	Tennessee	Cocke	10.8(8.9,12.9)
Georgia	Catoosa	9.2(7.2,11.5)	Tennessee	Coffee	9(7.4,10.8)
Georgia	Charlton	11.3(8.9,14.1)	Tennessee	Crockett	10(8.1,12.1)
Georgia	Chatham	9.5(7.4,11.9)	Tennessee	Cumberland	10.1(8.4,12)
Georgia	Chattahoochee	7.5(5.2,10.2)	Tennessee	Davidson	7.5(6.4,8.7)
Georgia	Chattooga	9.7(7.6,12)	Tennessee	Decatur	8.7(7,10.7)

Georgia	Cherokee	7.8(6.5,9.2)	Tennessee	DeKalb	9.1(7.4,11.1)
Georgia	Clarke	7.4(5.9,9.1)	Tennessee	Dickson	7.7(6.1,9.5)
Georgia	Clay	16.8(10.6,24.7)	Tennessee	Dyer	10.3(8.3,12.5)
Georgia	Clayton	9.7(8.1,11.4)	Tennessee	Fayette	9.7(7.9,11.7)
Georgia	Clinch	14.3(10.9,18.3)	Tennessee	Fentress	9.7(7.9,11.9)
Georgia	Cobb	7.4(6.1,8.8)	Tennessee	Franklin	8.3(6.8,10)
Georgia	Coffee	13.1(10.2,16.4)	Tennessee	Gibson	9.6(7.9,11.4)
Georgia	Colquitt	12(9.8,14.5)	Tennessee	Giles	9.2(7.5,11.1)
Georgia	Columbia	7.8(5.9,10)	Tennessee	Grainger	11.5(9.5,13.7)
Georgia	Cook	13.5(10.9,16.5)	Tennessee	Greene	10.2(8.4,12)
Georgia	Coweta	8.5(7,10.2)	Tennessee	Grundy	9.5(7.7,11.6)
Georgia	Crawford	9.5(7.2,12.1)	Tennessee	Hamblen	9.4(7.6,11.3)
Georgia	Crisp	13.4(10.1,17.3)	Tennessee	Hamilton	8.3(7.2,9.5)
Georgia	Dade	8.4(6.7,10.5)	Tennessee	Hancock	8.6(7,10.5)
Georgia	Dawson	9.1(7.5,10.9)	Tennessee	Hardeman	8.6(7.2,10.3)
Georgia	Decatur	12.6(10,15.5)	Tennessee	Hardin	9.7(8,11.5)
Georgia	DeKalb	8(6.7,9.4)	Tennessee	Hawkins	10.6(8.9,12.4)
Georgia	Dodge	13.1(9.5,17.4)	Tennessee	Haywood	10.2(8.4,12.2)
Georgia	Dooly	9.8(7.3,12.7)	Tennessee	Henderson	7.8(6.2,9.6)
Georgia	Dougherty	12.7(9.8,15.8)	Tennessee	Henry	7.8(6.3,9.5)
Georgia	Douglas	8.7(7,10.7)	Tennessee	Hickman	9.4(7.4,11.7)
Georgia	Early	12.2(8.6,16.4)	Tennessee	Houston	6.9(5.5,8.6)
Georgia	Echols	11.9(9,15.4)	Tennessee	Humphreys	8(6.1,10.3)
Georgia	Effingham	9(7.1,11.1)	Tennessee	Jackson	4.8(3.7,6.2)
Georgia	Elbert	11.6(9.3,14.2)	Tennessee	Jefferson	9.8(8,11.8)
Georgia	Emanuel	11.6(9.3,14.3)	Tennessee	Johnson	12.4(10.4,14.7)
Georgia	Evans	13.4(10.2,17.1)	Tennessee	Knox	8.3(7.1,9.5)

Georgia	Fannin	12.2(10,14.7)	Tennessee	Lake	9.8(7,13.1)
Georgia	Fayette	8.7(7,10.7)	Tennessee	Lauderdale	11(8.9,13.3)
Georgia	Floyd	9.1(7.4,11)	Tennessee	Lawrence	9.5(7.5,11.7)
Georgia	Forsyth	7.4(6.1,8.9)	Tennessee	Lewis	7.8(6.1,9.7)
Georgia	Franklin	10.3(8.2,12.7)	Tennessee	Lincoln	9.5(7.8,11.4)
Georgia	Fulton	8(6.9,9.1)	Tennessee	Loudon	11.5(9.6,13.7)
Georgia	Gilmer	10.4(8.4,12.7)	Tennessee	McMinn	9.6(7.9,11.4)
Georgia	Glascock	13.5(9.3,18.5)	Tennessee	McNairy	9.8(7.8,12.1)
Georgia	Glynn	9.5(7,12.4)	Tennessee	Macon	8.8(6.7,11.3)
Georgia	Gordon	9.2(7.7,11)	Tennessee	Madison	8.8(7.6,10.1)
Georgia	Grady	13.6(10.9,16.5)	Tennessee	Marion	10.3(8.5,12.4)
Georgia	Greene	10.9(8.5,13.6)	Tennessee	Marshall	7.9(6.4,9.5)
Georgia	Gwinnett	6.9(5.8,8.1)	Tennessee	Maury	8.3(6.7,10)
Georgia	Habersham	10(8.1,12.2)	Tennessee	Meigs	11.6(9.5,14)
Georgia	Hall	8.3(6.9,9.7)	Tennessee	Monroe	10.8(8.9,12.9)
Georgia	Hancock	11.4(8.6,14.5)	Tennessee	Montgomery	7(5.6,8.6)
Georgia	Haralson	9.7(7.7,12.1)	Tennessee	Moore	7.5(5.9,9.4)
Georgia	Harris	10.3(8.3,12.6)	Tennessee	Morgan	9.8(8,12)
Georgia	Hart	11.1(8.9,13.7)	Tennessee	Obion	9.1(7.1,11.4)
Georgia	Heard	9.7(7.6,12.1)	Tennessee	Overton	10.3(7.6,13.4)
Georgia	Henry	8.2(6.8,9.8)	Tennessee	Perry	11.5(8.9,14.5)
Georgia	Houston	8.1(5.9,10.7)	Tennessee	Pickett	14.4(11.4,17.7)
Georgia	Irwin	12.9(9.9,16.5)	Tennessee	Polk	9.7(8,11.7)
Georgia	Jackson	9.2(7.5,11.1)	Tennessee	Putnam	7.8(6.3,9.5)
Georgia	Jasper	9.6(7.7,11.7)	Tennessee	Rhea	9.5(7.6,11.6)
Georgia	Jeff Davis	11.3(8.7,14.3)	Tennessee	Roane	9.4(7.9,11.1)
Georgia	Jefferson	11.6(9.2,14.4)	Tennessee	Robertson	8.4(6.8,10.1)

Georgia	Jenkins	12.1(9.3,15.4)	Tennessee	Rutherford	6.6(5.5,7.9)
Georgia	Johnson	11.9(9.2,15)	Tennessee	Scott	10.5(8.6,12.6)
Georgia	Jones	9.7(7.6,12.1)	Tennessee	Sequatchie	9.1(7.4,11.1)
Georgia	Lamar	10.1(8,12.6)	Tennessee	Sevier	9.6(7.9,11.4)
Georgia	Lanier	13.4(9.7,17.7)	Tennessee	Shelby	9.2(7.8,10.6)
Georgia	Laurens	12.4(8.9,16.4)	Tennessee	Smith	9.5(7.5,11.8)
Georgia	Lee	10.3(7.8,13.2)	Tennessee	Stewart	9(7.2,11)
Georgia	Liberty	9.3(6.7,12.4)	Tennessee	Sullivan	10.6(9.2,12.1)
Georgia	Lincoln	12.6(9.4,16.4)	Tennessee	Sumner	7.5(6.1,9.2)
Georgia	Long	8.6(6.2,11.5)	Tennessee	Tipton	8.9(7.3,10.8)
Georgia	Lowndes	10.6(8.7,12.8)	Tennessee	Trousdale	10.7(8.3,13.5)
Georgia	Lumpkin	9.2(7.3,11.3)	Tennessee	Unicoi	10.4(8.5,12.4)
Georgia	McDuffie	9.3(6.9,12)	Tennessee	Van Buren	8.5(6.9,10.4)
Georgia	McIntosh	11.7(8.5,15.4)	Tennessee	Warren	8.6(7,10.3)
Georgia	Macon	12.4(9,16.2)	Tennessee	Washington	9.3(7.7,11)
Georgia	Madison	10.2(8.3,12.3)	Tennessee	Wayne	9.3(7.2,11.8)
Georgia	Marion	13.6(9.6,18.4)	Tennessee	Weakley	8.1(6.5,9.9)
Georgia	Meriwether	12(9.8,14.5)	Tennessee	White	10(7.9,12.2)
Georgia	Miller	16.3(10.5,23.6)	Tennessee	Williamson	6.3(5.2,7.6)
Georgia	Mitchell	12.4(10.1,15.1)	Tennessee	Wilson	8(6.5,9.6)
Georgia	Monroe	10.3(8.3,12.7)	Texas	Anderson	10.2(8.4,12.1)
Georgia	Montgomery	10.1(7,13.9)	Texas	Andrews	10(7.1,13.5)
Georgia	Morgan	10.1(8.2,12.3)	Texas	Angelina	11.6(9.8,13.8)
Georgia	Murray	10.5(8.6,12.6)	Texas	Aransas	13.4(9.3,18.5)
Georgia	Muscogee	10.6(8.5,12.9)	Texas	Archer	15(11,19.7)
Georgia	Newton	9.4(7.7,11.3)	Texas	Atascosa	12.2(9.8,14.9)
Georgia	Oconee	8.1(6.5,9.8)	Texas	Austin	9.8(8.1,11.7)

Georgia	Oglethorpe	10(8,12.3)	Texas	Bailey	10.5(6.4,15.8)
Georgia	Paulding	7.8(6.4,9.4)	Texas	Bandera	16.1(13,19.6)
Georgia	Peach	9.3(6.7,12.4)	Texas	Bastrop	9.5(7.8,11.4)
Georgia	Pickens	9.8(7.9,12)	Texas	Baylor	12.6(9.1,16.7)
Georgia	Pierce	12.6(9.6,16)	Texas	Bee	11.3(7.9,15.4)
Georgia	Pike	8.7(6.7,11)	Texas	Bell	8.7(7.2,10.4)
Georgia	Polk	9.9(8.1,12)	Texas	Bexar	10(8.8,11.2)
Georgia	Pulaski	11.8(8.3,16)	Texas	Blanco	14(11.6,16.7)
Georgia	Putnam	10.7(8.5,13.2)	Texas	Bosque	13.9(11.2,16.9)
Georgia	Quitman	12.2(8.6,16.7)	Texas	Bowie	10.7(8.3,13.5)
Georgia	Rabun	11.7(9.2,14.7)	Texas	Brazoria	8.8(7.2,10.5)
Georgia	Randolph	13.7(12.1,15.3)	Texas	Brazos	6.6(5.4,8)
Georgia	Richmond	10.1(8.2,12.2)	Texas	Brewster	12.7(8.1,18.4)
Georgia	Rockdale	9.4(7.6,11.4)	Texas	Briscoe	18(16.5,19.7)
Georgia	Schley	10.4(7,14.7)	Texas	Brooks	15.3(11.5,19.7)
Georgia	Screven	13.5(10.7,16.9)	Texas	Brown	10.4(7.4,14)
Georgia	Seminole	16.5(12.7,20.8)	Texas	Burleson	12.5(10.1,15.1)
Georgia	Spalding	9.6(8,11.4)	Texas	Burnet	11(8.8,13.4)
Georgia	Stephens	10.6(8.3,13.3)	Texas	Caldwell	9.6(7.8,11.4)
Georgia	Stewart	10.1(7.5,13.2)	Texas	Calhoun	9.5(7.2,12.1)
Georgia	Sumter	12.5(9.3,16.2)	Texas	Callahan	9.8(7,13.2)
Georgia	Talbot	14.9(11.8,18.3)	Texas	Cameron	12(9.9,14.2)
Georgia	Taliaferro	11.8(8.4,15.9)	Texas	Camp	11.6(9,14.5)
Georgia	Tattnall	10.4(8,13.1)	Texas	Carson	10.6(8.2,13.2)
Georgia	Taylor	12.9(9.5,17)	Texas	Cass	12.5(9.8,15.6)
Georgia	Telfair	12.6(9.2,16.4)	Texas	Castro	11.6(8.5,15.2)
Georgia	Terrell	15.1(11.2,19.6)	Texas	Chambers	9.3(7.4,11.5)

Georgia	Thomas	13.6(11.2,16.3)	Texas	Cherokee	11.5(9.7,13.4)
Georgia	Tift	12.2(9.7,15.1)	Texas	Childress	12.7(11.6,13.9)
Georgia	Toombs	12.1(9.1,15.7)	Texas	Clay	14.5(10.5,19.3)
Georgia	Towns	10.6(8.1,13.5)	Texas	Cochran	11.4(6.8,17.4)
Georgia	Treutlen	9.6(7.1,12.6)	Texas	Coke	15(10.7,20.2)
Georgia	Troup	11.1(9,13.5)	Texas	Coleman	10.4(7.2,14.3)
Georgia	Turner	13.1(10.3,16.4)	Texas	Collin	7(5.7,8.4)
Georgia	Twiggs	13.7(10.6,17.3)	Texas	Collingsworth	13.5(8.7,19.5)
Georgia	Union	13.2(10.4,16.4)	Texas	Colorado	9.5(7.6,11.7)
Georgia	Upson	11.7(9.1,14.7)	Texas	Comal	10.1(8.1,12.4)
Georgia	Walker	9.5(7.9,11.3)	Texas	Comanche	12.5(9,16.7)
Georgia	Walton	8.9(7.3,10.7)	Texas	Concho	13.6(8.9,19.7)
Georgia	Ware	13.1(10.3,16.2)	Texas	Cooke	11.1(8.5,14)
Georgia	Warren	12.3(8.6,16.7)	Texas	Coryell	8(6.2,10.1)
Georgia	Washington	11.6(8.3,15.5)	Texas	Cottle	17.5(16,19.1)
Georgia	Wayne	10.5(8.1,13.3)	Texas	Crane	12(8.7,15.8)
Georgia	Webster	12.3(7.4,18.5)	Texas	Crockett	12.5(9.2,16.4)
Georgia	Wheeler	13.1(9.3,17.5)	Texas	Crosby	8.6(6.2,11.5)
Georgia	White	9.7(7.6,12.1)	Texas	Culberson	14.8(13.5,16.1)
Georgia	Whitfield	9.4(7.6,11.5)	Texas	Dallam	9.1(5.1,14.5)
Georgia	Wilcox	12.4(9.4,16)	Texas	Dallas	9.3(7.9,10.7)
Georgia	Wilkes	11.7(8.9,15)	Texas	Dawson	11.5(6.4,18)
Georgia	Wilkinson	11.3(8.7,14.1)	Texas	Deaf Smith	9.7(6.2,14.2)
Georgia	Worth	11.4(9.1,14)	Texas	Delta	13.6(10.7,16.8)
Kentucky	Adair	11.4(8.9,14.3)	Texas	Denton	7.5(6.2,9.1)
Kentucky	Allen	9.9(7.9,12.2)	Texas	DeWitt	11.3(8.8,14)
Kentucky	Anderson	9.2(7.4,11.2)	Texas	Dickens	16.8(15.3,18.3)

Kentucky	Ballard	9.8(6.1,14.6)	Texas	Dimmit	14.6(11.4,18.2)
Kentucky	Barren	10.1(8,12.5)	Texas	Donley	13.2(8.5,19.1)
Kentucky	Bath	11.2(8.9,13.7)	Texas	Duval	14.9(10.6,20.1)
Kentucky	Bell	14.6(12.3,17.2)	Texas	Eastland	11.4(8.6,14.7)
Kentucky	Boone	8.6(6.9,10.5)	Texas	Ector	8.6(7,10.4)
Kentucky	Bourbon	10.7(8.5,13.1)	Texas	Edwards	15.3(11.8,19.4)
Kentucky	Boyd	11.7(9.8,13.7)	Texas	Ellis	9.9(8.3,11.7)
Kentucky	Boyle	10.6(8.5,12.9)	Texas	El Paso	11.6(10.6,12.7)
Kentucky	Bracken	10.4(8.4,12.6)	Texas	Erath	9.4(7.2,11.9)
Kentucky	Breathitt	16.8(13.7,20.3)	Texas	Falls	9.8(7.8,11.9)
Kentucky	Breckinridge	11.3(9,13.8)	Texas	Fannin	11.3(8.8,14)
Kentucky	Bullitt	9.5(7.6,11.8)	Texas	Fayette	10.2(8.5,12)
Kentucky	Butler	10(8,12.1)	Texas	Fisher	11.4(7.6,15.9)
Kentucky	Caldwell	10(7.9,12.4)	Texas	Floyd	14.1(10.2,18.8)
Kentucky	Calloway	8.1(6.5,9.9)	Texas	Foard	17.2(9.8,26.6)
Kentucky	Campbell	9.2(7.4,11.2)	Texas	Fort Bend	8.3(7.2,9.4)
Kentucky	Carlisle	9.6(6.8,12.9)	Texas	Franklin	11.7(9,14.6)
Kentucky	Carroll	10(6.1,15.1)	Texas	Freestone	11.4(9.2,13.8)
Kentucky	Carter	12.8(10.7,15.1)	Texas	Frio	12.4(9.4,15.9)
Kentucky	Casey	11.8(9.7,14)	Texas	Gaines	10.1(5.2,16.6)
Kentucky	Christian	8(6.5,9.5)	Texas	Galveston	10.8(8.6,13.3)
Kentucky	Clark	10.8(8.7,13.1)	Texas	Garza	13.1(9.2,17.8)
Kentucky	Clay	14.2(11.8,16.8)	Texas	Gillespie	12.3(9.1,16)
Kentucky	Clinton	9.5(6.8,12.7)	Texas	Goliad	14.5(11.2,18.3)
Kentucky	Crittenden	8.8(6.5,11.6)	Texas	Gonzales	10(8.3,11.8)
Kentucky	Cumberland	10.7(7.7,14.4)	Texas	Gray	11.9(10.9,13.1)
Kentucky	Daviess	9.3(7.3,11.4)	Texas	Grayson	10(7.8,12.4)

Kentucky	Edmonson	6.8(5.4,8.3)	Texas	Gregg	10.8(9.2,12.6)
Kentucky	Estill	11.8(9.3,14.7)	Texas	Grimes	12.3(10.1,14.7)
Kentucky	Fayette	7.4(6.2,8.9)	Texas	Guadalupe	9.6(7.9,11.4)
Kentucky	Fleming	12.8(10.4,15.3)	Texas	Hale	8.7(6.4,11.3)
Kentucky	Floyd	16.5(14,19.4)	Texas	Hall	15.9(14.5,17.3)
Kentucky	Franklin	8.6(6.8,10.6)	Texas	Hansford	10.4(6.8,15.1)
Kentucky	Fulton	7.8(4.8,11.6)	Texas	Hardeman	17(9.7,26.4)
Kentucky	Gallatin	5.5(3.9,7.5)	Texas	Hardin	10.7(8.8,12.9)
Kentucky	Garrard	10.8(8.8,13)	Texas	Harris	9.2(8.3,10.1)
Kentucky	Grant	9.6(7.8,11.7)	Texas	Harrison	11.8(9.7,14.1)
Kentucky	Graves	9.1(7.3,11)	Texas	Hartley	9.8(6.5,13.8)
Kentucky	Grayson	10.3(8.4,12.4)	Texas	Haskell	14.5(8.3,22.5)
Kentucky	Green	11.1(8.7,13.8)	Texas	Hays	7.2(5.6,8.8)
Kentucky	Greenup	12.5(10.5,14.7)	Texas	Henderson	12(10.2,14)
Kentucky	Hancock	10.9(8.3,13.9)	Texas	Hidalgo	12.8(11,14.7)
Kentucky	Hardin	8.9(7.5,10.5)	Texas	Hill	13.3(10.9,15.8)
Kentucky	Harlan	15.2(12.8,18)	Texas	Hockley	7.8(5.7,10.3)
Kentucky	Harrison	9.8(7.7,12.2)	Texas	Hood	11.2(8.7,14)
Kentucky	Hart	10.4(8.3,12.7)	Texas	Hopkins	11.4(8.5,14.8)
Kentucky	Henderson	9(7,11.4)	Texas	Houston	12.3(10.4,14.5)
Kentucky	Henry	9.1(6.7,11.9)	Texas	Howard	11.4(6.7,17.4)
Kentucky	Hickman	9.4(7,12.1)	Texas	Hudspeth	13.4(8.7,19.3)
Kentucky	Hopkins	9.3(7.4,11.3)	Texas	Hunt	10(8.1,12)
Kentucky	Jefferson	8(6.7,9.4)	Texas	Hutchinson	9.6(6.5,13.4)
Kentucky	Jessamine	9.1(7.3,11)	Texas	Irion	15.2(9.8,21.9)
Kentucky	Johnson	14.8(12.2,17.6)	Texas	Jack	13.2(10.2,16.6)
Kentucky	Kenton	9.1(7.5,10.8)	Texas	Jackson	10.4(8.3,12.8)

Kentucky	Knott	15(12.7,17.4)	Texas	Jasper	13.5(11,16.4)
Kentucky	Knox	13.1(10.7,15.7)	Texas	Jeff Davis	14.5(9.3,21.1)
Kentucky	Larue	10.6(8.7,12.9)	Texas	Jefferson	13.6(11,16.4)
Kentucky	Laurel	11.7(9.9,13.6)	Texas	Jim Hogg	15.7(11.4,20.7)
Kentucky	Lawrence	15.3(12.8,18.1)	Texas	Jim Wells	12(8.1,16.9)
Kentucky	Lee	9.5(7.5,11.7)	Texas	Johnson	10.3(8.6,12.3)
Kentucky	Leslie	13(10.5,15.8)	Texas	Jones	11.9(8,16.6)
Kentucky	Letcher	15.9(13.5,18.5)	Texas	Karnes	9.7(7.7,12)
Kentucky	Lewis	13.6(11.6,15.7)	Texas	Kaufman	10.9(9,13)
Kentucky	Lincoln	11.9(9.6,14.4)	Texas	Kendall	10.2(8,12.6)
Kentucky	Livingston	10.1(7.2,13.5)	Texas	Kent	13.3(7,22.1)
Kentucky	Logan	9.2(7.4,11.1)	Texas	Kerr	12.5(9.5,16)
Kentucky	Lyon	8.4(6.3,10.7)	Texas	Kimble	17.1(12,23.2)
Kentucky	McCracken	8.6(6.6,10.8)	Texas	Kinney	14.1(11,17.7)
Kentucky	McCreary	12.2(10,14.6)	Texas	Kleberg	10.5(6.6,15.3)
Kentucky	McLean	9.2(7.5,11.2)	Texas	Knox	16.1(14.8,17.5)
Kentucky	Madison	8.9(7.4,10.7)	Texas	Lamar	10.1(7.3,13.4)
Kentucky	Magoffin	16.6(13.8,19.7)	Texas	Lamb	11.1(8.1,14.5)
Kentucky	Marion	9.6(7.7,11.6)	Texas	Lampasas	9.8(7.4,12.6)
Kentucky	Marshall	9.2(7.3,11.4)	Texas	La Salle	11.5(8.8,14.5)
Kentucky	Martin	12.6(10.5,14.8)	Texas	Lavaca	10.4(8.4,12.6)
Kentucky	Mason	11.8(9.7,14)	Texas	Lee	12.2(10,14.6)
Kentucky	Meade	9.5(7.1,12.3)	Texas	Leon	12.8(10.7,15.2)
Kentucky	Menifee	11.1(8.8,13.6)	Texas	Liberty	12.7(10.7,15)
Kentucky	Mercer	10(8,12.3)	Texas	Limestone	11.1(9.2,13.1)
Kentucky	Metcalfe	11.4(8.7,14.3)	Texas	Lipscomb	13.9(12.7,15.3)
Kentucky	Monroe	11.8(9,15.1)	Texas	Live Oak	13.4(10.2,17.1)

Kentucky	Montgomery	8.6(6.7,10.8)	Texas	Llano	14.5(10.6,19.1)
Kentucky	Morgan	14.3(11.9,16.9)	Texas	Lubbock	8.5(7.2,9.9)
Kentucky	Muhlenberg	9.1(7.4,10.9)	Texas	Lynn	13.2(9.6,17.5)
Kentucky	Nelson	8.5(6.9,10.2)	Texas	McCulloch	14.4(8.5,21.9)
Kentucky	Nicholas	9.8(7.7,12.3)	Texas	McLennan	9.7(7.9,11.7)
Kentucky	Ohio	10.2(8.3,12.3)	Texas	McMullen	9.7(7.3,12.5)
Kentucky	Oldham	7.5(5.5,9.7)	Texas	Madison	9.9(8.2,11.9)
Kentucky	Owen	7.2(5.6,9)	Texas	Marion	15(12,18.4)
Kentucky	Owsley	16.7(13.6,20.2)	Texas	Martin	12.5(8,17.9)
Kentucky	Pendleton	9.9(7.9,12.1)	Texas	Mason	13.5(9.3,18.8)
Kentucky	Perry	15.2(12.8,17.7)	Texas	Matagorda	9.8(7.6,12.2)
Kentucky	Pike	14.3(12.3,16.4)	Texas	Maverick	12.3(10.5,14.2)
Kentucky	Powell	11.2(8.4,14.4)	Texas	Medina	11.4(9.1,14)
Kentucky	Pulaski	10.9(9.2,12.7)	Texas	Midland	8.5(7,10.3)
Kentucky	Robertson	13.7(10.7,17.1)	Texas	Milam	12.4(10.2,14.8)
Kentucky	Rockcastle	11.9(9.9,14.1)	Texas	Mills	13.2(9.7,17.4)
Kentucky	Rowan	10.2(8.4,12.2)	Texas	Mitchell	12.1(7.6,17.9)
Kentucky	Russell	11.8(9.4,14.5)	Texas	Montague	10.9(7.7,14.6)
Kentucky	Scott	8.4(6.8,10.2)	Texas	Montgomery	8.8(7.3,10.4)
Kentucky	Shelby	8.8(7,10.8)	Texas	Moore	10.6(7.3,14.8)
Kentucky	Simpson	9.1(7.2,11.1)	Texas	Morris	10.8(8.4,13.6)
Kentucky	Spencer	8.7(6.9,10.7)	Texas	Motley	18.5(16.9,20.2)
Kentucky	Taylor	9.9(7.8,12.1)	Texas	Nacogdoches	10.8(8.7,13.2)
Kentucky	Todd	9.5(7.6,11.6)	Texas	Navarro	10.6(8.7,12.7)
Kentucky	Trigg	10.2(8.2,12.5)	Texas	Newton	16.9(13.8,20.4)
Kentucky	Trimble	10(6.8,13.8)	Texas	Nolan	10.6(7,15.1)
Kentucky	Union	9.1(6.6,12.2)	Texas	Nueces	9.9(6.8,13.7)

Kentucky	Warren	7.4(6,8.9)	Texas	Ochiltree	11.1(6.3,17.5)
Kentucky	Washington	9.1(7.3,11)	Texas	Oldham	9.5(7.1,12.3)
Kentucky	Wayne	11.7(9.1,14.6)	Texas	Orange	12.9(10.4,15.6)
Kentucky	Webster	10.1(7.8,12.6)	Texas	Palo Pinto	12.3(9.5,15.6)
Kentucky	Whitley	11.7(9.8,13.7)	Texas	Panola	11(8.9,13.5)
Kentucky	Wolfe	15.5(12.5,18.9)	Texas	Parker	10.2(8.2,12.4)
Kentucky	Woodford	9.3(7.5,11.3)	Texas	Parmer	11.4(6.2,18.6)
Louisiana	Acadia	9.6(7.9,11.3)	Texas	Pecos	11.1(10.1,12.1)
Louisiana	Allen	10.5(8.7,12.5)	Texas	Polk	13.6(11.3,16.3)
Louisiana	Ascension	9(7.5,10.6)	Texas	Potter	9.5(7.6,11.7)
Louisiana	Assumption	11.1(9.4,12.9)	Texas	Presidio	15.3(13.9,16.7)
Louisiana	Avoyelles	10.7(9,12.5)	Texas	Rains	14(10.8,17.5)
Louisiana	Beauregard	9.7(7.9,11.6)	Texas	Randall	8.5(6.9,10.3)
Louisiana	Bienville	13.1(11,15.3)	Texas	Reagan	11(8.1,14.6)
Louisiana	Bossier	10(8.3,12)	Texas	Real	15.2(11.6,19.3)
Louisiana	Caddo	10.4(8.9,12)	Texas	Red River	14.1(10.7,18)
Louisiana	Calcasieu	10.5(8.8,12.3)	Texas	Reeves	13.4(8.7,19.3)
Louisiana	Caldwell	10.8(8.7,13)	Texas	Refugio	14.2(10.8,18.2)
Louisiana	Cameron	11.1(8.8,13.7)	Texas	Robertson	11.7(9.7,13.9)
Louisiana	Catahoula	10.2(8,12.6)	Texas	Rockwall	7.9(6.2,9.9)
Louisiana	Claiborne	13.2(10.8,15.8)	Texas	Runnels	14.4(10.4,19.2)
Louisiana	Concordia	11.8(9.4,14.4)	Texas	Rusk	11.1(9.3,13.1)
Louisiana	De Soto	11.8(9.6,14.2)	Texas	Sabine	13.2(10.5,16.3)
Louisiana	East Baton Rouge	9.5(8.3,10.8)	Texas	San Augustine	17.1(13.7,21)
Louisiana	East Carroll	7.3(5.1,9.8)	Texas	San Jacinto	13.7(11.2,16.6)
Louisiana	East Feliciana	11.6(9.5,13.9)	Texas	San Patricio	10.9(7.8,14.7)

Louisiana	Evangeline	9.7(8.1,11.6)	Texas	San Saba	10.9(8.4,13.8)
Louisiana	Franklin	11.7(7.8,16.4)	Texas	Schleicher	13(8.3,18.9)
Louisiana	Grant	10.2(8.2,12.5)	Texas	Scurry	10.2(6.3,15.2)
Louisiana	Iberia	9.8(8.2,11.6)	Texas	Shackelford	12.8(8.9,17.6)
Louisiana	Iberville	10.9(9.2,12.7)	Texas	Shelby	13.2(10.7,16)
Louisiana	Jackson	11(8.9,13.4)	Texas	Sherman	11.5(7.3,16.8)
Louisiana	Jefferson	10.8(9.4,12.4)	Texas	Smith	9.9(8.7,11.2)
Louisiana	Jefferson Davis	10.1(8.4,12)	Texas	Somervell	14.2(11,17.7)
Louisiana	Lafayette	7(5.8,8.3)	Texas	Starr	14.6(10.3,19.6)
Louisiana	Lafourche	10.2(8.6,11.9)	Texas	Stephens	12.8(9,17.3)
Louisiana	La Salle	10(8,12.3)	Texas	Sterling	12.7(8.6,17.6)
Louisiana	Lincoln	9.6(7.8,11.6)	Texas	Stonewall	13.9(7.9,21.8)
Louisiana	Livingston	8.8(7.2,10.5)	Texas	Sutton	11.9(7.6,17.2)
Louisiana	Madison	12.1(8.9,15.8)	Texas	Swisher	11.7(8.5,15.7)
Louisiana	Morehouse	13.9(11.3,16.8)	Texas	Tarrant	9(7.8,10.3)
Louisiana	Natchitoches	10.3(8.7,12.1)	Texas	Taylor	9.7(6.6,13.4)
Louisiana	Orleans	11(9.1,13)	Texas	Terrell	14.1(10.4,18.4)
Louisiana	Ouachita	11.2(9.4,13.2)	Texas	Terry	8.4(5.8,11.4)
Louisiana	Plaquemines	10.9(8.4,13.7)	Texas	Throckmorton	16.3(9,26.2)
Louisiana	Pointe Coupee	11.5(9.7,13.5)	Texas	Titus	8.3(5.7,11.4)
Louisiana	Rapides	11.4(9.8,13.1)	Texas	Tom Green	11.4(10.4,12.5)
Louisiana	Red River	12.7(10.4,15.3)	Texas	Travis	7.1(6.1,8.1)
Louisiana	Richland	12.7(9.6,16)	Texas	Trinity	17(13.9,20.4)
Louisiana	Sabine	12.4(10.2,15)	Texas	Tyler	14.7(11.8,18)
Louisiana	St. Bernard	10.1(7.4,13.4)	Texas	Upshur	11.2(9.2,13.4)
Louisiana	St. Charles	9.8(7.8,12.1)	Texas	Upton	10.7(7.9,14.1)
Louisiana	St. Helena	13.7(11.2,16.5)	Texas	Uvalde	11.3(8.9,14)

Louisiana	St. James	11.9(9.6,14.5)	Texas	Val Verde	11.4(10.4,12.5)
Louisiana	St. John the Baptist	10.4(8.6,12.3)	Texas	Van Zandt	11.7(9.6,14)
Louisiana	St. Landry	10.9(9.2,12.8)	Texas	Victoria	10.2(7.9,12.8)
Louisiana	St. Martin	10.2(8.6,12)	Texas	Walker	9.3(7.6,11.1)
Louisiana	St. Mary	11.1(9,13.3)	Texas	Waller	9.9(8.2,11.8)
Louisiana	St. Tammany	9.1(7.6,10.8)	Texas	Ward	11.5(8.4,15.2)
Louisiana	Tangipahoa	9.8(8.2,11.4)	Texas	Washington	12(10,14.2)
Louisiana	Tensas	13.5(10.4,16.9)	Texas	Webb	12.2(10.7,13.8)
Louisiana	Terrebonne	10.1(8.2,12.3)	Texas	Wharton	9.3(7.6,11.3)
Louisiana	Union	11.7(9.6,14.1)	Texas	Wheeler	14.2(9.2,20.4)
Louisiana	Vermilion	8.8(7.1,10.7)	Texas	Wichita	11.2(9.5,13)
Louisiana	Vernon	9.2(7.6,10.9)	Texas	Wilbarger	11.2(7.6,15.7)
Louisiana	Washington	12(10,14.3)	Texas	Willacy	13.9(10.4,18)
Louisiana	Webster	11.7(9.5,14.1)	Texas	Williamson	7.6(6.3,9.1)
Louisiana	West Baton Rouge	9.7(7.9,11.6)	Texas	Wilson	10.9(8.8,13.2)
Louisiana	West Carroll	13.3(9.5,17.7)	Texas	Winkler	11.6(7.4,16.9)
Louisiana	West Feliciana	9.3(7.5,11.4)	Texas	Wise	9.9(7.9,12.2)
Louisiana	Winn	11.1(9.1,13.4)	Texas	Wood	12.7(10.2,15.6)
Maryland	Allegany	11(9.4,12.7)	Texas	Yoakum	12.8(5.9,22.7)
Maryland	Anne Arundel	8.3(7.2,9.5)	Texas	Young	12.6(8.1,18.4)
Maryland	Baltimore	9.6(8.6,10.7)	Texas	Zapata	14.2(10.3,18.9)
Maryland	Calvert	8.7(7.2,10.3)	Texas	Zavala	12.9(10.1,16.2)
Maryland	Caroline	10.1(8.2,12.2)	Virginia	Accomack	11.5(8.8,14.7)
Maryland	Carroll	8.5(7.2,9.9)	Virginia	Albemarle	7.4(6.1,8.9)
Maryland	Cecil	8.7(7.2,10.2)	Virginia	Alleghany	10.1(7.9,12.7)

Maryland	Charles	8.9(7.5,10.5)	Virginia	Amelia	11.3(9.1,13.8)
Maryland	Dorchester	11.5(9.4,13.8)	Virginia	Amherst	9.6(7.7,11.7)
Maryland	Frederick	7.7(6.7,8.7)	Virginia	Appomattox	9.7(7.8,11.9)
Maryland	Garrett	11.5(9.6,13.5)	Virginia	Arlington	4.6(3.4,5.9)
Maryland	Harford	8.7(7.2,10.4)	Virginia	Augusta	8.9(7.1,11)
Maryland	Howard	7.2(6.1,8.3)	Virginia	Bath	10.9(8.4,13.9)
Maryland	Kent	9.5(7.4,11.9)	Virginia	Bedford	8.8(7.3,10.5)
Maryland	Montgomery	6.6(5.8,7.5)	Virginia	Bland	12.9(10.2,15.9)
Maryland	Prince George's	9.9(8.8,11.1)	Virginia	Botetourt	10.1(8,12.6)
Maryland	Queen Anne's	8.1(6.5,9.9)	Virginia	Brunswick	10(8.2,12)
Maryland	St. Mary's	8.5(6.8,10.5)	Virginia	Buchanan	13.6(11.1,16.5)
Maryland	Somerset	10.8(8.5,13.4)	Virginia	Buckingham	11(8.8,13.4)
Maryland	Talbot	9.6(7.8,11.6)	Virginia	Campbell	10.2(8.3,12.3)
Maryland	Washington	9.9(8.5,11.3)	Virginia	Caroline	9(7.1,11.2)
Maryland	Wicomico	10(8.2,12)	Virginia	Carroll	11(8.9,13.3)
Maryland	Worcester	11.3(9,13.9)	Virginia	Charles City	12.6(10.1,15.5)
Maryland	Baltimore City	11.4(9.8,13.2)	Virginia	Charlotte	9.2(7.5,11.1)
Mississippi	Adams	13.2(10.4,16.4)	Virginia	Chesterfield	8(6.6,9.5)
Mississippi	Alcorn	11.5(9.5,13.7)	Virginia	Clarke	8.3(6.6,10.1)
Mississippi	Amite	12.8(10.4,15.3)	Virginia	Culpeper	8.9(7.1,10.9)
Mississippi	Attala	14.7(12.5,17.1)	Virginia	Cumberland	9.7(7.8,12)
Mississippi	Benton	14.4(11.8,17.4)	Virginia	Dickenson	13.3(10.5,16.5)
Mississippi	Bolivar	11.6(9.4,14.1)	Virginia	Dinwiddie	10.1(8.3,12.1)
Mississippi	Calhoun	13(10.7,15.5)	Virginia	Essex	10.4(7.2,14.1)
Mississippi	Carroll	14.5(11.6,17.8)	Virginia	Fairfax	6(4.9,7.3)
Mississippi	Chickasaw	12.9(10.7,15.3)	Virginia	Fauquier	7.3(5.9,8.9)
Mississippi	Choctaw	13.1(10.2,16.4)	Virginia	Floyd	10.9(8.9,13.2)

Mississippi	Claiborne	14.4(11.2,18.1)	Virginia	Fluvanna	7.4(5.8,9.4)
Mississippi	Clarke	13.7(11.5,16)	Virginia	Franklin	10.4(8.5,12.5)
Mississippi	Clay	12.8(10.6,15.3)	Virginia	Frederick	8.1(6.6,9.7)
Mississippi	Coahoma	12.8(10.1,15.9)	Virginia	Giles	12.5(9.8,15.6)
Mississippi	Copiah	12.4(10.3,14.6)	Virginia	Gloucester	8.9(5.5,13.1)
Mississippi	Covington	13(10.8,15.3)	Virginia	Goochland	8.4(6.8,10.2)
Mississippi	DeSoto	9.3(7.8,10.9)	Virginia	Grayson	12(9.8,14.5)
Mississippi	Forrest	10.3(8.7,12.1)	Virginia	Greene	7.7(6,9.6)
Mississippi	Franklin	13.2(10.2,16.6)	Virginia	Greensville	11.8(9.4,14.4)
Mississippi	George	11(8.8,13.4)	Virginia	Halifax	10.6(8.7,12.7)
Mississippi	Greene	12.3(9.8,15.1)	Virginia	Hanover	8(6.5,9.6)
Mississippi	Grenada	12.8(10.2,15.8)	Virginia	Henrico	8.2(6.7,9.8)
Mississippi	Hancock	10.4(8.4,12.7)	Virginia	Henry	11.2(9.1,13.5)
Mississippi	Harrison	10.4(8.7,12.2)	Virginia	Highland	12.1(7.5,18.1)
Mississippi	Hinds	11.9(10.3,13.7)	Virginia	Isle of Wight	10.8(7.9,14.4)
Mississippi	Holmes	14.4(11.9,17.1)	Virginia	James City	8.6(6.3,11.2)
Mississippi	Humphreys	11.6(9.4,14.1)	Virginia	King and Queen	12.4(9.4,15.9)
Mississippi	Issaquena	12.8(9.8,16.3)	Virginia	King George	8(5.8,10.6)
Mississippi	Itawamba	11.4(9.5,13.5)	Virginia	King William	8.3(6.2,10.8)
Mississippi	Jackson	10.7(9,12.7)	Virginia	Lancaster	12.8(6.2,22.1)
Mississippi	Jasper	13.7(11.8,15.8)	Virginia	Lee	12.8(10.1,15.7)
Mississippi	Jefferson	16.3(12.7,20.2)	Virginia	Loudoun	5.5(4.5,6.6)
Mississippi	Jefferson Davis	12.7(10.4,15.3)	Virginia	Louisa	9.8(8,11.9)
Mississippi	Jones	11.5(9.8,13.4)	Virginia	Lunenburg	13.1(10.4,16.1)
Mississippi	Kemper	15.2(12.6,18)	Virginia	Madison	9.5(7.3,12)
Mississippi	Lafayette	8.5(7.1,10)	Virginia	Mathews	11.3(6.1,18.4)

Mississippi	Lamar	8.7(7.1,10.5)	Virginia	Mecklenburg	12.2(10,14.7)
Mississippi	Lauderdale	13.1(11.4,15)	Virginia	Middlesex	13.7(7.3,22.4)
Mississippi	Lawrence	12.4(10.3,14.8)	Virginia	Montgomery	6.9(5.4,8.6)
Mississippi	Leake	13.9(11.8,16.2)	Virginia	Nelson	9.4(7.5,11.4)
Mississippi	Lee	10.7(9.1,12.4)	Virginia	New Kent	8.3(6.4,10.5)
Mississippi	Leflore	12.6(10.3,15.2)	Virginia	Northampton	13.8(9.4,19)
Mississippi	Lincoln	11.7(9.8,13.7)	Virginia	Northumberland	10.6(5.9,16.9)
Mississippi	Lowndes	12.1(10.2,14.1)	Virginia	Nottoway	11(8.8,13.4)
Mississippi	Madison	10.5(9,12.2)	Virginia	Orange	10.3(8.3,12.5)
Mississippi	Marion	11.9(9.9,14.1)	Virginia	Page	10.4(8.2,12.9)
Mississippi	Marshall	13.3(11.2,15.6)	Virginia	Patrick	11.2(9.1,13.6)
Mississippi	Monroe	12.9(11,14.8)	Virginia	Pittsylvania	10.8(9.1,12.7)
Mississippi	Montgomery	14.6(10.9,18.9)	Virginia	Powhatan	8.7(6.7,10.9)
Mississippi	Neshoba	13.3(11.3,15.5)	Virginia	Prince Edward	8.7(7,10.7)
Mississippi	Newton	12.9(11,14.9)	Virginia	Prince George	9.2(7.4,11.3)
Mississippi	Noxubee	12(9.9,14.5)	Virginia	Prince William	6.2(4.9,7.7)
Mississippi	Oktibbeha	10.1(8.2,12.3)	Virginia	Pulaski	11(8.8,13.4)
Mississippi	Panola	13.1(10.6,15.9)	Virginia	Rappahannock	10(7.8,12.6)
Mississippi	Pearl River	10.9(9.4,12.6)	Virginia	Richmond	8.4(4.8,13.4)
Mississippi	Perry	12.2(10.2,14.5)	Virginia	Roanoke	9(7.4,10.7)
Mississippi	Pike	11.9(10.1,13.9)	Virginia	Rockbridge	9.5(7.6,11.5)
Mississippi	Pontotoc	11.2(9.3,13.3)	Virginia	Rockingham	8.3(6.7,10.1)
Mississippi	Prentiss	11.5(9.6,13.6)	Virginia	Russell	11.5(9.4,13.8)
Mississippi	Quitman	10.9(7.9,14.4)	Virginia	Scott	12.3(10,14.8)
Mississippi	Rankin	9.8(8.3,11.4)	Virginia	Shenandoah	8.9(7,11)
Mississippi	Scott	12.7(10.9,14.6)	Virginia	Smyth	10.4(8.3,12.8)

Mississippi	Sharkey	14.4(10.6,18.8)	Virginia	Southampton	11.3(9,13.8)
Mississippi	Simpson	12.3(10.3,14.4)	Virginia	Spotsylvania	7.5(6.1,9.1)
Mississippi	Smith	11.7(9.9,13.6)	Virginia	Stafford	6.3(5.1,7.7)
Mississippi	Stone	10.1(8.5,12)	Virginia	Surry	12.6(9.6,16.1)
Mississippi	Sunflower	11.4(9.2,13.8)	Virginia	Sussex	10.1(8,12.6)
Mississippi	Tallahatchie	12.6(10.4,15)	Virginia	Tazewell	12(9.7,14.6)
Mississippi	Tate	11.8(9.6,14.1)	Virginia	Warren	8.8(7,10.8)
Mississippi	Tippah	11.5(9.3,14.1)	Virginia	Washington	11.2(9.2,13.5)
Mississippi	Tishomingo	12.4(10.4,14.6)	Virginia	Westmoreland	12.5(8.1,17.9)
Mississippi	Tunica	13.8(11.4,16.4)	Virginia	Wise	12.3(10.1,14.7)
Mississippi	Union	11.3(9.4,13.3)	Virginia	Wythe	10.7(8.4,13.3)
Mississippi	Walthall	12.7(10.5,15)	Virginia	York	7.8(5.6,10.3)
Mississippi	Warren	11.3(8.6,14.4)	Virginia	Alexandria	5.6(4.2,7.1)
Mississippi	Washington	11.3(8.9,13.9)	Virginia	Bedford City	11.7(7.5,17)
Mississippi	Wayne	12.5(10.5,14.7)	Virginia	Bristol	10(7.2,13.3)
Mississippi	Webster	13.8(11.3,16.6)	Virginia	Buena Vista	10.4(6.5,15.5)
Mississippi	Wilkinson	12.7(10.1,15.7)	Virginia	Charlottesville	7(4.5,10.2)
Mississippi	Winston	14.9(12.3,17.7)	Virginia	Chesapeake	8.1(6.4,10.1)
Mississippi	Yalobusha	14.2(11.5,17.3)	Virginia	Colonial Heights	8.2(6.1,10.6)
Mississippi	Yazoo	12.1(10,14.4)	Virginia	Covington	9.9(6.2,14.8)
North Carolina	Alamance	9.7(8.4,11.2)	Virginia	Danville	11.4(7.8,15.8)
North Carolina	Alexander	10.3(8.3,12.5)	Virginia	Emporia	13.4(8.5,19.7)
North Carolina	Alleghany	8.9(7,11.1)	Virginia	Fairfax City	5.8(3.7,8.6)
North Carolina	Anson	11.9(10,14.1)	Virginia	Falls Church	6.3(4.4,8.7)

North Carolina	Ashe	11.8(9.6,14.3)	Virginia	Franklin City	14.9(10.6,20.2)
North Carolina	Avery	11.4(9.6,13.5)	Virginia	Fredericksburg	7.1(5.1,9.6)
North Carolina	Beaufort	12.1(9.5,15.1)	Virginia	Galax	13.3(9.6,17.8)
North Carolina	Bertie	12.5(9.8,15.5)	Virginia	Hampton	10.1(7.5,13.1)
North Carolina	Bladen	12.8(10.7,15.1)	Virginia	Harrisonburg	6.5(4.1,9.8)
North Carolina	Brunswick	11.5(9.3,13.8)	Virginia	Hopewell	12(8.8,15.9)
North Carolina	Buncombe	9.6(8.2,11.1)	Virginia	Lexington	6.7(4.2,10)
North Carolina	Burke	11(9.4,12.7)	Virginia	Lynchburg	8.3(6.3,10.6)
North Carolina	Cabarrus	9.2(7.9,10.6)	Virginia	Manassas	6.9(4.3,10.3)
North Carolina	Caldwell	11(9.3,12.9)	Virginia	Manassas Park	7.4(4.8,10.8)
North Carolina	Camden	10.4(7.3,14)	Virginia	Martinsville	11.8(7.6,17.2)
North Carolina	Carteret	10.7(7.9,14)	Virginia	Newport News	9.9(7.2,12.9)
North Carolina	Caswell	11.5(9.6,13.6)	Virginia	Norfolk	7.8(6,9.9)
North Carolina	Catawba	9.7(8.3,11.2)	Virginia	Norton	13.2(8.4,19.4)
North Carolina	Chatham	8.4(7.2,9.7)	Virginia	Petersburg	13(10.3,16)
North Carolina	Cherokee	11.1(8.9,13.5)	Virginia	Poquoson	10.7(7.1,15.2)
North Carolina	Chowan	16.5(6.4,30.1)	Virginia	Portsmouth	10.5(8.1,13.1)

North Carolina	Clay	10.1(7.8,12.6)	Virginia	Radford	5.8(4,7.9)
North Carolina	Cleveland	11.2(9.6,13.1)	Virginia	Richmond City	8.7(6.7,10.9)
North Carolina	Columbus	12.3(10.3,14.5)	Virginia	Roanoke City	10.9(7.9,14.5)
North Carolina	Craven	10.1(8.1,12.5)	Virginia	Salem	9(5.8,13.1)
North Carolina	Cumberland	9.8(8.5,11.3)	Virginia	Staunton	7.5(4.7,11.1)
North Carolina	Currituck	9.5(6.5,13.1)	Virginia	Suffolk	9.8(7.7,12.3)
North Carolina	Dare	8(4.6,12.6)	Virginia	Virginia Beach	6.9(5.2,9)
North Carolina	Davidson	9.9(8.6,11.2)	Virginia	Waynesboro	10.2(6.4,15.2)
North Carolina	Davie	10.7(8.8,12.7)	Virginia	Williamsburg	5.9(4,8.4)
North Carolina	Duplin	11.4(9.5,13.6)	Virginia	Winchester	7.3(4.6,10.9)
North Carolina	Durham	7.6(6.5,8.8)	West Virginia	Barbour	11.2(8.9,13.7)
North Carolina	Edgecombe	12.6(10.3,15.1)	West Virginia	Berkeley	9.4(7.6,11.4)
North Carolina	Forsyth	8.9(7.6,10.2)	West Virginia	Boone	13.4(11.2,15.8)
North Carolina	Franklin	9.9(8.4,11.7)	West Virginia	Braxton	12.8(9.6,16.4)
North Carolina	Gaston	10.1(8.5,11.9)	West Virginia	Brooke	12.8(10.2,15.7)
North Carolina	Gates	14.6(9.2,20.9)	West Virginia	Cabell	11.6(9.8,13.5)
North Carolina	Graham	12.4(10,15)	West Virginia	Calhoun	16.4(11.9,21.7)

North Carolina	Granville	9.8(8.2,11.5)	West Virginia	Clay	16.3(13.4,19.6)
North Carolina	Greene	11.9(9.6,14.5)	West Virginia	Fayette	14.3(12,16.8)
North Carolina	Guilford	9(7.9,10.2)	West Virginia	Gilmer	11.8(8.3,16.1)
North Carolina	Halifax	13(10.9,15.4)	West Virginia	Grant	12.6(10.3,15.2)
North Carolina	Harnett	9.3(7.9,10.9)	West Virginia	Greenbrier	14.1(11.6,16.9)
North Carolina	Haywood	10.7(9,12.4)	West Virginia	Hampshire	11.5(9.2,14)
North Carolina	Henderson	9.6(8,11.3)	West Virginia	Hancock	12.1(9.8,14.6)
North Carolina	Hertford	12.4(9.5,15.8)	West Virginia	Hardy	11.3(9,14)
North Carolina	Hoke	10.1(8.5,11.9)	West Virginia	Harrison	10.8(8.9,12.8)
North Carolina	Hyde	11.3(7.5,15.9)	West Virginia	Jackson	12.9(10.8,15.1)
North Carolina	Iredell	9.3(8.1,10.5)	West Virginia	Jefferson	9.1(7.3,11.2)
North Carolina	Jackson	9.2(7.6,10.9)	West Virginia	Kanawha	12(10.6,13.5)
North Carolina	Johnston	9.9(8.6,11.4)	West Virginia	Lewis	11.2(8.6,14.1)
North Carolina	Jones	9.9(8,12.2)	West Virginia	Lincoln	13.5(11.5,15.7)
North Carolina	Lee	9.3(7.3,11.5)	West Virginia	Logan	14.6(12.1,17.4)
North Carolina	Lenoir	11.7(9.6,14)	West Virginia	McDowell	16.2(13.5,19.2)
North Carolina	Lincoln	9.3(7.9,11)	West Virginia	Marion	11.4(9.4,13.7)

North Carolina	McDowell	11.8(9.9,13.9)	West Virginia	Marshall	11.6(9.5,13.9)
North Carolina	Macon	10.7(8.6,12.9)	West Virginia	Mason	12.3(10.2,14.7)
North Carolina	Madison	10.8(8.9,12.9)	West Virginia	Mercer	14(11.9,16.3)
North Carolina	Martin	13(10.6,15.8)	West Virginia	Mineral	10.7(8.5,13.3)
North Carolina	Mecklenburg	7.8(6.9,8.9)	West Virginia	Mingo	14.3(12.2,16.6)
North Carolina	Mitchell	11.5(9.3,13.9)	West Virginia	Monongalia	8(6.6,9.6)
North Carolina	Montgomery	11.1(9.5,12.9)	West Virginia	Monroe	13.8(11.2,16.6)
North Carolina	Moore	11(9.5,12.6)	West Virginia	Morgan	11.6(9.3,14.1)
North Carolina	Nash	10.9(9.2,12.8)	West Virginia	Nicholas	13.4(10.9,16.3)
North Carolina	New Hanover	9.1(7.4,11)	West Virginia	Ohio	11.7(9.6,14.1)
North Carolina	Northampton	14.1(11.6,16.9)	West Virginia	Pendleton	12.1(9.4,15.1)
North Carolina	Onslow	7.6(6.2,9.2)	West Virginia	Pleasants	10.2(7.5,13.4)
North Carolina	Orange	6.2(5.1,7.3)	West Virginia	Pocahontas	14.2(10.3,18.8)
North Carolina	Pamlico	11.4(8.2,15.2)	West Virginia	Preston	10.5(8.5,12.6)
North Carolina	Pasquotank	13.4(5.2,24.4)	West Virginia	Putnam	11(9.1,13)
North Carolina	Pender	11.3(9.5,13.3)	West Virginia	Raleigh	13.1(11.1,15.2)
North Carolina	Perquimans	16.2(6.5,28.7)	West Virginia	Randolph	10.5(7.8,13.7)

North Carolina	Person	9.8(8,11.7)	West Virginia	Ritchie	15.5(10.3,21.8)
North Carolina	Pitt	8.9(7.6,10.4)	West Virginia	Roane	14.2(11,17.9)
North Carolina	Polk	10.3(8.3,12.6)	West Virginia	Summers	14.1(11.6,16.8)
North Carolina	Randolph	9.6(8.3,10.9)	West Virginia	Taylor	11.3(9.1,13.6)
North Carolina	Richmond	12(10.1,14)	West Virginia	Tucker	12.3(9.7,15.3)
North Carolina	Robeson	12.1(10.7,13.7)	West Virginia	Upshur	11.1(8.7,13.8)
North Carolina	Rockingham	10.8(9.1,12.5)	West Virginia	Wayne	13.2(11,15.5)
North Carolina	Rowan	11.5(10,13.1)	West Virginia	Wetzel	11.4(9.4,13.6)
North Carolina	Rutherford	11.8(10.1,13.6)	West Virginia	Wirt	13.2(10.2,16.7)
North Carolina	Sampson	11.5(9.8,13.4)	West Virginia	Wood	13.3(11.1,15.8)
North Carolina	Scotland	12.5(10.5,14.8)	West Virginia	Wyoming	14.8(12.4,17.4)
North Carolina	Stanly	10.4(8.8,12.2)			

Table 3-3 WINBUGS estimate for the coefficients of covariates for model 8(Final model)

node	mean	sd	MC error	2.50%	median	97.50%
beta0[1]	-2.905	0.4188	0.02743	-3.698	-2.896	-2.135
beta0[2]	-2.904	0.4181	0.02686	-3.696	-2.892	-2.147
beta0[3]	-2.856	0.3711	0.02417	-3.55	-2.839	-2.182
beta0[4]	-2.909	0.4032	0.02632	-3.672	-2.904	-2.164
beta0[5]	-2.869	0.4363	0.0286	-3.684	-2.872	-2.068
beta0[6]	-2.812	0.4139	0.02689	-3.613	-2.801	-2.057
beta0[7]	-2.666	0.2695	0.01703	-3.164	-2.678	-2.147
beta0[8]	-2.951	0.4893	0.03209	-3.892	-2.936	-2.056
beta0[9]	-2.982	0.4019	0.02634	-3.743	-2.984	-2.226
beta0[10]	-2.917	0.3799	0.02479	-3.613	-2.931	-2.214
beta0[11]	-2.817	0.3383	0.02193	-3.448	-2.834	-2.189
beta0[12]	-2.963	0.4158	0.02718	-3.752	-2.965	-2.177
beta0[13]	-2.961	0.3988	0.0261	-3.72	-2.958	-2.219
beta0[14]	-2.657	0.4023	0.0264	-3.422	-2.647	-1.918
beta0[15]	-2.788	0.2808	0.01801	-3.303	-2.797	-2.249
beta0[16]	-2.936	0.4319	0.02822	-3.739	-2.947	-2.141
Beta1	1.381	0.04464	0.00162	1.292	1.38	1.468
Beta2	1.743	0.04718	0.00173	1.65	1.743	1.836
Beta3	-0.4211	0.05782	0.00172	-0.5345	-0.422	-0.3087
Beta4	-0.4211	0.04901	0.0019	-0.518	-0.4209	-0.3246
Beta5	0.2547	0.05675	0.00154	0.1453	0.2549	0.3653

Beta6	0.4339	0.05674	0.00153	0.3227	0.4344	0.5457
Beta7	-0.0865	0.05253	0.00196	-0.1892	-0.0867	0.01595
Beta8	-0.2466	0.05444	0.00206	-0.353	-0.2467	-0.1395
Beta9	0.4009	0.03618	7.81E-04	0.3302	0.4005	0.4728
beta10	-0.1956	0.01812	1.18E-04	-0.2313	-0.1955	-0.1601
beta11	-0.3995	0.02626	1.62E-04	-0.4508	-0.3995	-0.3481
beta12	-0.6614	0.02602	1.84E-04	-0.7125	-0.6613	-0.6104
beta13	-0.1726	0.02169	2.50E-04	-0.2145	-0.1727	-0.1294
beta14	-0.2215	0.02383	2.67E-04	-0.2676	-0.2216	-0.1748
beta15	-0.4434	0.02578	2.92E-04	-0.4933	-0.4436	-0.3923
beta16[1]	0.251	0.08432	4.64E-04	0.08471	0.2513	0.4167
beta16[2]	0.2809	0.1252	6.95E-04	0.03275	0.2825	0.5221
beta16[3]	0.4771	0.03786	2.50E-04	0.4029	0.4773	0.5515
beta16[4]	0.06498	0.1121	6.61E-04	-0.1587	0.06576	0.2825
beta16[5]	0.2669	0.08951	5.09E-04	0.09024	0.2673	0.4408
beta16[6]	0.1746	0.08581	4.29E-04	0.00594	0.1746	0.3422
beta16[7]	0.7909	0.08934	4.94E-04	0.6146	0.791	0.9645
beta16[8]	0.07951	0.08436	4.76E-04	-0.0877	0.07974	0.2433
beta16[9]	0.3097	0.07136	3.77E-04	0.1693	0.3098	0.4481
beta16[10]	0.4585	0.07559	3.94E-04	0.3096	0.4587	0.606
beta16[11]	0.6282	0.07221	3.95E-04	0.4872	0.6283	0.7702
beta16[12]	0.2122	0.07377	4.03E-04	0.06701	0.2121	0.3557
beta16[13]	0.3095	0.09674	5.22E-04	0.1191	0.3099	0.4981

beta16[14]	0.2535	0.05193	3.99E-04	0.1526	0.2532	0.3549
beta16[15]	0.01841	0.1336	7.10E-04	-0.2466	0.0202	0.2769
beta16[16]	0.3885	0.1125	5.68E-04	0.165	0.389	0.6054
beta17	0.03624	0.02245	0.00149	-0.005	0.03578	0.07961

$$\mathbf{logit(\theta_i) = \beta_{st(i)0} + X^T_{iv_1}\beta_{v_1} + X^T_{iv_2}\beta_{st(i),v_2} + b_{ct(i)}} + \boldsymbol{b_{st(i)}} \quad 3.4$$

Table 3-4 Models Investigated

Model	ν_1	ν_2	CAR		
			County	State	DIC
1	$\beta_0 - \beta_{17}$	No	Yes	No	85,354.1
2	β_0	$\beta_1 - \beta_{17}$	No	No	85,574.1
3	β_0	$\beta_1 - \beta_{17}$	No	Yes	85,574.5
4	β_0	$\beta_1 - \beta_{17}$	Yes	No	85,419.0
5	β_0	$\beta_1 - \beta_{17}$	Yes	Yes	85,430.6
6	No	$\beta_0 - \beta_{17}$	No	No	85,598.6
7	No	$\beta_0 - \beta_{17}$	Yes	No	85,424.5
8	β_0 and β_{16}	$\beta_1 - \beta_{15}$	Yes	No	85,350.8
9	β_0 and β_{16}	$\beta_1 - \beta_{15}$	Yes	Yes	85,362.0
10	β_0 and $\beta_{13} - \beta_{16}$	$\beta_1 - \beta_{12}, \beta_{14}, \beta_{15}$ and β_{17}	Yes	Yes	85,365.8
11	$\beta_0 - \beta_9$ and β_{16}	$\beta_{10} - \beta_{15}$ and β_{17}	Yes	No	85,315.4
12	$\beta_0 - \beta_3, \beta_5 - \beta_8$ and β_{17}	β_4 and $\beta_9 - \beta_{16}$	Yes	No	85,308.5
13	$\beta_0 - \beta_4$ and β_{16}	$\beta_5 - \beta_{15}$ and β_{17}	Yes	No	85,455.1

Where βs' are stands for

β_0	Overall effects across the states
β_1	Aged 45-64
β_2	Aged 65 and above
β_3	Male
β_4	White
β_5	Male Aged 45-64
β_6	Male Aged 65 and above
β_7	White Aged 45-64
β_8	White Aged 65 and above
β_9	White Male
β_{10}	Income2=[$35,000,$50,0000)
β_{11}	Income3=[$50,000,$75,0000)
β_{12}	Income4=$75,000 and above
β_{13}	Education2= Grade 12 or GED (High school graduate)
β_{14}	Education3= College 1 year to 3 years (Some college or technical school)
β_{15}	Education4= College 4 years or more (College graduate)
β_{16}	Insurance=No Insurance
β_{17}	State Poverty percentage

Aged 18-44, Femále, Black, Inceome1=<35,000, Education1=< High School and Insurance=Yes are reference groups.
ighlighted in yellow are models selected for analysis due to low DIC

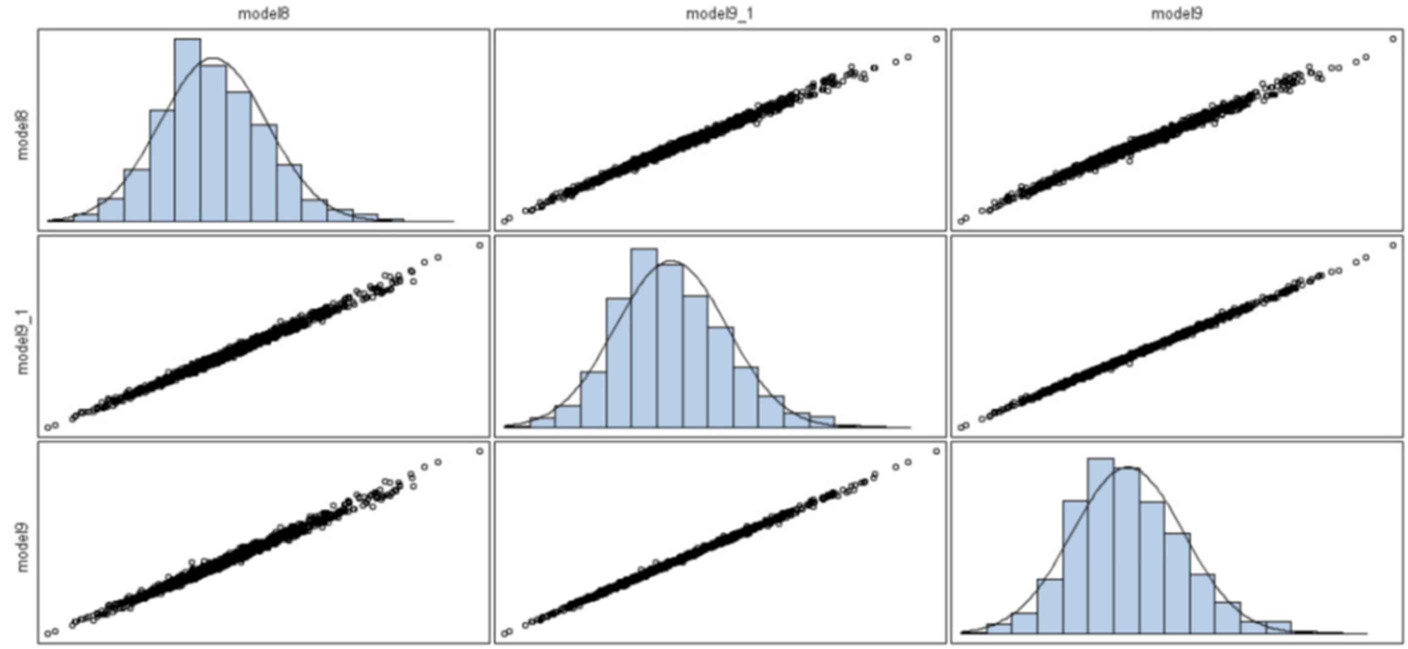


Figure 3-12 Scatter Plot Matrix with Histogram and Normal Fitting Curves, All counties

Table 3-5 Number of Counties with/Without Good Sample size

State	Estimate		Total
	Reliable	Not Reliable	
Alabama	28	33	61
Arkansas	9	46	55
Florida	62	1	63
Georgia	8	103	111
Kentucky	27	61	88
Louisiana	16	39	55
Maryland	23	1	24
Mississippi	33	30	63
North Carolina	30	61	91
Ohio	13	75	88
Pennsylvania	35	29	64
South Carolina	25	19	44
Tennessee	9	73	82
Texas	21	128	149
Virginia	8	100	108
West Virginia	17	25	42
Total County	**364**	**824**	**1188**

Table 3-6 Maryland state Credible Interval Width Difference among Selected Models

COUNTY NAME	Model 8			Model 9			Model 9_1			Interval Width Difference		
	Mean	Lower Limit	Upper Limit	Mean	Lower Limit	Upper Limit	Mean	Lower Limit	Upper Limit	Model 8 vs 9	Model 8 vs 9_1	Model 9 vs 9_1
Allegany	10.97	9.4	12.67	10.88	9.31	12.6	10.82	9.28	12.49	0.060000	0.060000	-0.080000
Anne Arundel	8.3	7.18	9.51	8.26	7.13	9.48	8.18	7.07	9.39	0.010000	0.010000	-0.030000
Baltimore	9.6	8.57	10.69	9.42	8.39	10.52	9.41	8.39	10.49	0.020000	0.020000	-0.030000
Calvert	8.71	7.21	10.35	8.76	7.26	10.41	8.6	7.12	10.22	0.040000	0.040000	-0.050000
Caroline	10.1	8.2	12.21	9.89	8.01	11.97	9.83	7.97	11.9	0.080000	0.080000	-0.030000
Carroll	8.46	7.2	9.85	8.52	7.23	9.93	8.37	7.11	9.75	0.010000	0.010000	-0.060000
Cecil	8.65	7.24	10.2	8.6	7.17	10.17	8.49	7.08	10.02	0.020000	0.020000	-0.060000
Charles	8.91	7.45	10.5	8.84	7.4	10.43	8.73	7.3	10.31	0.040000	0.040000	-0.020000
Dorchester	11.51	9.38	13.82	11.23	9.15	13.5	11.19	9.12	13.49	0.070000	0.070000	0.020000
Frederick	7.66	6.65	8.73	7.55	6.55	8.63	7.5	6.5	8.57	0.010000	0.010000	-0.010000
Garrett	11.47	9.58	13.55	11.44	9.53	13.52	11.39	9.51	13.46	0.020000	0.020000	-0.040000
Harford	8.71	7.22	10.36	8.59	7.14	10.21	8.55	7.09	10.17	0.060000	0.060000	0.010000
Howard	7.17	6.14	8.3	6.9	5.88	8.03	7.01	5.98	8.13	0.010000	0.010000	0.000000
Kent	9.52	7.4	11.93	9.33	7.25	11.69	9.37	7.29	11.72	0.100000	0.100000	-0.010000
Montgomery	6.6	5.79	7.46	6.41	5.6	7.27	6.49	5.67	7.34	0.000000	0.000000	0.000000
Prince George's	9.89	8.76	11.09	9.54	8.4	10.77	9.55	8.41	10.77	-0.030000	-0.030000	-0.010000
Queen Anne's	8.11	6.52	9.91	7.93	6.35	9.69	7.94	6.37	9.68	0.080000	0.080000	-0.030000
St. Mary's	8.53	6.81	10.45	8.54	6.83	10.47	8.45	6.75	10.37	0.020000	0.020000	-0.020000
Somerset	10.82	8.54	13.37	10.43	8.22	12.9	10.4	8.18	12.89	0.120000	0.120000	0.030000
Talbot	9.59	7.81	11.56	9.34	7.6	11.27	9.43	7.69	11.35	0.090000	0.090000	-0.010000
Washington	9.86	8.54	11.29	9.76	8.45	11.19	9.7	8.4	11.09	0.060000	0.060000	-0.050000
Wicomico	10	8.19	12.02	9.74	7.95	11.71	9.73	7.93	11.7	0.060000	0.060000	0.010000
Worcester	11.33	9.05	13.85	11.23	8.99	13.75	11.21	8.96	13.68	0.080000	0.080000	-0.040000
Baltimore City	11.42	9.77	13.2	11.12	9.46	12.91	11.08	9.45	12.84	0.040000	0.040000	-0.060000

Table 3-7 South Carolina state Credible Interval Width Difference among Selected Models

COUNTY NAME	Model 8			Model 9			Model 9_1			Interval Width Difference		
	Mean	Lower Limit	Upper Limit	Mean	Lower Limit	Upper Limit	Mean	Lower Limit	Upper Limit	Model 8 vs 9	Model 8 vs 9_1	Model 9 vs 9_1
Abbeville	11.78	9.86	13.87	11.91	9.97	14.03	11.87	9.93	14.01	-0.070000	-0.070000	0.020000
Aiken	9.91	8.64	11.27	9.77	8.49	11.13	9.92	8.62	11.33	-0.080000	-0.080000	0.070000
Allendale	9.97	8.25	11.88	10.28	8.45	12.29	10.22	8.42	12.22	-0.170000	-0.170000	-0.040000
Anderson	10.11	8.65	11.69	10.04	8.56	11.63	10.1	8.61	11.69	-0.040000	-0.040000	0.010000
Bamberg	13.09	11.03	15.35	13.48	11.37	15.79	13.38	11.25	15.7	-0.130000	-0.130000	0.030000
Barnwell	12.04	9.95	14.33	12.2	10.06	14.54	12.16	10.03	14.47	-0.060000	-0.060000	-0.040000
Beaufort	8.18	6.94	9.51	8.03	6.8	9.37	8.21	6.95	9.56	-0.040000	-0.040000	0.040000
Berkeley	9.86	8.57	11.23	9.78	8.47	11.21	9.91	8.58	11.36	-0.120000	-0.120000	0.040000
Calhoun	14.42	12.18	16.89	14.55	12.29	17.01	14.47	12.21	16.95	-0.030000	-0.030000	0.020000
Charleston	9.78	8.57	11.07	9.62	8.39	10.92	9.85	8.6	11.2	-0.100000	-0.100000	0.070000
Cherokee	10.77	8.94	12.8	10.77	8.9	12.84	10.75	8.88	12.85	-0.110000	-0.110000	0.030000
Chester	11.95	9.68	14.47	12.14	9.85	14.69	12.01	9.72	14.58	-0.070000	-0.070000	0.020000
Chesterfield	12.64	10.83	14.6	12.69	10.86	14.69	12.61	10.78	14.62	-0.070000	-0.070000	0.010000
Clarendon	13.63	11.75	15.65	13.8	11.88	15.88	13.73	11.82	15.82	-0.100000	-0.100000	0.000000
Colleton	12.2	10.56	13.96	12.32	10.65	14.13	12.26	10.58	14.08	-0.100000	-0.100000	0.020000
Darlington	13.15	11.1	15.4	13.19	11.12	15.45	13.2	11.11	15.49	-0.080000	-0.080000	0.050000
Dillon	12.9	10.95	15.03	13.12	11.12	15.29	13.02	11.02	15.17	-0.070000	-0.070000	-0.020000
Dorchester	9.81	8.23	11.57	9.68	8.09	11.46	9.83	8.22	11.61	-0.050000	-0.050000	0.020000
Edgefield	10.1	8.38	11.97	10.12	8.4	12	10.18	8.43	12.08	-0.060000	-0.060000	0.050000
Fairfield	13.21	11.22	15.37	13.67	11.64	15.89	13.52	11.49	15.75	-0.110000	-0.110000	0.010000
Florence	11.52	10.08	13.07	11.56	10.1	13.13	11.6	10.12	13.19	-0.080000	-0.080000	0.040000
Georgetown	11.2	9.61	12.87	11	9.42	12.65	11.13	9.55	12.81	0.000000	0.000000	0.030000
Greenville	9.37	8.23	10.6	9.3	8.12	10.56	9.46	8.27	10.75	-0.110000	-0.110000	0.040000
Greenwood	9.83	8.28	11.51	9.9	8.3	11.63	9.93	8.33	11.67	-0.110000	-0.110000	0.010000
Hampton	11.98	10.13	14	12.38	10.44	14.48	12.24	10.31	14.35	-0.170000	-0.170000	0.000000
Horry	11.05	9.68	12.54	10.81	9.41	12.31	10.98	9.58	12.5	-0.060000	-0.060000	0.020000
Jasper	10.8	8.78	13.03	11.18	9.08	13.5	11.12	9.05	13.45	-0.150000	-0.150000	-0.020000
Kershaw	11.61	9.93	13.42	11.46	9.77	13.26	11.52	9.81	13.37	-0.070000	-0.070000	0.070000
Lancaster	10.79	9.11	12.62	10.72	9.03	12.57	10.74	9.05	12.61	-0.050000	-0.050000	0.020000
Laurens	11.26	9.76	12.9	11.35	9.81	13.03	11.35	9.82	13.02	-0.060000	-0.060000	-0.020000
Lee	13.33	11.27	15.59	13.8	11.63	16.13	13.61	11.48	15.91	-0.110000	-0.110000	-0.070000
Lexington	9.29	7.92	10.77	9	7.62	10.5	9.2	7.79	10.73	-0.090000	-0.090000	0.060000
McCormick	13.92	11.32	16.83	13.84	11.22	16.75	13.93	11.29	16.87	-0.070000	-0.070000	0.050000
Marion	13.58	11.59	15.76	13.93	11.83	16.16	13.79	11.72	16	-0.110000	-0.110000	-0.050000
Marlboro	12.87	11.12	14.76	13.17	11.35	15.13	13.04	11.22	14.99	-0.130000	-0.130000	-0.010000
Newberry	11.67	9.96	13.49	11.75	10.06	13.6	11.73	10.01	13.6	-0.060000	-0.060000	0.050000
Oconee	9.84	8.34	11.45	9.57	8.07	11.22	9.72	8.19	11.36	-0.060000	-0.060000	0.020000
Orangeburg	13.69	12.25	15.23	14	12.51	15.62	13.92	12.42	15.53	-0.130000	-0.130000	0.000000
Pickens	8.81	7.16	10.67	8.72	7.03	10.62	8.86	7.16	10.78	-0.110000	-0.110000	0.030000
Richland	9.64	8.53	10.84	9.67	8.5	10.91	9.8	8.62	11.07	-0.140000	-0.140000	0.040000
Saluda	10.93	9.09	12.93	10.95	9.11	12.99	10.93	9.07	12.99	-0.080000	-0.080000	0.040000
Spartanburg	10.12	8.74	11.6	10.12	8.72	11.64	10.18	8.74	11.74	-0.140000	-0.140000	0.080000
Sumter	12.07	10.49	13.76	12.24	10.62	14.01	12.22	10.58	13.99	-0.140000	-0.140000	0.020000
Union	12.76	10.98	14.7	12.87	11.05	14.88	12.77	10.96	14.76	-0.080000	-0.080000	-0.030000
Williamsburg	14.41	12.49	16.47	14.74	12.78	16.87	14.63	12.68	16.73	-0.070000	-0.070000	-0.040000
York	9.63	8.15	11.23	9.47	7.98	11.11	9.62	8.1	11.29	-0.110000	-0.110000	0.060000

4 DISCUSSION

The aim of this dissertation was to fill up information gap, in terms of coverage, time and sample size, in surveys made to investigate the prevalence of diabetes in Counties around the United States. During the study, we found out that not only surveys have limitations on coverage and sample size but it is also difficult to conduct a survey every year because of the amount of resources it requires. For instance the questions conduct in the survey may not done every year or depends on each state decision to include the questionnaire every year. Moreover, Counties that were expected to conduct surveys every year were not able to carry out that responsibility for a variety of reasons. Therefore, surveys have limitations in providing recent data for relevant decision making. This left policy makers and budget allocators with the option of making decisions relying on data generated by direct estimations on such surveys.

In terms of coverage, the 2010 BRFSS survey was able to cover only 1,188 Counties among 1,497 Counties under our study. In fact states do conduct additional surveys in order to fill BRFSS's coverage gap, such as Florida (see Chapter 2). However that may not be carried out every year. From the 1,497 Counties covered in the BRFSS survey 824 were underrepresented or with small sample size (based on the Healthy people 2010 Criteria for Data Suppression). Moreover, from among 1,497 counties in 16 states that we included in our analysis, 305 of the counties lacked information when we aggregated individuals surveyed in the BRFSS survey, we have checked from 2000 to 2010.

The choice for policy makers is to either conduct all-small-area-covering survey every year- which is almost impossible to do so, if one considers budget and other resources that it requires - or to generate direct estimates for decision making. This dissertation attempted to provide a third plausible option using Bayesian Hierarchical Model of estimation which is believed to provide a reliable data as compared to direct estimation.

Our models helped us to estimate the prevalence of diabetes in underrepresented or Counties through borrowing data on recent surveys made in neighboring Counties. In doing so we were able to minimize errors from direct estimations generated for these areas.

Because of small sample size some of the counties incorporated for analysis do not have observations from certain groups. For instance, Charlotte, Collier, Martin, Sumter Counties do not have data for age group 18-44 (see the Florida Department of Health direct estimate for counties12). We however overcame this information gap by constructing BH models to borrow information from neighboring counties for estimating the prevalence of diabetes.

Our models therefore helped to estimate the prevalence of diabetes for all counties including those with small sample size and other Counties with missing information (such as Charlotte and Collier).

Our estimates demonstrated that people with high prevalence of diabetes reside in counties with the highest poverty levels. Our estimates moreover revealed racial disparities in diabetes prevalence. Accordingly, Blacks in all counties have been found to have higher prevalence of diabetes than Whites. In addition to this in almost all counties, the estimated prevalence of diabetes was higher in males than females.

This paper shows not only the advantage of BH over direct estimate but also the socioeconomic factor in dealing with this chronic epidemic disease. This in turn helps policy makers and fund allocators to allocate fund to appropriate areas with meaningful policy to tackle this epidemic.

In Chapter 2 we used the 2010 BRFSS data and drew estimates for Florida counties. The 2010 estimated prevalence of diabetes showed all counties in Florida have high prevalence compared to the national diabetes prevalence16, and this clearly shows the burden on Florida State. Having estimate at this level and for all counties would create an opportunity for policy makers to address the issue appropriately. The model estimates also show the estimated prevalence of diabetes varied across the counties, which indicates the need to design specifically targeted public health policies and allocation of fund.

Our findings also reveal that socioeconomic disparities among the Florida population are one of the factors for the high prevalence of diabetes in certain counties. Most of the counties with high prevalence of diabetes are those with high poverty rate. In addition to this socioeconomic factors and racial disparities reflect variations in the prevalence of diabetes.

Our study has some limitations as the BRFSS survey data generally underestimates the true prevalence of diabetes. About one-third of people with diabetes do not know they have it diabetes(1). Since the BRFSS is a telephone survey, households without telephones may not be included. Although telephone coverage is generally high, non-coverage may be high for certain population groups. For example, American Indians, rural Blacks in some southern states, and persons in lower socioeconomic groups typically have lower telephone coverage [(2)]. As diabetes is more common among racial and ethnic minority groups and among lower socioeconomic groups, BRFSS may underestimate diabetes prevalence for these subpopulations[13, 14].

5 CONCLUSION

The Bayesian Hierarchical Model is helpful to extend small area estimation to produce the needed reliable estimates for all areas including those small local areas with small sample size

Using this model the study was able to estimate the prevalence of diabetes in 1,479 counties all over the 16 states from 2010 BRFSS survey data.

The estimates were generated for the following categories of Counties.

5.1 Counties covered by the 2010 BRFSS survey with having a complete set information

A total of 1,188 Counties were analyzed in this category. 5 counties in Texas have a complete information but no adjacent counties. Based on the criterions stated in the Healthy people 2020 data suppression for BRFSS not all counties have a good sample size. Even though estimates were generated based on data from the 2010 BRFSS survey they could be used for all practical purposes for current and future decision making.

5.2 Counties covered by the 2010 BRFSS survey but have small sample size

A total of 824 Counties among 1,188 counties were analyzed here and estimates for the prevalence of diabetes were generated.

5.3 Counties that were not covered by the 2010 BRFSS survey

Here a total of 289 Counties were covered in our estimation. 6 counties didn’t have the population proportion for Blacks when we aggregated by age and sex from the Census. Without such estimates, decision makers would not have the ability to decide on important issues such as budget allocation for these areas. Or else make their decisions based on direct estimates.

The study was helpful in presenting relevant data for decision making with regards to control and prevention of diabetes. Instead of making decisions based on incomplete or insufficient data it is advisable to make use of an estimate with lower probability of error than direct estimates. This study is believed to help the decision making process in policy making through providing such estimates.

The burden of diabetes on the economy is huge. Type 2 Diabetes affects 29.1 million Americans. Besides the money spent on direct treatment of the disease, its tremendous effect on labor productivity is obvious. The socio economic burden of this disease can be mitigated by formulating the right policies of prevention and treatment accompanied by the budget needed. The estimates generated in this study will help provide a reliable data to this end.

From the results of this study it is safe to conclude that surveys will continue to have coverage, sample size and time gaps in providing information on the prevalence of diabetes. The use of estimates therefore will continue to be an essential part of data processing at the policy level.

Being a better tool of estimation, the Bayesian hierarchical small area model becomes handy for such kind of situations. This study delivered the importance of this method in providing better estimates and it is recommended to use them during survey data analysis or when conducting surveys becomes expensive.

6 FUTURE RESEARCH

Our result shows that southern parts of the U.S. have people with more diagnosed diabetes than other parts. On average people in southern states are 12% more likely to diagnose for diabetes than people in Southern states. However, further research needs to be made to investigate what other factors lead to such results. Public health professionals who need to investigate what other factors influence diabetes outcome besides age, sex, race, education attainment, income and health insurance can focus their research based on the results of this study. One other area of investigation suggested by researchers during our study was access to healthy food. Even though dining on healthy food might relate to other factors such as income and cultural diversity (or racial differences), that should also be investigated in a related research to be made in the future. Results from such studies could be principal sources of information for decision makers to control and prevent diabetes.

Our results can also be used to direct the focus of investigation for future studies. For instance, Counties with high level of estimation in prevalence of diabetes may call for special attention for future investigation. That in return could help policy makers to isolate factors in their effort of diabetes prevention in other parts of the country.

The Models we used in this research may be used as tool of estimation by other researchers to investigate prevalence of other diseases similar to diabetes – diseases that share similar factors for their prevalence

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Appendix A SAS Codes used for all Analysis

```
%Macro avg2(k);

Proc freq Data=logitfil.Diabeticbelt09012016;

tables _state*ctycode*Diab*sex*race*AGE3*EDUCAG*incom*insur/Out=State&k noprint;

        where _state in(&k) and ctycode not in(.,777,999) ;

    Run;


    Data state&k._1;

        Set state&k;

        _state=&k;

    Run;


    Ods HTML CLOSE;

    Ods HTML;


    Proc Append Base=logitfil.Allstatecomb1 Data=State&k._1 Force;

    Run;


    Dm log 'clear' Output;

    DM 'LOG;CLEAR;Out;CLEAR;RESULTS CLEAR'; /* CLEARING LOG AND Output WINDoWS */


%Mend avg2;

%Macro avg2_1(var1,var2);

    %Local i;

    %Do i=&var1 %To &var2;

        %avg2(&i);
```

```
        %End;
%Mend avg2_1;
%avg2_1(1,16);/*Number of States*/


/*****************************************************************************************
*******************************************************/
/*********** Overall Intial estimate for other
parameters*********************************************************/
Ods Listing close;
Proc genmod Data=logitfil.diabfinalstat_2;
        Model diab/pop= g2 g3 s1 r1 g2*s1 g3*s1 g2*r1 g3*r1 s1*r1 inc2 inc3 inc4 edu2 edu3 edu4  insu2 /
dist=binomial link=logit ;
        Title "State Al";
        Ods Output ParameterEstimates=myOballt/*(Keep=Parameter Estimate StdErr)*/;
Run;
/*****************************************************************/
Data allbetaEst(keep=Parameter Estimate );
        Set myOballt_1;
        If Parameter = "Intercept" Then Parameter = "beta1";
        If Parameter = "g2" Then Parameter = "beta2";
        If Parameter = "g3" Then Parameter = "beta3";
        If Parameter = "s1" Then Parameter = "beta4";
        If Parameter = "r1" Then Parameter = "beta5";
        If Parameter = "g2*s1" Then Parameter = "beta6";
        If Parameter = "g3*s1" Then Parameter = "beta7";
        If Parameter = "g2*r1" Then Parameter = "beta8";
```

```
            If Parameter = "g3*r1" Then Parameter = "beta9";

            If Parameter = "s1*r1" Then Parameter = "beta10";

            If Parameter = "inc2" Then Parameter = "beta11";

            If Parameter = "inc3" Then Parameter = "beta12";

            If Parameter = "inc4" Then Parameter = "beta13";

            If Parameter = "edu2" Then Parameter = "beta14";

            If Parameter = "edu3" Then Parameter = "beta15";

            If Parameter = "edu4" Then Parameter = "beta16";

            If Parameter = "insu2" Then Parameter = "beta17";


Run;


Data allbetaPerc(Keep= perc Parameter1);

Length Parameter1 $6;

            Set myOballt_1;

            If Parameter = "Intercept" Then Parameter1 = "taub1";

            If Parameter = "g2" Then Parameter1 = "taub2";

            If Parameter = "g3" Then Parameter1 = "taub3";

            If Parameter = "s1" Then Parameter1 = "taub4";

            If Parameter = "r1" Then Parameter1 = "taub5";

            If Parameter = "g2*s1" Then Parameter1 = "taub6";

            If Parameter = "g3*s1" Then Parameter1 = "taub7";

            If Parameter = "g2*r1" Then Parameter1 = "taub8";

            If Parameter = "g3*r1" Then Parameter1 = "taub9";

            If Parameter = "s1*r1" Then Parameter1 = "taub10";

            If Parameter = "inc2" Then Parameter1 = "taub11";

            If Parameter = "inc3" Then Parameter1 = "taub12";
```

```
            If Parameter = "inc4" Then Parameter1 = "taub13";
            If Parameter = "edu2" Then Parameter1 = "taub14";
            If Parameter = "edu3" Then Parameter1 = "taub15";
            If Parameter = "edu4" Then Parameter1 = "taub16";
            If Parameter = "insu2" Then Parameter1 = "taub17";
            Perc=Round(perc,.001);
Run;
/*******************************************************************/
/************ CREATING CAR b from Missing counties for Alabama States***/
/****** Follow Simillar Patter for other states and counties*/

Proc IMPORT Out= WORK.taub
          DataFILE= "\\cdc.gov\private\M120\gwj6\Training from local D
rive\Dissertation\Openbugs\2010 BRFSS Analysis New Run\Israe final Paper
_Result and Map\Winbugs\All Process for Winbugs\Model 8\Model 8  beta CAR.xlsx"
          DBMS=EXCEL REPLACE;
    RANGE="'tau#b posterior$'";
    GETNAMES=YES;
    MIXED=NO;
    SCANTEXT=YES;
    USEDATE=YES;
    SCANTIME=YES;
Run;

%Macro st;
            %Do i= 1 %To 16;
                        Data taub&i;
```

```
                Set taub;

                Keep Runs taub  FIPS;

                FIPS=&i;

            Run;

            Proc Append Base=stord.Allsttaub Data=taub&i Force;

            Run;

        %End;

%Mend st;

%st;


Data stord.AllmisCARB;

        Set stord.AllCARB;

        Where FIPS=1000;

        cty=.;

        Keep FIPS Runs cty;

Run;


%Macro adj1(st,cty,adjcty);

        Data carb&cty._&st;

            Set stord.AllCARB;

            Where FIPS=&st;

            CTY=&cty;

            Keep Runs FIPS &adjcty CTY;

            Proc Sort;

            By Runs;

        Run;
```

```
        Data stord.AllmisCARB;
        Retain  FIPS CTY Runs;
                Set stord.AllmisCARB carb&cty._&st;
        Run;

%Mend adj1;
%adj1(1,62,CARB3 CARB40 CARB47 CARB50 CARB52)
%adj1(1,63,CARB10 CARB13 CARB24 CARB54 CARB56 CARB57)
%adj1(1,64,CARB30 CARB42 CARB49 CARB55 CARB58)
%adj1(1,65,CARB1 CARB6 CARB19 CARB22 CARB47)
%adj1(1,66,CARB4 CARB10 CARB22 CARB30 CARB42)
%adj1(1,67,CARB6 CARB12 CARB22 CARB42 CARB46)

%Macro adj2(st,cty,cars,n);

        Data estmiss&cty;
                Merge stord.AllCARB1(Where=(FIPS=&st)) stord.Allsttaub(Where=(FIPS=&st));
                carb&cty=(&cars)/&n;
                taubn= 1/SQRT(taub*&n);
                Newbcar= Rand("Normal",carb&cty,taubn);
        Run;

        Data estmiss&cty._1;
                Set estmiss&cty;
                FIPS=&st;
                Rename newbcar=CARB&cty;
                Keep Runs Newbcar FIPS;
```

```
        Proc Sort;
        By FIPS Runs;
    Run;

    Data Misscty;
        Merge misscty estmiss&cty._1;
        By FIPS Runs;
    Run;

%Mend adj2;

%adj2(1,62,CARB3+CARB40+CARB47+CARB50+CARB52,5)
%adj2(1,63,CARB10+CARB13+CARB24+CARB54+CARB56+CARB57,6)
%adj2(1,64,CARB30+CARB42+CARB49+CARB55+CARB58,5)
%adj2(1,65,CARB1+CARB6+CARB19+CARB22+CARB47,5)
%adj2(1,66,CARB4+CARB10+CARB22+CARB30+CARB42,5)
%adj2(1,67,CARB6+CARB12+CARB22+CARB42+CARB46,5)
/****************** Creating CAR b for counties Ends*************************/
/***************************************************************************/
/**********Covariates in the analysis****************************************
combination of the followings
Age(1,2,3)
Sex(1,2)
Race(1,2)
Income(1,2,3,4)
Education(1,2,3,4)
Insurance(1,2)**************************************************************/
```

```
Libname grpn 'Dissertation';


%Macro crtecov1(var1,var2,num);/*creating covariates*/

        Data covr&var2;

                Set grpn.ALL384Subgroups;

                Rename &var2=&var2.c1;

                FIPS=&var1;

                Keep FIPS &var2 ;

        Run;


        %Local i;

        %Do i=2 %To &num;

                Data covr&i;

                        Set grpn.ALL384Subgroups;

                        Keep &var2;

                        Rename &var2=&var2.c&i;

                Run;


                Data covr&var2;

                        Merge covr&var2 covr&i;

                Run;

                Proc DataSets library=work;

                        Delete covr&i;

                Run;

        %End;

/*dm "Out;clear;log;clear;";*/

%Mend crtecov1;
```

```
/*%crtecov1(1,G1S1R1Inc1Edu1Insu1,1);*/


%Macro crtecov2(var1,var2);
        %Local i;
        %Local j;
        %Local k;
        %Local l;
        %Local m;
        %Local n;
         %Do i = 1 %To 1;
          %Do j = 1 %To 1;
            %Do k = 1 %To 1;
             %Do l = 1 %To 1;
               %Do m = 1 %To 1;
                                %Do n=1 %To 1;
                                        %crtecov1(&var1,G&i.S&j.R&k.Inc&l.Edu&m.Insu&n,&var2);
                                %End;/* Do Insu */
               %End; /* Do Edu */
              %End; /* Do Inc */
            %End; /* Do Race */
           %End; /* Do Sex */
         %End; /* Do Age */
%Mend crtecov2;
%crtecov2(1,67);/*similarly for other states and counties*/
Option Nofmterr;
Libname covrtd 'Dissertation';
Libname stordn 'Dissertation';
```

```
%Macro crtecov(var,st,beg,end);

        Data covr&var;

                Set covrtd.D&var._2;

                Where FIPS=&st;

                KEEP &var.c&beg-&var.c&End;

        Run;


        Data betaest;

                Set stordn.Allcombbetas;

                Where FIPS=&st;

                Drop FIPS;

        Run;


        Data Carall1;

                Set stordn.AllCARB3;

                Where FIPS=&st;

                Keep CARB&beg-CARB&End;

        Run;


        /*************************** Puting covariates in matrix

form*********************************************/


        Proc iml;

         * Read Data into IML ;

         use covr&var;

         read all ;

         y=&var.c1;
```

```
%Macro test;
    %Local o;
    %Do o=2 %To &End;
        y=y || &var.c&o;
    %End;
    /*print y;*/
%Mend test;
%test;

/******************************************************************/

 * Read Data into IML ;

 use betaest;
 read all ;
 beta=beta1;
%Macro test1;
    %Local p;
    %Do p=2 %To 18;
        beta=beta || beta&p;
    %End;
%Mend test1;
%test1;

betax=beta * y;
/**********************************************************************/
 * Read Data for CAR model into IML ;
```

```
        use Carall1;
        read all ;
        BCAR=CARB1;
        %Macro test2;
                %Local q;
                %Do q=2 %To &End;
                        BCAR=BCAR || CARB&q;
                %End;
        %Mend test2;
        %test2;

        /* Estimating the probability*/
        logitp=beta * y + BCAR;
        Pprob=(exp(logitp))/(1+exp(logitp));

        /* Estimating Posterior Probability*/
        create &var.Pprob&st from Pprob; /** create Data Set **/
        append from Pprob;      /** write Data in vectors **/
        close &var.Pprob&st; /** close the Data Set **/
Data prob&st..&var.Pprob;
        Set &var.Pprob&st;
Run;
        Proc DataSets library=work;
                Delete &var.Pprob&st;
        Run;
        Dm log 'clear' Output;
```

```
            DM 'LOG;CLEAR;Out;CLEAR;RESULTS CLEAR';  /* CLEARING LOG AND Output WINDoWS*/
 Quit;
%Mend crtecov;
%Macro strd3(var1,var2,var3);
            %Local i;
            %Local j;
            %Local k;
            %Local l;
            %Local m;
            %Local n;
              %Do i = 1 %To 3;
               %Do j = 1 %To 2;
                   %Do k = 1 %To 2;
                     %Do l = 1 %To 4;
                        %Do m = 1 %To 4;
                                                    %Do n=1 %To 2;

            %crtecov(G&i.S&j.R&k.Inc&l.Edu&m.Insu&n,&var1,&var2,&var3);
                                                    %End;/* Do Insu */
                        %End; /* Do Edu */
                      %End; /* Do Inc */
                   %End; /* Do Race */
                 %End; /* Do Sex */
              %End; /* Do Age */
%Mend strd3;
%strd3(1,1,67)
/****************************************************************/
```

```
/****** creating population Probability by Age, Sex and Race****************/

Data Probprotst1cty1;
        Set Probprotst1cty1;
        G1WHTMALE=ProbG1S1R1inc1edu1Insu1* NewG1S1R1Inc1Edu1Insu1 +
                                        .
                                        .
                                        .
                + ProbG1S1R1INC4EDU4INSU2* NEWG1S1R1INC4EDU4INSU2;
        G1WHTFEM=ProbG1S2R1INC1EDU1INSU1* NEWG1S2R1INC1EDU1INSU1 +
                                        .
                                        .
                                        .
        + ProbG1S2R1INC4EDU4INSU2* NEWG1S2R1INC4EDU4INSU2;
        G1BLKMALE=ProbG1S1R2INC1EDU1INSU1* NEWG1S1R2INC1EDU1INSU1+

                                        .
                                        .
                                        .
        + ProbG1S1R2INC4EDU4INSU2* NEWG1S1R2INC4EDU4INSU2;
        G1BLKFEM=ProbG1S2R2INC1EDU1INSU1* NEWG1S2R2INC1EDU1INSU1+

                                        .
                                        .
                                        .
        + ProbG1S2R2INC4EDU4INSU2* NEWG1S2R2INC4EDU4INSU2;
        G2WHTMALE=ProbG2S1R1INC1EDU1INSU1* NEWG1S1R1INC1EDU1INSU1 +

                                        .
                                        .
                                        .
        + ProbG2S1R1INC4EDU4INSU2* NEWG1S1R1INC4EDU4INSU2;
        G2WHTFEM=ProbG2S2R1INC1EDU1INSU1* NEWG1S2R1INC1EDU1INSU1 +

                                        .
                                        .
                                        .
        + ProbG2S2R1INC4EDU4INSU2* NEWG1S2R1INC4EDU4INSU2;
```

```
G2BLKMALE=ProbG2S1R2INC1EDU1INSU1* NEWG1S1R2INC1EDU1INSU1 +
                    .
                    .
                    .
+ ProbG2S1R2INC4EDU4INSU2* NEWG1S1R2INC4EDU4INSU2;
G2BLKFEM=ProbG2S2R2INC1EDU1INSU1* NEWG1S2R2INC1EDU1INSU1 +
                    .
                    .
                    .
+ ProbG2S2R2INC4EDU4INSU2* NEWG1S2R2INC4EDU4INSU2;
G3WHTMALE=ProbG3S1R1INC1EDU1INSU1* NEWG1S1R1INC1EDU1INSU1 +
                    .
                    .
                    .
+ ProbG3S1R1INC4EDU4INSU2* NEWG1S1R1INC4EDU4INSU2;
G3WHTFEM=ProbG3S2R1INC1EDU1INSU1* NEWG1S2R1INC1EDU1INSU1 +
                    .
                    .
                    .
+ ProbG3S2R1INC4EDU4INSU2* NEWG1S2R1INC4EDU4INSU2;
                    .
                    .
                    .
+ ProbG3S1R2INC4EDU4INSU2* NEWG1S1R2INC4EDU4INSU2;
G3BLKFEM=ProbG3S2R2INC1EDU1INSU1* NEWG1S2R2INC1EDU1INSU1 +
                    .
                    .
                    .
+ ProbG3S2R2INC4EDU4INSU2* NEWG1S2R2INC4EDU4INSU2;
Keep ctycode G1BLKFEM G1WHTFEM G1BLKMALE G1WHTMALE
G2BLKFEM G2WHTFEM G2BLKMALE G2WHTMALE
G3BLKFEM G3WHTFEM G3BLKMALE G3WHTMALE;
Run;
```

```
/************ Getting population from Census to calculate**************
******weighted Pop of Florida County by Age*Sex*Race ******************/
Option nofmterr;
Libname Censu 'Dissertation\census';
Data DiabBelt;
	Set censu.V2011statecountybridgecensus2010;
	Where year=2010 AND STfips IN(1,5 ,12,13, 21,22,24,28,37,39,42,45,47,48,51,54);
	If 18<=Age_Actual<=44 Then agegrp=1;
	Else If 45<=Age_Actual<=64 Then agegrp=2;
	Else If Age_Actual >=65 Then agegrp=3;
	Else agegrp=.;
	Keep Year StFips CO_FIPS Den agegrp sex race Age_Actual;
	Proc Sort Data=DiabBelt;
	By StFips CO_FIPS;
Run;
Proc Means Data=DiabBelt;
	By StFips CO_FIPS;
	Class agegrp sex race;
	Var den;
	Output Out=TempDSSum;
Run;
Data pop;
	Set Allpopwithinteraction_3;
	where agegrp>0 and sex>0 and race in(1,2);
	If agegrp=1 and sex=1 and race=1 Then newcd='G1WM';
	If agegrp=1 and sex=2 and race=1 Then newcd='G1WF';
	If agegrp=1 and sex=1 and race=2 Then newcd='G1BM';
```

```
        If agegrp=1 and sex=2 and race=2 Then newcd='G1BF';
        If agegrp=2 and sex=1 and race=1 Then newcd='G2WM';
        If agegrp=2 and sex=2 and race=1 Then newcd='G2WF';
        If agegrp=2 and sex=1 and race=2 Then newcd='G2BM';
        If agegrp=2 and sex=2 and race=2 Then newcd='G2BF';
        If agegrp=3 and sex=1 and race=1 Then newcd='G3WM';
        If agegrp=3 and sex=2 and race=1 Then newcd='G3WF';
        If agegrp=3 and sex=1 and race=2 Then newcd='G3BM';
        If agegrp=3 and sex=2 and race=2 Then newcd='G3BF';
        Proc SORT;
        By FIPS CTY;
Run;
Proc Transpose Data=pop Out=pop1(Drop=_NAME_ );
        Var pop;
        By FIPS cty;
        Id newcd;
Run;
%Macro prct(i,var2,st);
        Data agesexNEW&st.cty&i;
                Merge stprob&st..Post&st.cty&i._2(in=a) censpop.Censuspoptranspose(in=b);
                By cty;
                If a;
                Where FIPS=&st and CTY=&i;
                /********** Age Group 1 by Sex ****************************/
                G1male= (G1BLKMALE*G1BM + G1WHTMALE*G1WM)/(G1BM + G1WM);
                G1female= (G1BLKFEM*G1BF + G1WHTFEM*G1WF)/(G1BF + G1WF);
```

```
G1=((G1BLKMALE*G1BM + G1WHTMALE*G1WM) + (G1BLKFEM*G1BF + G1WHTFEM*G1WF))/(G1BM + G1WM
+G1BF + G1WF);
          /********** Age Group 2 By Sex ****************************/
          G2male=(G2BLKMALE*G2BM + G2WHTMALE*G2WM)/(G2BM + G2WM);
          G2female=(G2BLKFEM*G2BF + G2WHTFEM*G2WF)/(G2BF + G2WF);
          G2=((G2BLKMALE*G2BM + G2WHTMALE*G2WM) + (G2BLKFEM*G2BF +
G2WHTFEM*G2WF))/(G2BM + G2WM +G2BF + G2WF);
          /********** Age Group 3 By Sex ****************************/
          G3male=(G3BLKMALE*G3BM + G3WHTMALE*G3WM)/(G3BM + G3WM);
          G3female=(G3BLKFEM*G3BF + G3WHTFEM*G3WF)/(G3BF + G3WF);
G3=((G3BLKMALE*G3BM + G3WHTMALE*G3WM) + (G3BLKFEM*G3BF + G3WHTFEM*G3WF))/(G3BM + G3WM
+G3BF + G3WF);
          /************************ By Sex ****************************************/
          Male=((G1BLKMALE*G1BM + G1WHTMALE*G1WM)+(G2BLKMALE*G2BM +
G2WHTMALE*G2WM)+(G3BLKMALE*G3BM + G3WHTMALE*G3WM))/(G1BM + G1WM+G2BM + G2WM+G3BM +
G3WM);
          Female=((G1BLKFEM*G1BF + G1WHTFEM*G1WF)+(G2BLKFEM*G2BF +
G2WHTFEM*G2WF)+(G3BLKFEM*G3BF + G3WHTFEM*G3WF))/(G1BF + G1WF+G2BF + G2WF+G3BF + G3WF);
          /******************** Age By Race**************************/
          G1Blk=(G1BLKMALE*G1BM + G1BLKFEM*G1BF)/(G1BM+G1BF);
          G1WHT=(G1WHTMALE*G1WM + G1WHTFEM*G1WF)/(G1WM+G1WF);
          G2Blk=(G2BLKMALE*G2BM + G2BLKFEM*G2BF)/(G2BM+G2BF);
          G2WHT=(G2WHTMALE*G2WM + G2WHTFEM*G2WF)/(G2WM+G2WF);
          G3Blk=(G3BLKMALE*G3BM + G3BLKFEM*G3BF)/(G3BM+G3BF);
          G3WHT=(G3WHTMALE*G3WM + G3WHTFEM*G3WF)/(G3WM+G3WF);
```

```
Blk=((G1BLKMALE*G1BM + G1BLKFEM*G1BF)+(G2BLKMALE*G2BM + G2BLKFEM*G2BF)+(G3BLKMALE*G3BM +
G3BLKFEM*G3BF))/(G1BM+G1BF+G2BM+G2BF+G3BM+G3BF);
WHT=((G1WHTMALE*G1WM + G1WHTFEM*G1WF)+(G2WHTMALE*G2WM + G2WHTFEM*G2WF)+
(G3WHTMALE*G3WM + G3WHTFEM*G3WF))/(G1WM+G1WF+G2WM+G2WF+G3WM+G3WF);
          /*************** Overall Mean *********************************/
          G1sum=(G1BLKMALE*G1BM + G1WHTMALE*G1WM) + (G1BLKFEM*G1BF + G1WHTFEM*G1WF);
          G2sum=(G2BLKMALE*G2BM + G2WHTMALE*G2WM) + (G2BLKFEM*G2BF + G2WHTFEM*G2WF);
          G3sum=(G3BLKMALE*G3BM + G3WHTMALE*G3WM) + (G3BLKFEM*G3BF + G3WHTFEM*G3WF);
OVERALL=(G1sum+G2sum+G3sum)/(G1BM+G1BF+G2BM+G2BF+G3BM+G3BF+G1WM+G1WF+G2WM+G2WF+G3
WM+G3WF);
          keep FIPS CTY g1male G1female G1BLKMALE G1WHTMALE G1Male G1Female
          g2male g2female G2BLKMALE g2WHTMALE g2Male g2Female
          g3male g3female G3BLKMALE g3WHTMALE g3Male g3Female
          Male Female
          G1Blk G1WHT g2Blk g2WHT g3Blk g3WHT Blk WHT
          overall overall
          G1BM G1BF G2BM G2BF G3BM G3BF G1WM G1WF G2WM G2WF G3WM G3WF G1 G2 G3;
     Run;
     Proc Univariate Data=agesexNEW&st.cty&i;
      var &var2;
      Output Out=percentiles&i Mean=mean Pctlpts=2.5 97.5 Pctlpre=P;
 Run;
     Data percentiles&i;
          Length Category $40;
          Set percentiles&i;
          Category="&var2";
          ctcd=&i;
```

```
            FIPS=&st;
        Run;
        Proc Append Base=stprob&st..allpercentilestate&st Data=percentiles&i Force;
        Run;
        Data stprob&st..allposteriorprobst&st.cty&i;
            Set agesexNEW&st.cty&i;
        Run;
        Proc DataSets library=work;
            Delete percentiles&i agesexNEW&st.cty&i;;
        Run;
        Dm log 'clear' Output;
        DM 'LOG;CLEAR;Out;CLEAR;RESULTS CLEAR';  /* CLEARING LOG AND Output WINDoWS*/
%Mend prct;
%Macro prct1(var1,var2,st);
        %Local i;
        %Do i=&var1 %To &var2;
            %prct(&i,g1male,&st)
            %prct(&i,G1female,&st)
            %prct(&i,G1BLKMALE,&st)
            %prct(&i,G1WHTMALE,&st)
            %prct(&i,G1Male,&st)
            %prct(&i,G1Female,&st)
            %prct(&i,G1,&st)
            %prct(&i,g2male,&st)
            %prct(&i,g2female,&st)
            %prct(&i,g2BLKMALE,&st)
            %prct(&i,g2WHTMALE,&st)
```

```
            %prct(&i,g2Male,&st)
            %prct(&i,g2Female,&st)
            %prct(&i,g2,&st)
            %prct(&i,g3male,&st)
            %prct(&i,g3female,&st)
            %prct(&i,g3BLKMALE,&st)
            %prct(&i,g3WHTMALE,&st)
            %prct(&i,g3Male,&st)
            %prct(&i,g3Female,&st)
            %prct(&i,g3,&st)
            %prct(&i,Male,&st)
            %prct(&i,Female,&st)
            %prct(&i,G1Blk,&st)
            %prct(&i,G1WHT,&st)
            %prct(&i,g2Blk,&st)
            %prct(&i,g2WHT,&st)
            %prct(&i,g3Blk,&st)
            %prct(&i,g3WHT,&st)
            %prct(&i,Blk,&st)
            %prct(&i,WHT,&st)
            %prct(&i,overall,&st)
      %End;
%Mend prct1;
%prct1 (1,67,1)/*Similarly for other states and counties*/
/********** Creating weighted posterior probability ends***************/
```

```
/******* Mapping the posterior probability**********************/
/*****************************************************************/
******************* Step 1 creating Ranges*******************;
%Macro imp2(var1,var2,var3);
        Data &var2;
                Set &var1;
                where Category="&var2" /*and FIPS1=&st*/;
                Run;
                Proc rank Data=&var2
           groups=4
                 Out=&var2.qt(rename=(Ctycode=county FIPS=state)keep=prob  x1q Ctycode CTCD FIPS1 FIPS);
                var prob;
                ranks x1q;
        Run;
        Data &var2.qt;
                Set &var2.qt;
                x1q=x1q+1;
        Run;
        Data &var2.qtall;
                Set &var2.qt /*ctmiss*/;
                x1q=x1q+1;
                Proc sort;
                By x1q;
        Run;
        Data test;
                Set &var2.qtall;
                By x1q ;
```

```
        Proc sort;
        By x1q prob;
Run;
Data test_1;
        Set test;
        By x1q;
        If first.x1q Then mean1=prob;
        If last.x1q Then mean2=prob;
Run;
Data test1;
        Set test_1;
        keep x1q mean1;
        If mean1 ne .;
Run;
Data test2;
        Set test_1;
        keep x1q mean2;
        If mean2 ne .;
Run;
Data &var2.range;
        Length type $50;
        merge test1 test2;
        By x1q;
        type="&var3";
Run;
Data noData;
        Length type $50;
```

```
                type="&var3";
                x1q=1;
                mean1=0;
                mean2=0;
        Run;
        Data &var2.range;
                Set  noData &var2.range;
                Run;
        Proc append base=allrange2 Data=&var2.range force;Run;
%Mend imp2;
%imp2(allprob,overall, overall);%imp2(allprob ,G1, Aged 18-44);
%imp2(allprob ,g2, Aged 45-64);%imp2(allprob ,g3, Aged 65 and Above)
%imp2(allprob ,Male, Male);%imp2(allprob ,Female, Female)
%imp2(allprob ,WHT, White);%imp2(allprob ,Blk, Black)
 /* Setting the graphics environment */
goptions reSet=all cback=white border htitle=12pt htext=10pt;
Data newmap;
   Set maps.counties;
   If state ne 2 and state ne 15 and state ne 72;
Run;
Proc sort Data=newmap;
By state;
Quit;
Proc gproject Data=newmap Out=map;
  id state county;
Run;
Quit;
```

```
Proc gremove Data=map Out=states;
  By state;
  Id state county;
Run;
Quit;
Data states;
  Set states;
  By state;
  Retain flag num 0;

  If first.state Then Do;
     flag=0;
     num=0;
  End;
  If x=. and y=. Then Do;
    flag=1;
    num + 1;
    Delete;
  End;
  If flag=1 Then segment + num;
  Drop flag num;
Run;


 /* Create an annotate Data Set named ANNO for the state Outlines */
Data anno;
  Length function color $8;
```

```
 Retain xsys ysys '2' when 'a' color 'black' size 1.5;
 Drop xsave ysave;
 Set states;
 By state segment;
 If first. Segment Then function='poly';
 Else function='polycont';
 Output;
Run;
Data ctmiss1;
        Set adjcty.Allcountinfo;
        Where Car=1;
        Prob=0;
        x1q=0;
        Rename STFIPS=FIPS CtyFIPS=CTYCODE;
        Keep STFIPS CtyFIPS prob x1q;
Run;
Data ctmiss2;
        Set Notbeltstate;
        Prob=0;
        x1q=0;
        Rename state=statename state1=FIPS county=CTYCODE;
        Keep state1 county prob x1q;
Run;
Data ctmiss;
        Set /*ctmiss1*/ ctmiss2;
        Rename ctycode=county FIPS=state;
Run;
```

```
%Macro imp1(var1,var2,var3,var4);

        Data &var2;

                Set &var1;

                where Category="&var2";

                Run;

                Proc rank Data=&var2

                    groups=4

                            Out=&var2.qt(rename=(ctycode=county FIPS=state)keep=prob  x1q FIPS Ctycode);

                var prob;

                ranks x1q;

        Run;

        Data &var2.qt;

                Set &var2.qt;

                x1q=x1q+1;

        Run;

        Data &var2.qtall;

                Set &var2.qt ctmiss;

                x1q=x1q+1;

                If prob=. Then prob=0;

                If x1q=. Then x1q=0;

                Proc sort;

                By x1q;

        Run; %all;

* fill patterns for the map areas (gray-scale fills);

  pattern1  value=solid color=white/*white*/;

  pattern2  value=solid color=Hb17d9dd;
```

```
  pattern3  value=solid color=He00aadd;

  pattern4  value=solid color=He0066ee;

  pattern5  value=solid color=navy;


Title1 "Estimated Prevalence of Diagnosed Diabetes, &var3, for Counties in Diabetic Belt using Bayesian Analysis,
2010";
        Ods Listing close;
        Ods pdf file="Dissertation\Output";           /* Generate a county map with thick state boundaries */
        Proc Gmap Data=&var2.qtall map=map;
          Id state county;
          choro x1q / anno=anno cOutline=H0784F00 discrete;
            format x1q &var4..;
           label x1q='Estimated Prevalence of Diagnosed Diabetes Rank';
        Run;
        Quit;
        Ods pdf close;
        Ods Listing;
%Mend imp1;
%imp1(allprob,overall, overall, overall);%imp1(allprob ,G1, Aged 18-44, Aged18_44v)
%imp1(allprob ,g2, Aged 45-64, Aged45_64v);%imp1(allprob ,g3, Aged 65 and Above, Aged65Above)
%imp1(allprob ,Male, Male,Male);%imp1(allprob ,Female, Female,Female)
%imp1(allprob ,WHT, White,White);%imp1(allprob ,Blk, Black,Black)
```

Appendix B WinBUGS Code for Models in Chapter

Appendix B.1 Bayesian Hierarchicalwith CAR(spatial dependency) model

```
# Bayesian Hierarchicalwith CAR (spatial dependency) model
model
{
  for(j in 1 :9545) {
    diab[j]~ dbin(p[j],pop[j])
    logit(p[j]) <- beta1 + beta2 * g2[j] + beta3 * g3[j]  + beta4 * s1[j] + beta5 * r1[j] +
                beta6 * g2s1[j] + beta7 *g3s1[j] + beta8 * g2r1[j] + beta9 * g3r1[j] +
                beta10 * s1r1[j] + beta11 * inc2[j] + beta12 * inc3[j] + beta13 * inc4[j] +
                beta14 * edu2[j] + beta15 * edu3[j] + beta16*edu4[j] + beta17 *
                povt[ct[j]] + b[ct[j]] }
#CAR for Florida counties
  b[1:N]~car.normal(adj[],weights[],num[],tau.b)
  for(k in 1:sumNumNeigh){
    weights[k]<-1
  }
For(l in 1:17){
  beta[l] ~ dnorm(0.0, 1.0E-2)
}
  tau.b~dgamma(0.5,0.5)
  sigma.b<-sqrt(1/tau.b);{
```

Appendix B.2 Bayesian HierarchicalCounty Specific and CAR

```
model
{
for(j in 1 :9545) {
diab[j]~ dbin(p[j],pop[j])
logit(p[j]) <- beta1[ct[j]] + beta2[ct[j]] * g2[j] + beta3[ct[j]] * g3[j]  + beta4[ct[j]] * s1[j] +
beta5[ct[j]] * r1[j] + beta6[ct[j]] * g2s1[j] + beta7[ct[j]] * g3s1[j]  +  beta8[ct[j]] * g2r1[j] +
beta9[ct[j]] * g3r1[j] + beta10[ct[j]] * s1r1[j] +    beta11[ct[j]] * inc2[j] + beta12[ct[j]] * inc3[j] +
beta13[ct[j]] * inc4[j] +  beta14[ct[j]] * edu2[j] + beta15[ct[j]] * edu3[j] +
beta16[ct[j]]*edu4[j] + beta17[ct[j]] * povt[ct[j]] + b[ct[j]]
  }
  b[1:N]~car.normal(adj[],weights[],num[],tau.b)
  for(k in 1:sumNumNeigh){
    weights[k]<-1
  }
 for(i in 1:63){
       for(j in 1:17){
  beta[i,j] ~ dnorm(b[j],taub[j])
  b[j]~ dnorm(0.0, 1.0E-2)
 taub[j]~dgamma(0.5,0.5)
             }
       }
```

```
   tau.b~dgamma(0.5,0.5)
   sigma.b<-sqrt(1/tau.b);
}
```

Appendix B.3 Bayesian Hierarchicalwith CAR (spatial dependency) model

```
# Bayesian Hierarchicalwith CAR (spatial dependency) model
model
{
   for(j in 1 :9545) {
      diab[j]~ dbin(p[j],pop[j])
      logit(p[j]) <- beta1 + beta2 * g2[j] + beta3 * g3[j]  + beta4 * s1[j] + beta5 * r1[j] +
                      beta6 * g2s1[j] + beta7 *g3s1[j] + beta8 * g2r1[j] + beta9 * g3r1[j] +
                      beta10 * s1r1[j] + beta11 * inc2[j] + beta12 * inc3[j] + beta13 * inc4[j] +
                      beta14 * edu2[j] + beta15 * edu3[j] + beta16*edu4[j] + beta17 *
                      povt[ct[j]]  }
#CAR for Florida counties
   b[1:N]~car.normal(adj[],weights[],num[],tau.b)
   for(k in 1:sumNumNeigh){
      weights[k]<-1
   }
For(l in 1:17){
   beta[l] ~ dnorm(0.0, 1.0E-2)
}
```

```
          tau.b~dgamma(0.5,0.5)

          sigma.b<-sqrt(1/tau.b);

        {
```

Appendix B.4 Model with both uncorrelated and correlated spatial random effects

```
model

{

  for(j in 1 :9545) {

    diab[j]~ dbin(p[j],pop[j])

logit(p[j]) <- beta1 + beta2 * g2[j] + beta3 * g3[j]  + beta4 * s1[j] + beta5 * r1[j] + beta6 * g2s1[j]

             + beta7 * g3s1[j]  +  beta8 * g2r1[j] + beta9 * g3r1[j] + beta10 * s1r1[j]

            + beta11 * inc2[j] + beta12 * inc3[j] + beta13 * inc4[j]+  beta14 * edu2[j]

           + beta15 * edu3[j] + beta16*edu4[j] + beta17 * povt[ct[j]] + b[ct[j]] +e[j]

        e[j]~dnorm(0,tau.h)

  }

  b[1:N]~car.normal(adj[],weights[],num[],tau.b)

  for(k in 1:sumNumNeigh){

    weights[k]<-1

  }

  For(i in1:17){

  beta[i] ~ dnorm(0.0, 1.0E-2)

        }
```

```
    tau.h~dgamma(0.5,0.0005)

    sigma.h<-sqrt(1/tau.h) ;

    tau.b~dgamma(0.5,0.5)

    sigma.b<-sqrt(1/tau.b);

}
```