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Area-level factors associated with spatial variation of prostate cancer incidence for black men

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Original Article

Abstract

Purpose: Black men are disproportionately affected by prostate cancer (CaP) compared to any other racial/ethnic groups within the United States. Identifying CaP hotspots along with associated local area-level risk factors is crucial to tackling the significant burden of CaP and the disparity seen in Black men. The objective of this study was to determine the scope of geographical variation in CaP incidences and to assess the degree to which this variation is associated with county-level risk and protective factors. **Methods:** The study population was Black men diagnosed with prostate cancer between 2006-2010 in Florida. County-level CaP incidence rates were computed as the ratios of the numbers of new CaP cases diagnosed between 2006 and 2010 to the corresponding 2000 US census population of Black men 20 and over years old data (US Census 2000). Other county-level environmental and health care factors were also obtained. A random effects Poisson model and Geographical Information System (GIS) were used to map and assess the spatial patterns of CaP incidences in 67 Florida counties. These statistical techniques involved a Bayesian approach for estimating the underlying county-specific CaP risk since the data are very sparse. **Results:** The findings showed that an increasing CaP incidence of Black Men in Florida was significantly associated with an increasing unemployment rate (β_2 = .1379 with 95% CI: (.0025, .2703), does not include zero suggesting significance) and with increasing number of physicians per capita after controlling for other county characteristics. There was a negative association between poverty and CaP incidence. Regarding spatial distribution of CaP incidence, we observed that there are clustering and hotspots of high CaP incidence rates in Palm Beach county in South Florida, and Alachua and Marion counties in north Florida. **Conclusion:** Our findings showed that indicators of socioeconomic status and accessibility of health care services such as poverty, unemployment and health care providers are important variables that explain spatial variation of prostate cancer incidence rates of Black Men. Better understanding of such risk factors and identifying specific counties with a disproportionate burden of CaP disease may help formulate targeted interventions and resource allocation by state and local public officials.

Keywords: Bayesian inference, Health disparity, Prostate cancer, Poisson model.

1. Introduction

Prostate cancer (CaP) is one of the most common cancers experienced by men in the United States (US), and the second leading cause of cancer-related deaths.¹ Black men are disproportionately affected by CaP compared to any other racial/ethnic groups in the US. Compared to US White men, Black men are about two times more likely to develop CaP and die from the disease.**¹** Although the causes for these disparities are not yet completely known, genetic heritage, variation in life styles, health care availability, environmental risk factors have been suggested as plausible explanations.**2-8** To examine the influence of environmental risk factors on CaP incidence in a geographic context, the study objectives were: (1) to estimate the association between

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county-specific relative risk for prostate cancer and county-level characteristics such as socio-economic status, health care access, poverty, unemployment and water supply, and (2) to develop spatial mapping of CaP incidence for Black men in Florida.

Although some studies have examined the relationship between environmental factors and cancer incidence spatial variations**9-14**, there is limited publications on the spatial pattern variations of CaP incidence in Florida Black men. Knowledge of the spatial distribution of CaP incidence has significant public health implication. For example, the CaP burden can be mitigated through identifying major health determinants, and allocating proper public health resources and policies at the local level. For this study, we examined the association between spatial variations in CaP incidence and the following county-level environmental and health care factors: availability of physicians, body weight, environmental exposures, demographic indicators and socio-economic indicators.**¹⁵** Specifically, determining the role of spatial, environmental, and socio-economic heterogeneity in prostate cancer disparities provides a basis for developing public health interventions that will prevent and control prostate cancer in affected communities.

In this paper, we used Bayesian spatial models to describe the spatial pattern of CaP incidence for Black men in Florida's 67 counties. In addition, we assessed the contribution of socioeconomic, environmental, and health care availability in explaining area-level variations.

2. Methods and Materials

2.1. Study setting and sources of data

The study setting was Florida and the targeted population was all Black men diagnosed with CaP between 2006 and 2010. County-level CaP cases were obtained from the Florida Cancer Data System (FCDS) database which is Florida's legislatively mandated,
population-based, statewide cancer registry.¹⁶ population-based, County-level CaP incidence rates are computed as the ratios of the numbers of new CaP cases diagnosed between 2006 and 2010 to the corresponding 2000 US census population of Black men 20 and over years old data (US Census 2000). The 2000 US Census is chosen so that presumed exposures occurred before CaP diagnosis 2006-2010, the study period. The County characteristics that may be associated with CaP incidence were identified from the Florida Department of Health Division of Public Health Statistics & Performance Management (see Table 1). Some of these characteristics are socio-economic indicators (e.g. percentage of unemployed adults, high school graduation), demographic indicators (e.g. percentage of individuals with rural residence), health care resources (e.g. licensed Florida physicians; adults who could not see a doctor at least once in the past year due to cost), environment indicator (e.g. community water supply). We used the most representative data available for these county-level characteristics for the period of 2006-2010.

Characteristics	Mean	SD.	Min	Max
Prostate cancer cases	163.6	347.512	1.0	1963.0
Unemployed for $Yr. 2008$ (%)	6.209	1.332	4.000	10.20
Median income for Yr. 2009				
	43960	7554.062	29640	63630
Number of physicians for Yr. 2008 (per 100,000)	139.7	98.361	12.6	615.2
High school graduate for Yr. 2009 (%)	80.58	8.055	58.60	96.50
Below poverty level for Yr. 2009 (%)	15.48	4.861	7.40	26.40
Two or more servings of fruit for Yr. 2007 (%)	32.49	5.610	18.50	46.10
Current smoker for Yr. 2007 (%)	22.23	4.775	14.20	33.60
Medical checkup for Yr. 2007 (%)	66.87	7.025	47.30	79.80
Overweight for Yr. 2010 (%)	66.89	5.723	54.30	82.00
Community water supply rate for Yr. 2010	2.1890	0.9086	0.5168	5.305
Black population for Yr. 2010 (%)	14.59	9.346	3.10	55.20
Not seek medical due to cost for Yr. 2007 (%)	15.24	6.037	6.20	43.30
Rural resident for Yr. 2010 $(\%)$	42.02	33.762	0.10	100.00

Table 1: Description statistics of county-level characteristics

2.2. Statistical methods

We considered a geographical region divided into G contiguous small areas (e.g., counties) represented as $i = 1, ..., G$. Let Y_i denote observed counts of disease cases (e.g., prostate cancer) and a q-dimensional vector X_i contains county-level covariates with associated parameters β . We assumed that Y_i follows a Poisson distribution with mean μ_i satisfying

$$
\log(\mu_i) = \log(E_i) + \log(\theta_i) \tag{1}
$$

where E_i is the expected number of cases in the ith county, and calculated as $E_i = N_i(\frac{\Sigma Y_i}{\Sigma N_i})$; N_i is number by of individuals at risk of prostate cancer; and θ_i is an unknown county-specific relative risk of prostate cancer and further decomposed as

$$
\log(\theta_i) = \alpha + X_i \beta + \epsilon_i \tag{2}
$$

In Model (2), the county-specific random effects, ϵ_i = $u_i + v_i$, was further decomposed into an unstructured heterogeneity u_i and a spatially structured local random effects v_i to account for the tendency of neighboring counties to have similar relative risks because of sharing common risk factors.**¹⁷** Model (2), the county-specific random effects, $\epsilon_i = 5$ MRs were
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$$

The covariates in (3) were defined in Section 2.1 and Table 1.

The above random-effect Poisson regression models were used to produce smoothed spatial maps of CaP incidence rates by incorporating the associations between incidence and county-level covariates. The relative risk in each county was estimated using a Bayesian approach based on Markov chain Monte Carlo (MCMC) methods which were implemented in WinBUGS software.**¹⁸** WinBUGS has a built-in conditional autoregressive (CAR) distribution for handling spatial autocorrelation. Non-informative prior distributions were used for the unknown parameters of (3), and sensitivity analyses with different prior specifications

were conducted to assess the effect of choices of vague priors.

3. Results

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standardized morbidity ratio of the number of observed cases (expected number of cases (E_i) for each county.

decomposed into an unstructu Based on the FCDS, a total of 10,799 Black men were diagnosed with prostate cancer between 2006 and 2010 in Florida. The map in Figure 1 shows the number of prostate cancer cases per County, with the lowest in Dixie County and highest in Miami-Dade and Broward Counties. There is a strong variation in geographical distributions of these CaP cases. The variation may be due to some counties having low cases, sparse sizes of population of adult Black men, or both. To incorporate the variation in population sizes across counties, we calculated the expected number of CaP cases for each counties as $E_i = N_i(\sum_i^6 Y_i/\sum_i^6 N_i)$. Then, the standardized morbidity ratio (SMR) was computed as the ratio of the number of observed cases (Y_i) to expected number of cases (E_i) for each county. These SMRs were mapped in Figure 2. The changes from observed cases to SMR are most striking in Charlotte and Levy counties, showing that the CaP cases (4 and 21, respectively) in these counties are very small. The spatial pattern variation across the counties suggests that there is local instability in both observed counts and SMR since they do not take into consideration for sampling errors. A solution for filtering the signal from the random noise is to use statistical methods by introducing random effects and county-level covariates to explain such strong heterogeneity across counties.

 $+\beta_{10}$ *Education*_i + 1. The posterior means, standard deviations and 95% $u_i + v_i$ (3) increasing CaP incidence of Black Men in Florida is Random-effect Poisson regression models described in (Ref# 1,3) were fitted to the observed data to get geographical maps of county-specific relative risks of CaP and assess the associations between county-specific relative risks and county-level covariates given in Table credible interval (CI) of the coefficients of the covariates are presented in Table 2. The results show that an significantly associated with increasing unemployment rate (β_2 = 1379 with 95% CI: (.0025, .2703), which does not include zero) and with increasing number of physicians per capita in a county (β_{11} =.00212 with 95% CI: (.00006, .0042) after controlling for other county characteristics. This implies that the more the number of physicians in a county, the higher CaP diagnosed cases due to accessibility to health services. In the case of poverty, however, there is an inverse relationship between CaP incidence and percent of adult individuals who were below poverty level in 2009 in a county. That is, a decreasing CaP incidence of Black Men in Florida is significantly associated with increasing percentage of persons below poverty level (β_3 =-.0583 with 95% CI: (-.1039, -.0132), which confirms findings of other studies.**¹⁹**

Figure 1: Spatial distribution of prostate cancer cases for Black Men in Florida (2006-2010)

Figure 2: Spatial distribution of ratios of observed and expected cases for Black Men in Florida (2006-2010).

Men in Florida (2006-2010).

A byproduct of the random-effect Poisson regression model is the estimated CaP relative risk in each county after adjusting for the effect of county-level characteristics. The posterior median of the smoothed CaP relative risk was mapped in Figure 3 which shows the spatial pattern inherent in the observed cases (see Figure 1). Looking at the map in Figure 3, we observe that there are clustering and hotspots of high CaP incidence rates in Palm Beach county in South Florida,

and Alachua and Marion counties in north Florida. At least 60% of the counties in Florida exhibit disproportional burden of prostate cancer by having more than expected relative risk ($\hat{\theta} > 1$). Thus, further investigation into identifying and understanding underlying causal mechanisms in the communities is paramountly significant for reducing the burden of this disease. Specifically, targeted interventions can also be

easily carried out using the publicly available WinBUGS package.**¹⁸** This makes our approach quite powerful and

There are some limitations to our study. The current study has a spatial dimension only since aggregate data over the 2006-2010 study periods were used but ignores the temporal feature of the observed cases. The reason is that the observed cases are very sparse at county level for each year in the study period and thus not enough data for analyzing temporal trend. For

accessible to practitioners in the field.

designed for those counties with high prostate cancer relative risks.

4. Discussion

In this spatial study, we assessed the link between the geographical variation of CaP incidence for Black men in Florida and potential County-level risk factors. The results show that County- specific CaP relative ratios are higher in counties where there are higher proportion of unemployed, higher number of Florida licensed physician, and lower proportion of persons below poverty level. Although not statistically significant at county level, median income, percentage of overweight, percentage of current smoking status, community water supply per capita, percentage of Blacks, percentage of medical checkup, percentage of persons consuming two or more fruits daily, high school graduation, and percentage of rural residents have positive association with prostate cancer incidence. These findings are also shown in some other studies.**20,21**

After adjusting for County-level characteristics, the smoothed CaP incidence for Black men was used to identify Counties with higher or lower than expected ratios (see Figure 3) if every County is equally likely to have CaP cases. Accordingly, some Counties in northeast, central and south Florida tend to have higher CaP incidence than expected. These findings suggest that more detailed study of CaP incidence in Counties with higher concentration of cases is warranted. In addition, looking into variation within the black ethnicity such as US-born, Caribbean-born and Africa-born may throw light on endogenous and exogenous health determinants, which are unique to each subgroup.

It is noted that, as in any ecological study, caution needs to be taken when interpreting ecological analysis results.**²²** This is because associations assessed between risk factors and CaP incidence at a county level may not necessarily imply that the risk factors are associated with an individual's chance of having CaP. Unmeasured confounders (e.g., prostate-specific antigen (PSA) or digital rectal exam (DRE) screening) are potential sources of discrepancies between results of county level and individual level analysis.**23,24** Thus, the goal of this article is to investigate risk factors that may contribute to the geographic pattern of CaP incidence of Black men within Florida using a Bayesian approach.

The Bayesian method was chosen since it is flexible to incorporate a spatially structured variation via a conditional autoregressive function, accounting for spatial dependence of adjacent neighbors, and heterogeneity.**25,26** The Bayesian method uses MCMC to estimate the parameters of the Poisson random effects model based on non-informative prior distributions for coefficients of covariates, spatial and heterogeneity parameters. Furthermore, the estimation process can be

example, 14 out of the 67 counties have less or equal to

10 cases aggregated over the 5 year period. The county-level covariates chosen for the analysis are limited by the availability of data on important protective and risk factors for CaP. Other measures of environmental exposure, diet intake, socio-economic and demographic characteristics of the 67 counties should be considered in future analysis.

5. Conclusion

This study shows that county-level indicators of socioeconomic background and health care services such as number of physicians explain spatial heterogeneity of prostate cancer incidence rates. Better understanding of such risk factors and identifying specific counties with a disproportionate burden of CaP disease may help formulate targeted interventions and resource allocation by state and local public officials. In future, given availability of data, further analysis focusing on geographic variation of treatment modality and mortality will be useful.

Conflict of interest

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