SUPPLEMENTARY MATERIAL FOR:

Spatial epidemiology of diabetes: Methods and insights

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Diabetes disease mapping

We included countries that reported DM questions and collected corresponding geographic coordinates for each primary sample unit (PSU) for spatial analyses. This selection criteria yielded the inclusion of nine countries (Albania, Benin, India, Kenya, Lesotho, Senegal, Timor-Leste, Tajikistan, and Zambia). Table S1 shows the detailed information for each country including survey year, number of males and females, ages for males and females, number of survey locations, and DM questions. The DHS included a DM self-reported status (e.g. "has a doctor or other health professional ever told you that you had diabetes?). The answer to these questions ranged from "yes", "no", and "do not know". We excluded participants who answered the DM question different from "yes" or "no". The final analytical samples for each country were: Albania (21,142 individuals in 715 PSUs), Benin (11,363 individuals in 555 PSUs), India(799,811 individuals in 28,518 PSUs), Kenya (27,539 individuals in 1,594 PSUs), Lesotho (8,473 individuals in 399 PSUs), Senegal (20,617 individuals in 391 PSUs), Timor-Leste (4,264 individuals in 455 PSUs), Tajikistan (10,718 individuals in 366 PSUs), and Zambia (13,683 individuals in 545 PSUs).

DM prevalence at each PSU was calculated as the number of positive cases divided by the total number of participants with "yes" or "no" responses at each PSU. We employed a kernel smoothing method to generate a continuous kernel density surface to illustrate the local spatial variations of DM prevalence for each country (Figure 2). Note that the kernel density maps for Tajikistan and Zambia represent DM prevalence for females only.

Supplementary Table 1 Summary of demographic and health survey data

Country	Year	Sample Size		Sample age		# of Sample locations question	Diabetes
		Female	Male	Female	Male		
Albania	2017-18	15000	6142	15-59	15-59	715	Type of chronic illness: Diabetes (0--no; 1--yes)
Benin	2017-18	15,928	7,595	15-49	15-64	555	Ever told by health professional that has high blood sugar or diabetes
India	2015-16	699,686	112,122	15-49	15-54	28526	Currently has diabetes
Kenya	2014	31,079	12,819	15-49	15-54	1594	Blood sugar or diabetes?
Lesotho	2014	6621	2931	15-49	15-54	381	diagnosed as diabetes
Senegal	2010-2011	15688	4929	15-49	15-59	392	Suffering from: diabetes
Timor-Leste	2016	12607	4622	15-49	15-59	455	Ever diagnosed with high blood sugar or diabetes by doctor or nurse

Tajikistan	2017	10,718	0	15-49	-	366	Ever told that has high blood sugar or diabetes by health worker
Zambia	2018-19	13683	12132	15-49	15-59	545	Ever told by doctor or health worker that have raised blood sugar or diabetes (only females)

Note: Tajikistan did not include male respondents in the 2017 DHS. Zambia DHS had asked diabetes questions for females only.

Spatial methods for the study of diabetes distribution

The remarkable rise in prevalence of DM across the world has posed a severe threat to public health [1]. There are growing interests to employ several spatial analysis methods to investigate spatial variations of DM prevalence in the last two decades.

In this section we present a series of studies using different spatial methods to study the spatial structure of DM. First, many studies have implemented spatial clustering techniques like *Local Moran's I*, *Getis-Ord Gi** statistics to identify geographical hotspots of DM prevalence in west Adelaide, Australia[2-4], in India [5, 6], in Nigeria [7], and in the city of Oslo, Norway [8]. Some studies have employed *spatial statistic scan* techniques to detect the spatial clusters of DM prevalence in India [9], and in the city of Winnipeg, Canada [10]. These studies have found that the spatial heterogeneity of DM prevalence was present across various local areas or regions. Second, some other studies have employed *geographically weighted regression* to examine spatial heterogeneity in the associations between DM prevalence and social and environmental risk factors in the U.S. [11-13], and in Netherlands [14]. In addition, [15]implimented a *spatial regression model* to examine the relationships between prevalence of diagonosed hypertension and DM and social determinants of health including poverty, minority status, food access, walkability, foreclosure risk, and crime. [16] used ordinary least square and *spatial autoregressive models* to explore the spatial variations of DM prevalence for women aged 35-49 years across 640 districts in India. Third, some studies have implemented *multilevel models with random slope* to investigate the geographic variations of DM prevalence in Netherlands [17], in China [18, 19], and in France [20, 21]. Fourth, a growing number of studies aggregated DM data to small-area level (i.e. census tracts, statistical areas) and investigated the associations between DM prevalence and environmental and sociodemographic risk factors [22-28].

Several studies have implemented multilevel analyses with Bayesian model approaches to analyze spatio-temporal distributions of the prevalence of DM [29-32]. Likewise, some studies used regression-based β-convergence approach accounting for spatial autocorrelation to examine the spatio-temporal changes in county-level diagnosed DM prevalence/incidence among U.S. adults during 2004-2009 [33] and during 2004-2012 [34]. [35] conducted sparse Poisson convolution and sparse Poisson MCAR models to investigate the spatial variations of DM incidences in young in US.

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