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Modelling geographical heterogeneity of diabetes prevalence and socio-economic and built environment determinants in Saudi City - Jeddah

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Abstract

Type-2 diabetes is a growing lifestyle disease mainly due to increasing physical inactivity but also associated with various other variables. In Saudi Arabia, around 58.5% of the population is deemed to be physically inactive. Against this background, this study attempts explore the spatial heterogeneity of Type-2 diabetes prevalence in Jeddah and to estimate various socio-economic and built environment variables contributing to the prevalence of this disease based on modelling by ordinary least squares (OLS), weighted regression (GWR) and multi-scale geographically weighted (MGWR). Our OLS results suggest that income, population density, commercial land use and Saudi population characteristics are statistically significant for Type-2 diabetes prevalence. However, by the GWR model, income, commercial land use and Saudi population characteristics were significantly positive while population density was significantly negative in this model for 70.6%, 9.1%, 26.6% and 58.7%, respectively, out of 109 districts investigated; by the MGWR model, the corresponding results were 100%, 22%, 100% and 100% of the districts. With the given data, the corrected Akaike information criterion (AICc), the adjusted R^2, the log-likelihood and the residual sum of squares (RSS) indices demonstrated that the MGWR model outperformed the GWR and OLS models explaining 29% more variance than the OLS model, and 10.2% more than the GWR model. These results support the development of evidence-based policies for the spatial allocation of health associated resources for the control of Type-2 diabetes in Jeddah and other cities in the Arabian Gulf.

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Key words: Geographically weighted regression model; multi-scale geographically weighted regression model; Type-2 diabetes prevalence; Jeddah; Saudi Arabia.

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Introduction

Urban health is a common subject of interdisciplinary research (Martynenko, 2021) and it is frequently focused on the research of lifestyle diseases (Pinter-Wollman *et al*., 2018). Earlier scholars have documented that the urban built environment shapes the health conditions of urban residents by influencing human behaviour in various ways including physical activities (Sridhar *et al*., 2010; Wang *et al*., 2019). Physical inactivity is one of the biggest public health challenges of our time because of the magnitude of its associated health risks (Kohl *et al*., 2012). There is robust evidence that lack of physical activity causes many noncommunicable diseases including Type-2 diabetes, coronary heart disease, breast, and colon cancers (Lee *et al*., 2012). In fact, this disease can be described as a global pandemic that has become acute in several developed and developing countries (Susan van *et al*., 2010; Colagiuri, 2010; Hu *et al.*, 2015). Importantly, while Type-2 diabetes is mainly an outcome of lifestyle (Temelkova-Kurktschiev and Stefanov, 2012), Type-1 diabetes is a genetic disorder (Atkinson *et al*., 2014).

According to the World Health Organisation (WHO), Saudi Arabia ranks the seventh highest for high Type-2 diabetes prevalence world-wide, and second highest in the Middle East (Dawish *et al*., 2016). In 2016, around 14.4% of Saudi Arabia's population had diabetes, many of whom with risk factors, such as overweight (68.2%), obesity (33.7%) and physical inactivity (58.5%), which are associated with Type-2 diabetes (WHO, 2016). Studies have confirmed that both lifestyle, including physical movement and food habits on the one hand and genetic factors on the other, contribute to the higher prevalence of diabetes in Saudi Arabia (Elhadd *et al*., 2007; Gazzaz, 2020).

Increased physical activity is one of the key interventions to prevent Type-2 diabetes (Aguiar *et al*., 2014). Such interventions could be facilitated by the adequate provision of connected pedestrian walkways (Wilson *et al*., 2014; Glazier *et al*., 2014) together with provision of green infrastructure and community gardens (Pasala *et al*., 2010; Ngom *et al*., 2016). Other vital factors related to the prevalence of Type-2 diabetes also include the prevailing mix of land use, the proportion of commercial areas in the neighbourhood, income, population density, population ethnicity and the proportion of the population above 65 years of age (Gariepy *et al*., 2015).

Earlier, several interdisciplinary studies confirm that the prevalence of Type-2 diabetes is associated with several socio-economic and built environment factors (Mangla *et al*., 2020; Mandic *et al*., 2020). However, there is lack of studies on spatial heterogeneity of Type-2 diabetes at the local level, particularly in Saudi cities (Quiñones *et al*., 2021). Geographical or spatial heterogeneity could be defined as the dissimilarity in space in the distribution of a point pattern, or the deviation of a qualitative or quantitative value of a surface pattern (Arnaldo and Torres, 2005). Earlier studies have confirmed that geographically weighted regression (GWR) and multi-scale geographically weighted regression (MGWR) models are useful in the study of geographical variability of diseases and in finding how local patterns shape public health policies (Tu *et al*., 2012; Oshan *et al*., 2020). Given the enormity of Type-2 diabetes in Saudi Arabian cities, this study has the following objectives: i) to explore the spatial heterogeneity of type-2 diabetes prevalence in Jeddah; ii) to estimate the variables contributing to Type-2 diabetes prevalence in Jeddah through various socio-economic and built environment variables using global or ordinary least squares (OLS) and local and MGWR) models.

Literature review

Geographically weighted regression in epidemiological studies

Over the past two or so decades, GWR has been repeatedly used to examine geographical variability and contributory variables resulting into health-related outcomes and associated risk factors. Chan *et al*. (2014) traced geographically disparities in obstructive pulmonary disease mortality rates in Taiwan, while Goovaerts *et al*. (2015) found that GWR can detect local patterns of late-stage prostate cancer, and Jiang *et al*. (2018) concluded that spatially varying social development formed distinct geographical clusters of life expectancy in China. In the United States (U.S.), Tu and Tu (2018) applied GWLR to investigate the spatial relationship between preterm birth and air pollution in Georgia, USA and Tabb *et al*. (2020) used GWR to explore the spatial variability in cardiovascular health among the black and white population.

A recent study established that global and local GWR models can effectively model socio-economic determinants, coverage, accessibility and geographical variability of vulnerability with respect to heart ischemic diseases (Dutra *et al*., 2021).

Built environment components and geographically weighted regression

Our review of the literature reveals that only few studies have explored and modelled the relationship between the built environment and human behaviour using GWR. For instance, a recent study in Jeddah used geographically weighted Poisson regression (GWPR) to divulge spatial heterogeneity of pedestrian fatalities through existing transportation infrastructure (Aljoufie and Tiwari, 2021), while a similar study reported a positive association between pedestrian safety and the quality of bus stop access in Delhi by GWPR models (Lakhotia *et al*., 2020). Additionally, Torun *et al*. (2020) demonstrated a GWR model based on sociodemographics parameters estimating children's recreation/transportation through walking through urban constructions in Istanbul, Turkey. Another study observed that excessive use of private car in constrained geographical areas, such as a university campus, might lead to spatial clustering of high concentrations of small particulate matter (PM2.5) in the ambient air, potentially resulting in higher risk of respiratory and cognitive diseases (Tiwari and Aljoufie, 2021).

Materials and methods

Study area

Jeddah, the second largest city of the Kingdom of Saudi Arabia and the largest city in Hejaz Region and Makkah Province, comprised the study area. Called the pearl of the Red Sea, the city serves as a gateway for the holy cities of Makkah and Medina that are visited by millions of Muslim pilgrims every year. Jeddah is well connected to the world and to other cities of the kingdom by King Abdulaziz International Airport, Jeddah Islamic Port, Al-Haramin Railway, Al-Haramin Express way and many smaller roads. The city is divided into 110 administrative districts covering a geographical area of 1600 km^2 with a population of 4.6 million (Aljoufie and Tiwari, 2015a).

Data

This study examined Type-2 diabetes cases sampled from the primary health centres of Jeddah. We obtained data on the prevalence rate of Type-2 diabetes (dependent variable) from the Ministry of Health (MOH) office in Jeddah for the year 2018-2019.

We used previous studies to select independent variables proven to be associated with Type-2 diabetes prevalence and decided to include as variables commercial land use, population density, Saudi population characteristics and income. We used Google Map data to estimate green areas, walkways and commercial areas in each district. For population data, we obtained information from the General Authority of Statistics database for the year 2015 on local population, the proportion of those above 65 years of age and median income (Table 1).

Methods

The ordinary least square model

The ordinary least square (OLS), known as the global regression model, is a well-known inferential statistical technique used to estimate a dependent variable on other independent parameters. The basic assumption of the OLS model is that variables have a stationary and constant association over space. However, this assumption may not hold in case of spatial additional effects, *e.g*., those due to the geography (Hutcheson, 1999). This is the reason why the results of OLS models are usually compared with the results of local models (GWR and MGWR) that permit drawing conclusions based also on local spatial inferences (Tiwari and Aljoufie, 2021).

The OLS model could be expressed as:

$$y_i = \beta_0 + b_1x_1 + b_2x_2 + e \quad (1)$$

where y_i is the dependent variable (the prevalence rate of Type-2 diabetes in our case) at the i^{th} location; β_0 the estimated intercept; b_1 the estimator for x_1 ; x_n denotes the set of independent variables; and e the error term.

Multicollinearity indicates that independent variables in a given dataset is correlated which might lead to less reliable results, so it is crucial to find any sort of this problem in the given dataset before modelling. It is reflected by the variance inflation factor (VIF) (Mansfield and Helms, 1982) and, as a rule of thumb, VIF values higher than 10 indicate multicollinearity; however, to be sure, some authors use a cut-off as low as 2.5 (Salmerón *et al.*, 2018). After computing the VIF for all the independent variables, we observed acceptable multicollinearity for the regression models at scores less than 2 (Table 2).

Geographically weighted regression

GWR is a regression model technique for spatial analysis that considers non-stationary estimators that permits modelling the associations between these parameters and a dependent outcome of concern at the local level (Brunsdon *et al.*,1998; Wheeler and Páez, 2010).

A conventional GWR equation is:

$$y_i = \beta_0\,(u_i,v_i) + \textstyle\sum_j \beta_j\,(u_i,v_i)\,x_{ij} + \varepsilon_i \quad (2)$$

where $\beta_0\,(u_i,v_i)$ is the intercept; x_{ij} the j^{th} predictor variable; $\beta_j\,(u_i,v_i)\,x_{ij}$ the j^{th} coefficient; ε_i the error term; and y_i the response variable.

Multi-scale geographically weighted regression

MGWR is a modified form of GWR (Fotheringham *et al.*, 2017) where the assumption of scale, *i.e.* that all the parameters modelled operate at the same geographical scale, is relaxed (Oshan *et al.*, 2019).

MGWR equation is expressed as:

$$y_i = \beta_0\,(u_i,v_i) + \textstyle\sum_j \beta_{bwj}\,(u_i,v_i)\,x_{ij} + \varepsilon_i \quad (3)$$

where β_{bwj} denotes the bandwidth applied for calibrating the j^{th} conditional relationship; the other terms are same as mentioned in Equation 2 above.

The t-scores are generally used in regression tests and t-tests and denotes the distance of an observation from its mean when the given dataset follows a t-distribution (Lamotte, 1994).

MGWR 2.2 software (https://sgsup.asu.edu/sparc/multiscale-gwr) was used to obtain and calibrate the OLS, GWR and MGWR models. It is worth mentioning that OLS is a generic approach that estimates the relationship between one or more quantitative independent variables and a dependent variable through coefficients and liner regression equations (Lewis-Beck *et al.*, 2003).However, the OLS approach does not provide information related to the varying relationship between independent and dependent variables over space. As a solution, a technique that permits the estimation of varying parameter estimates over space, *i.e.* GWR, was developed (Rogerson, 2009). Again, the MGWR technique is a modified version of GWR, where the difference is that GWR calibrates the regression model at the same spatial scale while MGWR uses different spatial scales. The GWR and MGWR models provide additional spatial-weighted information about the relationship between independent and dependent variables. We used GWR and MGWR in this study because of our interest in understating spatial hetero-

Table 1. Data sources.

Data	Unit	Year
Type-2 diabetes prevalence rate	Cases registered by district per 10,000 population	2018-2019*
Median income	District level median income (Saudi riyals)	2015*
Population density	District level population density	2015*
Walkways	Used as dummy variable; 1=Available; 0=Not available	2021
Commercial land use	Proportion of commercial land use at the district level	2021
Green areas	Proportion of green areas at the district level	2021
65+ population	Proportion of the 65+ population at the district level	2015*
Saudi population	Proportion of the Saudi population at the district level	2015*

*Adjusted for the year 2021 based on sample registrations.

Table 2. The variable variance inflation factors.

Type	Variable	VIF
Dependent variable	Diabetes prevalence rate	-
	Income	1.79
Independent variables	Population density	1.2
	Walkways	1.23
	Commercial land use	1.09
	Green areas	1.33
	65+ population	1.01
	Saudi population	1.39

VIF, variance inflation factor.

geneity of Type-2 diabetes cases in Jeddah and their relationship with the selected independent variable.

Method comparison

To compare the performance of three proposed models (OLS, GWR and MGWR), we used the corrected Akaike information criterion (AICc), the adjusted R^2, the log-likelihood and the residual sum of squares (RSS).

The AICc is an indicator of estimation error during the modelling process (Hurvich and Tsai, 1993; Tiwari and Aljoufie, 2021), where a lower value for a given dataset prompts for a better model fit, while the adjusted R^2 modifies the outcome according to the number of estimators in the model (Miles, 2005; Gelman *et al.*, 2019) and evaluates the explanatory power of linear regression models with higher values indicating a better performing model. The log-likelihood is a measure of model fit that tells you how suitable a parameter is in explaining observed values (Ishiguro *et al.*, 1997), where higher values suggest better model suitability, and RSS measures the amount of variance in a given dataset that remains unexplained by the regression model (Morgan and Tatar, 1972). Thus, a lower RSS value shows a better performing model.

Results

Comparing the performance of OLS, GWR and MGWR (Tables 3 and 4) shows that the lowest AICc value was reached by the MGWR model and the highest by OLS model, while the OLS model had the highest.

Overall, the outcome demonstrates that the quality of MGWR model is better than GWR model, while the GWR model is better than OLS one. Thus, the comparison supports the choice of the MGWR and GWR techniques over the traditional OLS approach.

In the global regression model (OLS), four parameters (income, population density, commercial land use and the proportion of Saudi population stand out ($P=<0.05$); however, the effect of providing walkways and green spaces and the proportion of the 65+ aged population was not significant ($P>0.05$).

Income was found to be positively significant at the global level. At the local level, the GWR model indicated positive significance for 70.6% of the districts, which are mostly clustered in the northern part of Jeddah city. The MGWR model showed positive significance for all districts (t-score ≥1.96) (Figure 1).

Also, Saudi population variable was significant in the 26.6% districts with positive sign that are clustered at the central part of Jeddah, and population density in 58.7% districts with negative sign that are clustered in northern, central, southern, and eastern part of the city (Figures 1-4).

Population density was found to be negatively significant at the global level and also for 58.7% districts by the GWR model and all districts by the MGWR model (t-score≥1.96) at the local level (Figure 2). This negative association seems logical as residents in low-density areas need to drive more distances everyday which reduces their physical activities, thus contributing to the prevalence of type-2 diabetes.

The proportion of commercial land use turned also out to be positively significant at the global level; locally by the GWR model it was significant for 9.17% districts clustered near the old city, some parts of northern Jeddah and a district at the eastern periphery. The MGWR model showed positive significance for all districts (t-score≥1.96) (Figure 3).

Table 3. General model comparison.

Criterion	OLS model	GWR model	MGWR model
AICc	253.494	242.944	238.153
Adjusted R2	0.477	0.566	0.624
Log-likelihood	–120.335	–102.347	–101.383
RSS	58.059	41.737	41.006

OLS, ordinary least squares; GWR, geographically weighted regression; MGWR, multi-scale GWR.

Table 4. Performance of the models investigated.

Variable	OLS (global model) Est.	SE	t(Est./SE)	P-value	GWR (local model) t-score	MGWR (local model) t-score
Intercept	0	0.072	0	1		
Income	0.572	0.075	7.633	0	>1.96 for 70.6% dist.	>1.96 for 100% dist.
Population density	–0.25	0.091	–2.748	0.006	≤1.96 for 58.7% dist.	≤11.96 for 100% dist.
Walkways	–0.075	0.077	–0.974	0.585	Not significant	Not significant
Commercial land use	0.185	0.084	2.205	0.027	>1.96 for 9.17% dist.	>1.96 for 22.0% dist.
Green spaces	–0.081	0.074	–1.087	0.277	Not significant	Not significant
65+ population	–0.036	0.071	–0.51	0.61	Not significant	Not significant
Saudi population	0.149	0.082	1.813	0.04	>1.96 for 26.6% dist.	>1.96 for 100% dist.

OLS, ordinary least squares; GWR, geographically weighted regression; MGWR, multi-scale GWR; Est, parameter estimates; dist, districts; SE, standard error; t, t test.

The percentage of Saudi population was also found to be positively significant at the global level. At the local level it is significant for 26.6% districts by the GWR model and all districts by the MGWR model (t-score≥1.96) (Figure 4). This relationship is obvious as the lifestyle of the Saudi population is comparatively more comfortable than that of the expatriate population.

A thorough comparison of the three models shows that MGWR outperformed among all, whereas GWR model performed better than its classical OLS counterpart (Table 2). Figure 5 demonstrates the distribution of beta coefficients in the local model for Jeddah which confirms the spatial variability in the fit of predictor variables for four of the variables (income, population density, commercial land use and the Saudi population). Moreover, GWR model explained 18.6% more variance than GWR model while MGWR explained 10.2% more variance than GWR model. In brief, among local models MGWR model performed better than GWR model, and GWR model performed better than global OLS model based on AICc, Adjusted R2, Log-likelihood, and RSS values.

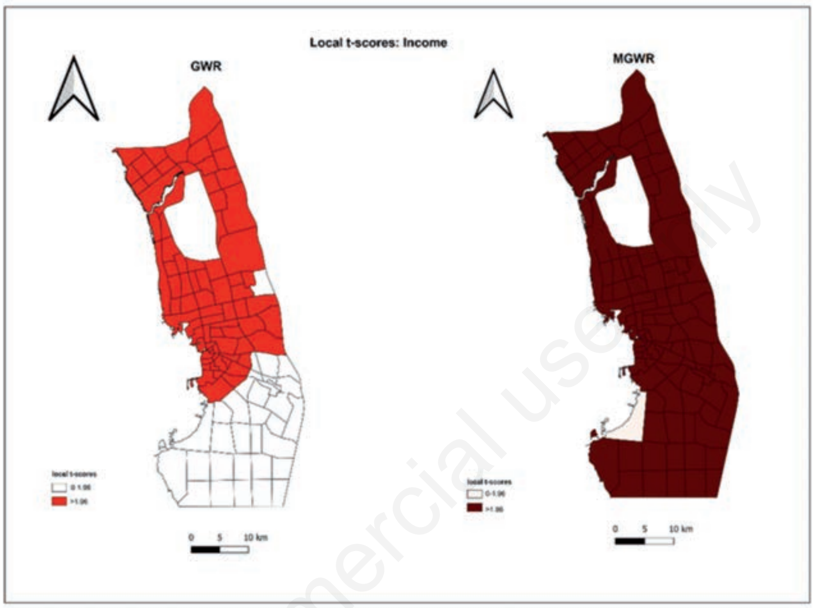

Figure 1. Local t-score for the variable income modelled by geographically weighted regression (GWR) and multi-scale GWR (MGWR).

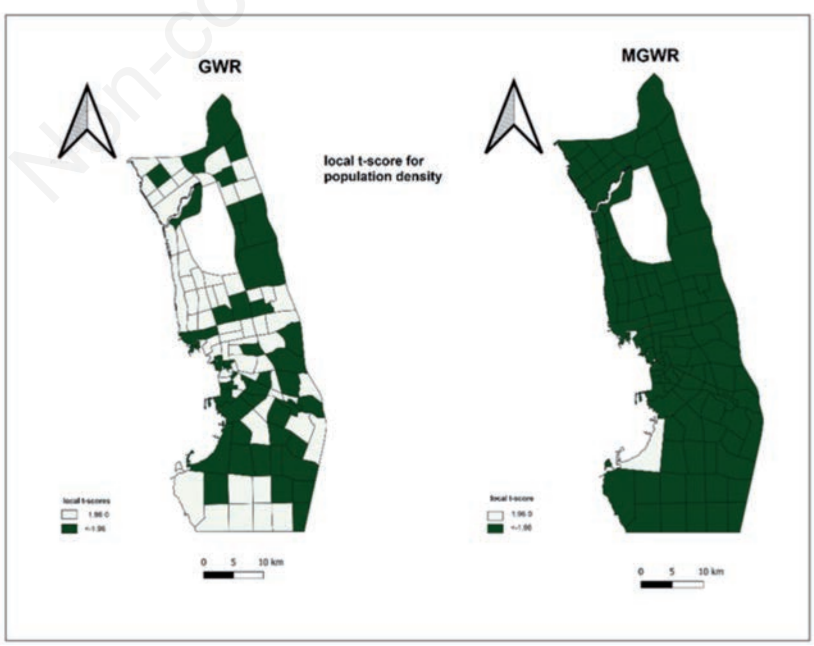

Figure 2. Local t-score for the variable population density modelled by geographically weighted regression (GWR) and multi-scale GWR (MGWR).

Discussion

Type-2 diabetes is considered a lifestyle disease, the prevalence of which is comparatively high in Saudi Arabia. The problem of physical inactivity and obesity is common in Saudi cities and this study explored the spatial heterogeneity of this and other linked estimators in Jeddah through the application of OLS, GWR and MGWR models (Figure 5). The global model (OLS) suggests that income, population density, commercial land uses, and the characteristics of the Saudi population are significantly associated with Type-2 diabetes prevalence and this is shown to be supported by the two local models GWR and MGWR. This relationship is not surprising, as many earlier studies found Type-2 diabetes prevalence associated with income levels.

Built environment features, such as the availability of adequate green areas and pedestrian walkways, encourage physical activities among residents that works as an effective intervention for Type-2 diabetes management (Aguiar *et al*., 2014; Wilson *et al*., 2014; Glazier *et al*., 2014). However, green areas were not found to be significant in all of our models since the per capita availability of green areas in Jeddah is low (Aljoufie and Tiwari, 2015b). Also, most of the districts in Jeddah do not have walkways that would facilitate physical activity and promote change of lifestyle.

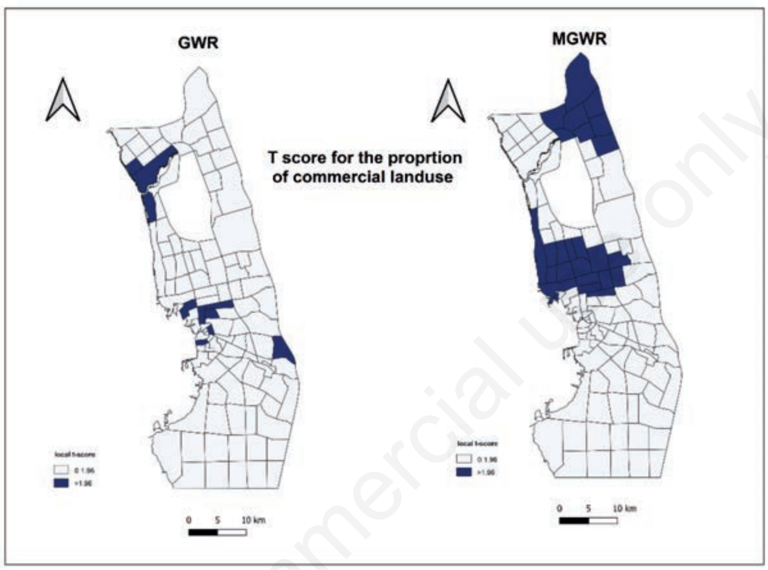

Figure 3. Local t-score for the variable proportion of commercial land use modelled by geographically weighted regression (GWR) and multi-scale GWR (MGWR).

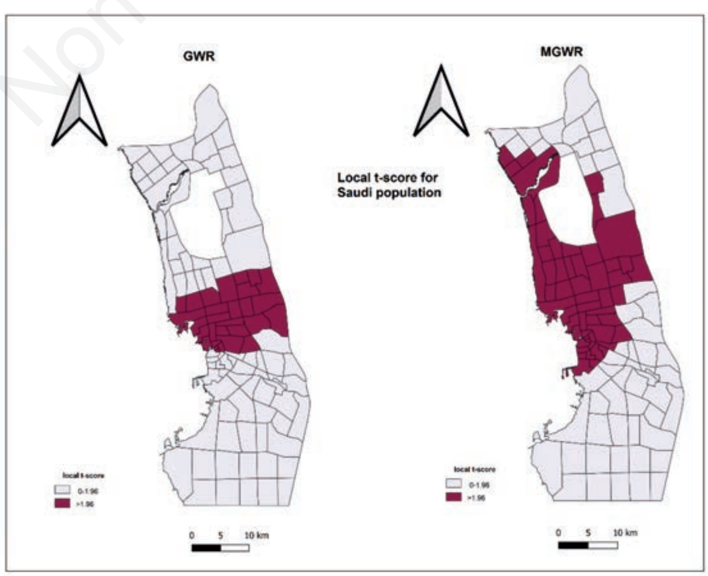

Figure 4. Local t-score for the variable Saudi population modelled by geographically weighted regression (GWR) and multi-scale GWR (MGWR).

This study also investigated some socio-economic determinants for the spatial heterogeneity of Type-2 diabetes prevalence rates in Jeddah. With respect to income, our findings reinforce the results of Hipp and Chalise (2015) who found this variable to be a major determinant for the prevalence of Type-2 diabetes. On the other hand, while a Korean study linked the population above 65 years of age with Type-2 diabetes incidence (Seo and Lee, 2016), this variable was found to be insignificant in Jeddah according to our study.

The diversity of land use is a determining factor for Type-2 diabetes control; for example a good mix of commercial land use promotes walkability (Glazier *et al*., 2014). However, a negative association was discovered between commercial land use and the prevalence of Type-2 diabetes. Although seemingly counter-intuitive, this association is logical as access to most of the commercial areas in Jeddah is car-dependent unlike many cities in Europe where commercial areas are comparatively more inclined for pedestrian use. In fact, the majority of commercial establishments in Jeddah are accessible by car and this hampers walkability (Aljoufie and Tiwari, 2020).

In contrast to Hipp and Chalise (2015), who reported population density as a non-significant predictor in a nation-wide study in the U.S., we found this variable to be significantly linked to the prevalence of Type-2 diabetes. It can happen for two reasons, the first is that there is a difference in the geographical scale of the two studies. The earlier study is at the national scale while the later at a city scale. Secondly, we have experienced that most of the walkways that facilitates walkability are built in medium density districts rather in high density districts. However, further research is recommended on this issue.

In accordance with earlier studies that have confirmed a high prevalence of Type-2 diabetes among Saudis because of an inclination for a physically less active lifestyle, food habits and genetic proclivity (Elhadd *et al*., 2007; Gazzaz, 2020), we noted that the Saudi population is significantly linked with the presence of Type-2 diabetes.

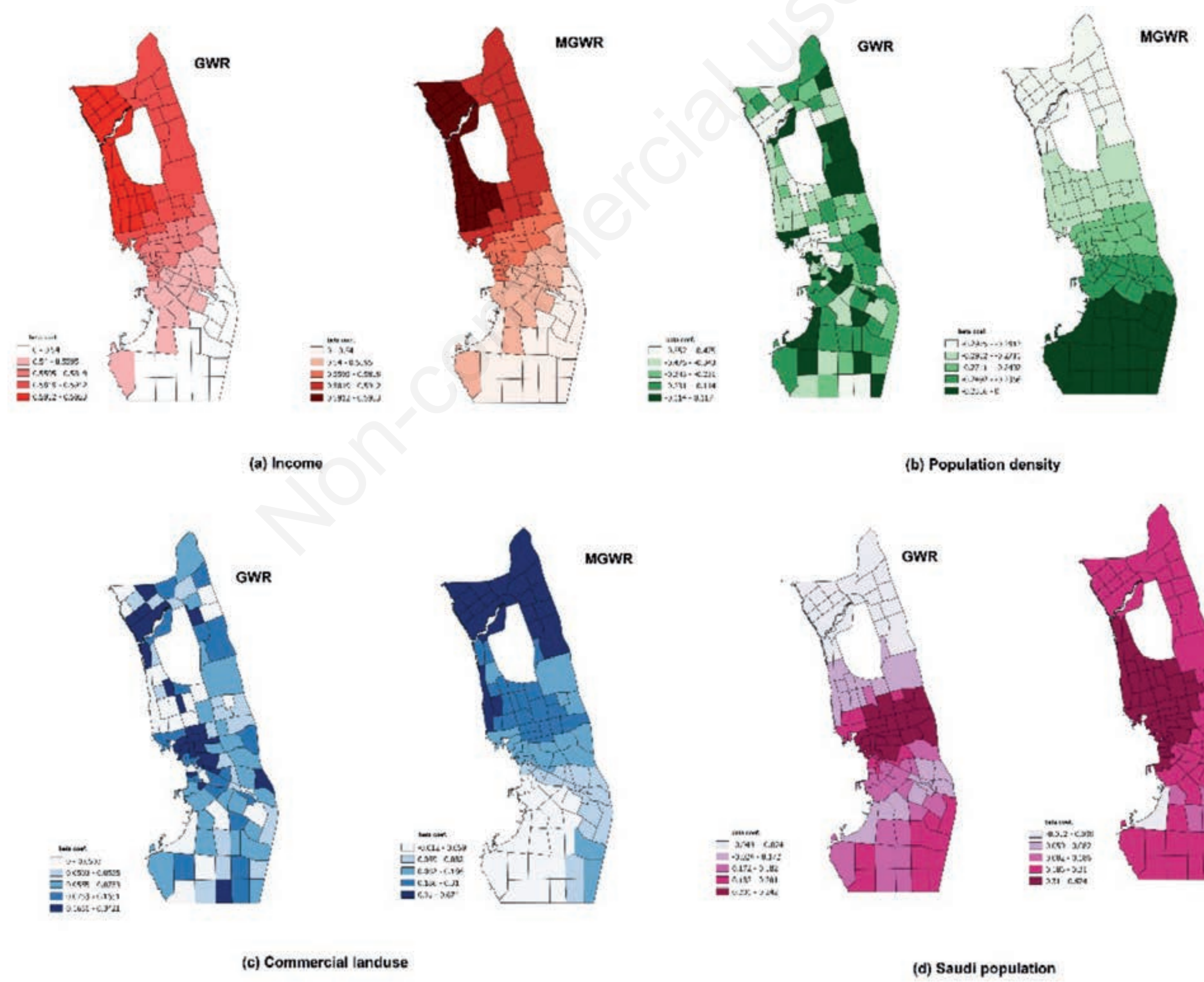

Figure 5. Beta coefficient for the significant variables modelled by geographically weighted regression (GWR) and multi-scale GWR (MGWR).

Conclusions

Our work shows that the GWR and MGWR models provide strong estimations at the local level in Jeddah, where the latter model offers additional inferences due to the multiple geographical scales used in model calibration. Our study is important because it permits an evidence base for the spatial allocation and optimization of resources aimed at Type-2 diabetes control in the city. Results of this study can be used to design evidence-based policies on the spatial allocation and optimization of resources to control Type-2 diabetes in Jeddah and other cities in the Arabian Gulf.

References

Aguiar EJ, Morgan PJ, Collins CE, Plotnikoff RC, Callister R, 2014. Efficacy of interventions that include diet, aerobic and resistance training components for Type 2 diabetes prevention: a systematic review with meta-analysis. Int J Behav Nutr Phys Act 11:2.

Aljoufie M, Tiwari A, 2015a. Climate change adaptions for urban water infrastructure in Jeddah, Kingdom of Saudi Arabia. J Sustain Dev 8:3.

Aljoufie M, Tiwari A, 2015b. Valuing 'green infrastructure' in Jeddah: a city lost in 'grey' infrastructure. J Archit Urban 39:248-59.

Aljoufie M, Tiwari A, 2020. Exploring housing and transportation affordability in Jeddah. Hous Policy Debate, October 1-27. Available from: https://doi.org/10.1080/10511482.2020. 1815070

Aljoufie M, Tiwari A, 2021. Modeling road safety in car-dependent cities: case of Jeddah City, Saudi Arabia. Sustainability 13:1816.

Arnaldo PS, Torres LM, 2005. Spatial distribution and sampling of Thaumetopoea pityocampa (Den. & Schiff.) (Lep. thaumetopoeidea) populations on Pinus pinaster Ait. in Montesinho, N. Portugal. For Ecol Manag 210:1-7.

Atkinson MA, Eisenbarth GS, Michels AW, 2014. Type 1 diabetes. Lancet 383:69-82.

Brunsdon C, Fotheringham S, Charlton M, 1998. Geographically weighted regression. J Roy Stat Soc D-Sta J 47:431-43.

Dutra AC, Silva LL, Pedroso RB, Tchuisseu YP, da Silva MT, Bergamini M, Scheidt JFSC, 2021. The impact of socioeconomic factors, coverage and access to health on heart ischemic disease mortality in a Brazilian Southern state: a geospatial analysis. Global Heart 16:770.

Chan TC, Chiang P, Su M, Wang H, Liu MS, 2014. Geographic disparity in chronic obstructive pulmonary disease (COPD) mortality rates among the Taiwan population. PLoS One 9:e98170.

Colagiuri R, 2010. Diabetes: a pandemic, a development issue or both? Expert Rev Cardiovasc Ther 8: 305-9.

Dawish MAA, Robert AA, Braham R, Hayek AAA, Saeed AA, Ahmed RA, Sabaan FSA, 2016. Diabetes mellitus in Saudi Arabia: a review of the recent literature. Curr Diabetes Rev 12:359-68.

Dieren SV, Beulens JWJ, Schouw YTVD, Grobbee DE, Nealb B, 2010. The global burden of diabetes and its complications: an emerging pandemic. Eur J Prev Cardiol 17:s3-8.

Elhadd TA, Al-Amoudi AA, Alzahrani SA, 2007. Epidemiology, clinical and complications profile of diabetes in Saudi Arabia: a review. Ann Saudi Med 27:241-50.

Fotheringham AS, Yang W, Kang W, 2017. Multiscale geographically weighted regression (MGWR). Ann Assoc Am Geogr 107:1247-65.

Gariepy G, Kaufman JS, Blair A, Kestens Y, Schmitz N, 2015. Place and health in diabetes: the neighbourhood environment and risk of depression in adults with Type 2 diabetes. Diabet Med 32:944–50.

Gazzaz ZJ, 2020. Knowledge, attitudes, and practices regarding diabetes mellitus among university students in Jeddah, Saudi Arabia. Diabetes Metab Syndr Obes Targets Ther 13:5071-78.

Gelman A, Goodrich B, Gabry J, Vehtari A, 2019. R-Squared for Bayesian regression models. Am Stat 73:307-9.

Glazier RH, Creatore MI, Weyman JT, Fazli G, Matheson FI, Gozdyra P, Moineddin R, Kaufman-Shriqui V, Booth GL, 2014. Density, destinations or both? a comparison of measures of walkability in relation to transportation behaviors, obesity and diabetes in Toronto, Canada. PLoS One 9:e85295.

Goovaerts P, Xiao H, Adunlin G, Ali A, Tan F, Gwede CK, Huang Y, 2015. Geographically-weighted regression analysis of percentage of late-stage prostate cancer diagnosis in Florida. Appl Geogr 62:191-200.

Hipp JA, Chalise N, 2015. Spatial analysis and correlates of county-level diabetes prevalence, 2009-2010. Prev Chronic Dis 12:140404.

Hu FB, Satija A, Manson JE, 2015. Curbing the diabetes pandemic. JAMA 313:2319.

Hurvich CM , Tsai CL, 1993. A corrected Akaike information criterion for vector autoregressive model selection. J Time Ser Anal 14:271-9.

Hutcheson GD, 1999. Ordinary least-squares regression. The Multivariate Social Scientist. SAGE Publ., London, UK, pp. 56-113.

Ishiguro M, Sakamoto Y, Kitagawa G, 1997. Bootstrapping log likelihood and EIC, an extension of AIC. Ann Inst Stat Math 49:411-34.

Jiang J, Luo L, Xu P, Wang P, 2018. How does social development influence life expectancy? a geographically weighted regression analysis in China. Public Health 163:95-104.

Jo EK, Seo EW, Lee KS, 2016. Spatial distribution of diabetes prevalence rates and its relationship with the regional characteristics. Health Policy Manag 26:30-8.

Kohl HW, Craig CL, Lambert EV, Inoue S, Alkandari JR, Leetongin G, Kahlmeier S, 2012. The pandemic of physical inactivity: global action for public health. Lancet 380:294-305.

Lakhotia S, Lassarre S, Rao KR, Tiwari G, 2020. Pedestrian Accessibility and Safety around Bus Stops in Delhi. IATSS Res 44:55-66.

LaMotte LR, 1994. A note on the role of independence in t statistics constructed from linear statistics in regression models. Am Stat 48:238-40.

Lee IM, Shiroma EJ, Lobelo F, Puska P, Blair SN, Katzmarzyk PT, 2012. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet 380:219-29.

Lewis-Beck M, Bryman AE , Liao TF, 2003. The Sage encyclopaedia of social science research methods. Sage Publications, London, UK.

Mandic S, Jackson A, Lieswyn J, Mindell JS, Bengoechea EG, Spence JC, Coppell K, Wade-Brown C, Wooliscroft B, Hinckson E, 2020. Development of key policy recommenda-

tions for active transport in New Zealand: a multi-sector and multidisciplinary endeavour. J Transp Health 18:100859.
Mangla P, Gupta S, Chopra A, Bhatia V, Vishwakarma R, Asthana P, 2020. Influence of socio-economic and cultural factors on type 1 diabetes management: report from a tertiary care multi-disciplinary diabetes management Center in India. Indian J Pediatr 87:520-25.
Mansfield ER, Helms BP, 1982. Detecting multicollinearity. Am Stat 36:158-60.
Martynenko TS, 2021. Lifestyle diseases: health in the contemporary city. Rudn J Sociol 21:18-35.
Miles J, 2005. R squared, adjusted R-squared. In: Encyclopaedia of Statistics in Behavioral Science; John Wiley & Sons, Ltd.: Chichester, UK.
Morgan JA, Tatar JF, 1972. Calculation of the residual sum of squares for all possible regressions. Technometrics 14:317-25.
Ngom R, Gosselin P, Blais C, Rochette L, 2016. Type and proximity of green spaces are important for preventing cardiovascular morbidity and diabetes - a cross-sectional study for Quebec, Canada. Int J Environ Res 13:423.
Oshan TM, Smith JP, Fotheringham AS, 2020. Targeting the spatial context of obesity determinants via multiscale geographically weighted regression. Int J Health Geogr 19:11.
Oshan, T, Li Z, Kang W, Wolf L, Fotheringham A, 2019. Mgwr: a python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. ISPRS Int J Geoinf 8:269.
Pasala SK, Rao AA, Sridhar GR, 2010. Built environment and diabetes. Int J Diabetes Dev Ctries 30:63.
Pinter-Wollman N, Andrea J, Nancy MW, 2018. The impact of the built environment on health behaviours and disease transmission in social systems. Philos Trans R Soc Lond B Biol Sci 373:20170245.
Quiñones S, Goyal A, Ahmed ZU, 2021. Geographically weighted machine learning model for untangling spatial heterogeneity of type 2 diabetes mellitus (T2D) prevalence in the USA. Sci Rep 11:6955.
Rogerson PA, 2009. Monitoring changes in spatial patterns. The SAGE handbook of spatial analysis. SAGE, USA, pp.343-354.
Salmerón R, García CB, García J, 2018. Variance inflation factor and condition number in multiple linear regression. J Stat Comput Simul 88:2365-84.
Saudi Gazette Report, 2020. Jeddah Boasts of 23 Walkways, Covering 49 km. Saudi Gazette, July 22, 2020. Available from: https://saudigazette.com.sa/article/595843
Tabb LP, Ortiz A, Judd S, Cushman A, McClure LA, 2020. Exploring the spatial patterning in racial differences in cardiovascular health between blacks and whites across the United States: The REGARDS Study. J Am Heart Assoc 9:016556.
Temelkova-Kurktschiev T, Stefanov T , 2012. Lifestyle and genetics in obesity and type 2 diabetes. Exp Clin Endocrinol 120:1-6.
Tiwari A, Aljoufie M, 2021. Modeling spatial distribution and determinant of PM2.5 at micro-level using geographically weighted regression (GWR) to inform sustainable mobility policies in campus based on evidence from King Abdulaziz University, Jeddah, Saudi Arabia. Sustainability 13:12043.
Torun AÖ, GöçerK, Yeşiltepe D, Argın G, 2020. Understanding the role of urban form in explaining transportation and recreational walking among children in a logistic GWR model: a spatial analysis in Istanbul, Turkey. J Transp Geogr 82:102617.
Tu J, Tu W, 2018. How the relationships between preterm birth and ambient air pollution vary over space: a case study in Georgia, USA using geographically weighted logistic regression. Appl Geogr 92:31-40.
Tu J, Tu W, Tedders SH, 2012. Spatial variations in the associations of birth weight with socioeconomic, environmental, and behavioral factors in Georgia, USA. Appl Geogr 34:331-44.
Wang L, Chen R, Sun W, Yang X, Li X, 2019. Impact of high-density urban built environment on chronic obstructive pulmonary disease: a case study of Jing'an District, Shanghai. Int J Environ Res 17:252.
Wheeler DC, Páez A, 2010. Geographically weighted regression. In: Handbook of Applied Spatial Analysis, 461-86. Springer, Berlin Heidelberg, Germany.
WHO, 2016. Diabetes country profiles. World Health Organization, Geneva, Switzerland. Available from: https://www.who.int/diabetes/country-profiles/sau_en.pdf
Wilson N, Brander B, Mansoor OD, Pearson AL, 2014. Building a reliable measure for unobtrusive observations of street-connecting pedestrian walkways. J Urban Health 91:1129-35.